ISPRS WG VIII/10 Workshop 2006

Remote Sensing Support to Crop Yield Forecast and Area Estimates

Stresa, Italy

Editors
B. Baruth, A. Royer, G. Genovese

Organisers
Joint Research Centre
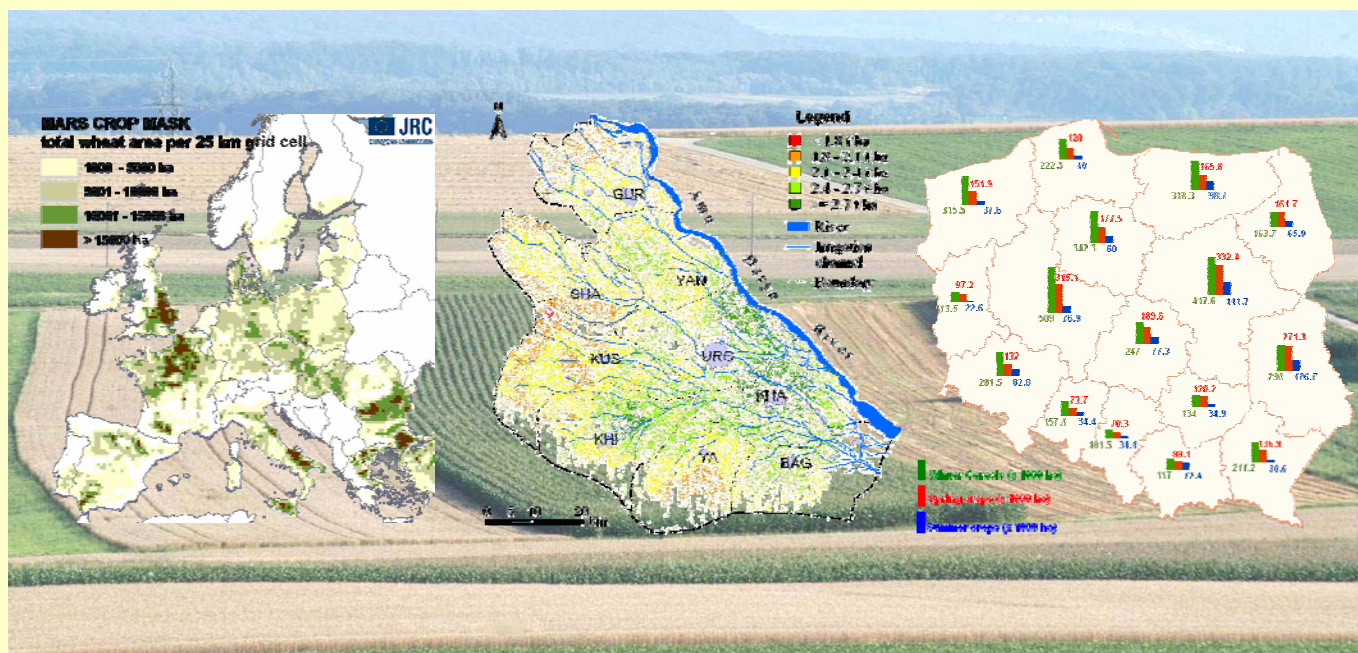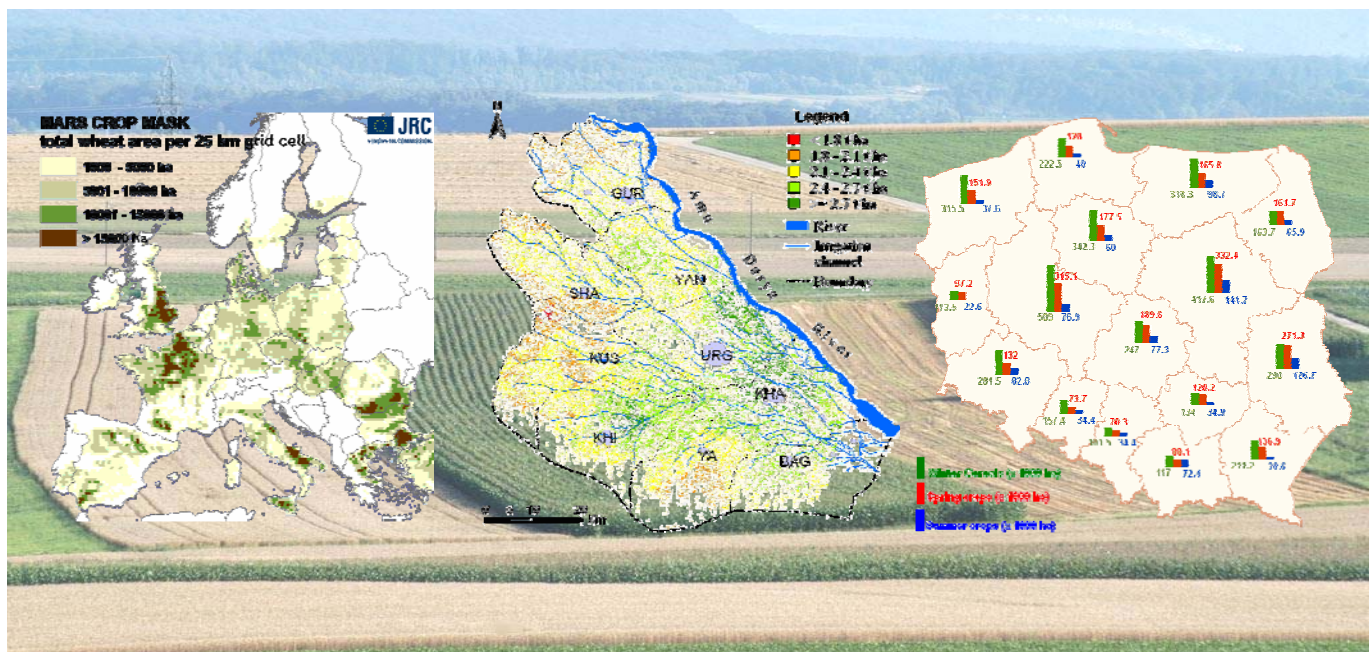Institute for the Protection and Security of the Citizen

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Workshop Organising Committee:

Antoine Royer, Joint Research Centre, Ispra, Italy
Bettina Baruth, Joint Research Centre, Ispra, Italy
Giampiero Genovese, Joint Research Centre, Italy

Foreword

The workshop was held from the 30th of November until the 1st of December in Stresa (Italy) jointly organized by the Joint Research Centre, Institute for the Protection and Security of the Citizen, Agriculture Unit, MARS STAT action and the ISPRS working group VIII/10.

Almost 80 participants from 25 countries came together under the workshop topic 'remote sensing support to crop yield forecast and area estimates' to review the main use of remote sensing information for yield forecast and area estimates at national or regional level. The two days workshop shared national, GEOLAND FP 6 project and JRC experiences in the use of satellite data in crop monitoring.

Reviewing the use of remote sensing for crop yield forecast, research in progress was presented as well as operational systems integrating remote sensing information for the yield forecasting using various sensors and approaches. The state of the art was presented for the estimation of crop area estimates from remote sensing as well as an assessment of remote sensing capabilities to achieve area estimates.

We would like to express our sincerest gratitude to all the authors, speakers and participants contributing to a lively and interesting workshop

Bettina Baruth   Giampiero Genovese   Antoine Royer

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CROP YIELD FORECAST WITH NOAA AND SPOT-VEGETATION DATA IN MOROCCO

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KEYWORDS: Yield forecasting; Regression; Wheat; Morocco; NDVI; AVHRR; SPOT-VEGETATION; Land Cover.

EXTENDED ABSTRACT

The purpose of this study is to prospect the feasibility of early wheat (Triticum aestivum L.) yields forecasting models for Morocco based mainly on 1km spatial resolution Normalized Difference Vegetation Index (NDVI) information. The forecasting models could help Moroccan producers and policy-makers to make early decisions and plan annual imports, as actually the official estimations are based on costly field surveys, while the data are released only a few days before or even after the end of the season (harvest in May-June). In Morocco, wheat grain yields are mainly determined by weather, while technological and socio-economic factors are relatively negligible. In fact, there was no evidence of wheat yield trend during the last 15 years in Morocco, probably masked by the high (38%) inter-annual yield variability. In this study, the analysis dealt with data of the period from 1990 to 2005, and the evaluation was performed at national level. The NDVI data was taken from both the earth observation systems NOAA-AVHRR (data from 1990 to 2004, taken from The MARS-STAT unit of the EC Joint Research Centre at Ispra, Italy) and SPOT-VEGETATION (data from 1999 to 2005, taken from Vlaamse Instelling voor Technologisch Onderzoek at Mol, Belgium). The complete series were available for SPOT-VEGETATION, while 3 of the 15 years (1991, 1993, and 2004) were missing because of lacking NDVI data in this crucial period for NOAA-AVHRR. Correlations between wheat yields and NDVI were improved by enhancing in advance the NDVI-imagery registered by both sensors: (1) use of dekadal (10-days) NDVI composites, computation of the median of the cropland pixels, as spatial distribution of NDVI pixels displays a non-Gaussian shape at national level, and; (2) temporal integration, by summing the NDVI values over important crop growing stages, over the 9 dekads in the months February to April (indicated by ΣNDVI, with potential range from 1.35 to 6.75). The Global Land Cover map of the year 2000 for Africa (GLC2000, version 5.0) which also has a 1 km resolution was used to select only the NDVI pixels that are related to rainfed agricultural lands. In the GLC2000, the agricultural parts are defined as areas with over 50% cultures and/or pastures. High correlations were observed between official wheat yields statistics and the median values of the dekadal NDVI for both AVHRR and SPOT, slightly higher than the mean values. The correlation increased linearly and continuously from the first dekad of February (R2 >40%*** and R2 >10%***, for NOAA and SPOT respectively) to the second dekad of March (R2 >70%*** for both sensors), indicating the stable property of NDVI as a predictor. High correlation (R2=71%***) was found between the dekadal NDVI's from the two sensors (from January to April, 69 dekads), for the 1998-2005 time period. The regression line between the NDVI's of the two sensors was not significantly different from line 1:1, but with a significant bias of +0.08 for the dekadal NDVI/SPOT, indicating a possible joint use of the two datasets for crop yield predictions. The correlations between official wheat yields and the median ΣNDVI were high, reaching R2=85%*** and 80%*** at the third dekad of April, respectively for AVHRR and SPOT. A multiple linear regression model was used to forecast wheat yields based on a combination of seasonal precipitations and the ΣNDVI/AVHRR as predictors, and data from 1990 to 2004. An additional part (14%) of the remaining unexplained yield variation was accounted for by two non intercorrelated and non-overlapped seasonal precipitations (partial R2=7%*** for both autumn and spring seasons), collected for the same time period from all the available 31 synoptic weather stations of the country. Whereas ΣNDVI and precipitation explain the bulk of the variability in Moroccan wheat grain yields, the remaining "unexplained variance" must be due to a plethora of other factors, mainly errors in the basic inputs (official statistics, precipitation and remote sensing data) and effects not covered by the regression models like diseases or hot winds that sometimes occur during spring season. A true validation of the multiple linear regression model based on the ΣNDVI/AVHRR and two-season precipitations predictors was performed for the year 2005, which was relatively dry (average annual precipitation = 228mm at national level). The incorporated ΣNDVI value in the model for the year 2005 were taken from SPOT VEGETATION sensor, as AVHRR images were not available for this year. Compared to official statistics, national wheat yield was early predicted with only -100 kg.ha-1 (-9%) error at the third dekad of April, which is relatively low if compared to the high year to year wheat yield variation in Morocco. The proposed approach is relatively simple, low cost, robust and could be applied to accurately early forecast wheat yields in Morocco at national level based on few data.

CROP MASKING – NEEDS FOR THE MARS CROP YIELD FORECASTING SYSTEM

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KEY WORDS: Agriculture, Land Cover , GIS, Remote Sensing

ABSTRACT:

The objective of the Mars Crop Yield Forecasting Systems is to provide precise, scientific, traceable independent and timely forecasts for the main crops yields at EU level. The forecasts and analysis are used since 2001 as a benchmark by analysts from DG – Agriculture and Rural Development in charge of food balance estimates. Core of the Crop Yield Forecasting System is a spatialized crop growth models that works on simulation units with assumed homogenous growth conditions. These results are aggregated at regional level to be used as yield predictors. Within this process the usage of crop masks for an accurate aggregation is envisaged. Therefore specific crop masks needs have been identified and crop masks tested.

1. INTRODUCTION

The objective of the Mars Crop Yield Forecasting System (MCYFS) is to provide precise, scientific, traceable independent and timely forecasts for the main crops yields at EU level. The forecasts and analysis are used since 2001 as a benchmark by analysts from DG – Agriculture and Rural Development in charge of food balance estimates. The MARS Bulletin with the forecast results and additional analysis is published, nearly monthly, on paper and on an internet site: http://mars.jrc.it/stats/bulletin with public access.

Core of the Crop Yield Forecasting System is a spatialized crop growth model that requires input concerning the area cropped to ensure a proper aggregation of the forecasted results.

Currently this is assessed for the crop growth model via the soil suitability for the simulation unit. Aggregation to higher administrative levels is directly based on area statistics. As the currently used soil suitability doesn't reflect properly the crop pattern, efforts were made to investigate the use of different crop masks.

In addition the system is supported by the use of Remote Sensing data, namely SPOT-VEGETATION, NOAA-AVHRR, MSG-SEVIRI and MODIS TERRA. In this context crop masks are needed for a better exploitation of the mixed signal due to the coarse resolution. Moreover crop masks are used by the experts of the team to focus the analysis.

These different applications request different crop masks in terms of stratification, spatial resolution and update frequency.

2. CROP MASKS

The actual crop pattern results from natural factors, technology and market conditions. Whereas technology and market conditions are difficult to catch, natural factors can be characterized and thereof a maximum cropping area defined. The interaction of these factors and the resulting crop acreage is reflected in the statistics which are in general based on administrative units. As a result crop mask creation can be a process of disaggregating crop area statistics to spatial units suitable for specific crop production derived from biophysical conditions. This process is often supported by land use / land cover information derived from Remote Sensing (e.g. Corine Land Cover 2000, EEA, 2000) or area frame surveys, like LUCAS (EEA, 2006). The finally obtained crop mask can indicate the presence or the acreage of a crop within a spatial unit (e.g. pixel of 1 km * 1 km or landscape units).

2.1 Crop masks for remote sensing

In the frame of the MCYFS mainly sensors with a coarse spatial resolution (1 km) like NOAA-AVHRR and SPOT VGT are used. As a consequence mixed signals are derived that need to be unmixed to better reflect the crop behaviour in the signal. As work is done on profile analysis of time series the crop masks have to ensure enough spatial and temporal aggregation to capture the changing land cover pattern over time, e.g. crop rotation scheme. Typically a crop mask used within the remote sensing work of MARS STAT should indicate the presence or non presence of non-irrigated arable land and crop present, ideally expressed as a percentage of a 1 km resolution map.

2.2 Crop masks in the frame of CGMS

For the crop growth model which is used in the frame of the MCYFS crop masks can be used for the aggregation process of simulated crop growth parameters to derive yields and production estimates for administrative regions. For a better understanding of the crop masks requirements the aggregation method is explained in the next section.

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* Corresponding author.

2.3 CGMS aggregation approach. The crop growth model WOFOST (Diepen, 1989) which is used within CGMS is a point model. In order to apply this model throughout Europe regions have to be identified where homogenous crop growth conditions can be assumed. This is done by taking into account climatic conditions and soil properties.

Therefore the soil mapping units (SMU) of the Soil Geographical Database of Europe (SGDBE) are intersected with the MARS climatic grid cells, which have a resolution of 50 km by 50 km. This intersection called Elementary Mapping Unit (EMU) is the smallest simulation unit for which results are produced by the CGM – system. Based on these simulation units the obtained results are aggregated to administrative regions, using acreage statistics, so that they can be used as regional yield predictors (JRC, MARS STAT, 2004).

This aggregation is performed in several steps. Firstly the soil mapping unit which is delineated in the soil map, consists of one or more soil types. Qualitative and quantitative attributes are only given for these soil types. The composition of these soil types (called soil typological unit, STU) that form the soil mapping unit are given in percentage. For these STUs an assessment is performed whether they are suitable or not for crop growth to determine the suitable crop growth area within the SMU. The following parameters are used to assess the crop specific soil suitability: slope, texture, agriculture limiting phase, rooting depth, drainage, salinity and alkalinity. But as a result the selection based on these parameters led to a general overestimation of cultivated areas for the majority of the crops and to a general underestimation of the cultivated area for maize and root crops (European Commission, 2006). As a consequence only very basic soil suitability rules are used in order to exclude non-suitable soils like rocks or sealed areas.

If once the suitable area for possible crop growth is established within the EMU, the simulation result of each EMU is multiplied by the EMU area suitable divided by the sum of all the area suitable in the selected statistical region, in this case NUTS 2 regions (NUTS – Nomenclature of territorial units for statistics).

For the next aggregation level to NUTS 1 a weighted sum is calculated based on NUTS 2 area statistics. This implies that crop masks to be used in the aggregation process from the EMU to the selected administrative unit (NUTS 2) have to be based at least on NUTS 3 statistics or making use of a finer spatial disaggregation by means of enhanced statistical procedures like it was performed for the CAPRI-Dynaspat land cover masks (Koeble 2006).

2.4 Crop masks for the analysis and derivation of C-indicators Within the analysis and interpretation of results from the crop growth models experts concentrate their analysis on the main production areas. In this context actual crop masks are of great importance as there are shifts in production areas from year to year. Furthermore a big part of the analysis is based on indicators weighted by the occurrence of the relevant crop (respectively non irrigated arable land) within a predefined spatial unit (in general NUTS 2), the so called C-indicators (Genovese, 2001).

3. MARS CROP MASK APPROACH

Due to the different crop masks purposes within the MCYFS it is clear that there is not a unique solution in terms of thematic stratification and spatial resolution that can solve all the requirements.

For the aggregation process, ideally a European wide land-use map with yearly updates showing the crop pattern based on at least NUTS 3 statistics should be used. As this is not realistic for the time being a simple solution which is easy to update has been chosen to produce the crop masks in order to facilitate the analysts work.

3.1 Methodology

Corine Land Cover 2000 and Global Land Cover 2000 (Bartholome & Belward, 2005) are used to spatially distribute official statistical data about crop acreages into CGMS grids with 50 km and 25 km resolution.

The processing includes the following steps:
- compilation of arable land mask using selected CLC/GLC data
- GIS overlay n^o1: NUTS regions vs. arable land mask
- calculation of the total area of the arable land in each NUTS region
- calculation of crop ratios for each NUTS region: $R_i=C_i/NA_i$ where C is crop area and NA is total area of arable land in each NUTS region
- GIS overlay n^o2: CGMS 25km/50km grid vs. GIS overlay n^o1
- calculation of crop areas in each grid: $GA_j=\sum(R_i*GNA_i)$ where R_i is crop ratio for each NUTS region and GNA_i is the area of arable land from NUTS region falling into selected grid
- based on these crop areas per grid re-distribution of statistical crop acreage data.

Homogeneous distribution of each crop over the arable land in each NUTS region is assumed in this approach. The smaller the NUTS region areas (i.e. more detailed crop statistical data) are, the more precise results may be expected.

Based on the availability of input data the following area was covered: EU25 countries plus Bulgaria, Norway, Switzerland, Romania and Turkey. The following crops were selected: soft wheat, durum wheat, wheat total, barley, rye, grain maize, rape, sunflower, potato, sugar beet and rice.

3.2 Data sources

3.2.1 Land cover data. An arable land mask is needed to describe the spatial distribution of arable land inside the NUTS regions and CGMS grids. CLC2000 database represents the most comprehensive and homogeneous data layer to be used for this purpose. Nevertheless CLC2000 data do not cover the entire CGMS area where the individual crop masks are targeted. Therefore, the Global Land Cover 2000 data were used for Norway, Switzerland and Turkey to fill the gaps in the CLC2000 database.

Based on comparisons between EUROSTAT and FAO acreage statistics it was decided to choose the following combination of CLC classes to generate arable land mask:

Arable (except rice): CLC 2.1.1 (non-irrigated arable land) + 2.1.2 (permanently irrigated land) + 2.4.1(Annual crops associated with permanent crops) + 2.4.4 (Agro-forestry areas).

The only exception from this rule is the NUTS2 region ES11 in Spain, because none of the classes where mapped, but the

EUROSTAT statistics show more than 300 000 ha of arable land. It was decided to use CLC 2.4.2 class (complex cultivation pattern) as arable land mask in this region.

For the countries covered by GLC the class 'cultivated and managed areas' has been selected.

This combination of classes ensures the best match between the statistics and the derived area from the CLC, but nevertheless they are partly large discrepancies between the estimated areas in the different data sources (Table 1).

Table 1: Differences in percentage between arable land in ha derived from EUROSTAT statistics and the area derived from Corine Land Cover class 2.1.*.

Differences (%) between EUROSTAT arable land and CLC 200 arable land (2.1.*)					
AT	20,48	FI	26,55	MT	97,81
BE	22,36	FR	15,89	NL	23,34
BG	-15,21	GR	1,20	PL	0,66
CY	-195,53	HU	-10,23	PT	20,79
CZ	-5,43	IE	50,87	RO	13,09
DE	-15,89	IT	3,22	SE	-11,06
DK	-0,65	LT	23,51	SI	36,24
EE	21,39	LU	67,66	SK	-14,47
ES	9,03	LV	50,60	UK	4,96

source: EUROSTAT CRONOS data 2000

3.2.2 Statistical data about crop acreages. Considering NUTS 2 data, the most complete dataset is available through Eurostat Regions Database (http://epp.eurostat.ec.europa.eu /portal/page?_pageid=1335,47078146&_dad=portal&_schema= PORTAL). It gives consistent and reliable data of all main crops for EU 25. However some less important crops are not included (oats, beans, peas). To reduce the influence of yearly variations in crop acreages the time period 2000 – 2003 was used for most countries, as no actual data was available and this time period is close to the GLC 2000 data set.

Table 2: Total number and average area of NUTS2 and NUTS3 regions by country

COUNTRY		NUTS2		NUTS3	
		No. of regions	Average area [ha]	No. of regions	Average area [ha]
AT	AUSTRIA	9	929 540	35	239 703
BE	BELGIUM	12	254 627	43	71 309
BG	BULGARIA	6	1 843 474	28	395 703
CY	CYPRUS	1	924 821	1	924 769
CZ	CZECH REP.	8	982 537	14	563 325
DE	GERMANY	40	889 600	439	81 352
DK	DENMARK	1	4 266 920	15	285 811
EE	ESTONIA	1	4 320 851	5	868 775
ES	SPAIN	18	2 807 922	52	973 046
FI	FINLAND	6	5 434 450	20	1 640 793
FR	FRANCE	26	2 449 652	100	637 932
GR	GREECE	13	1 011 353	51	258 012
HU	HUNGARY	7	1 317 014	20	462 217
IE	IRELAND	2	3 494 358	8	877 193
IT	ITALY	20	1 499 666	103	291 689
LT	LITHUANIA	1	6 459 428	10	648 920
LU	LUXEMBOURG	1	258 722	1	259 588
LV	LATVIA	1	6 428 561	6	1 076 723
MT	MALTA	1	31 583	2	15 794
NL	NETHERLANDS	12	292 465	40	88 083
PL	POLAND	16	1 941 805	45	693 098
PT	PORTUGAL	7	1 315 689	30	307 290
RO	ROMANIA	8	2 967 082	42	566 528
SE	SWEDEN	8	5 472 586	21	2 097 427
SI	SLOVENIA	1	2 022 405	12	168 954
SK	SLOVAKIA	4	1 221 864	8	612 826
UK	UNITED KINGDOM	37	657 515	133	183 707
TR	TURKEY	26	2 964 070	81	952 233
CH	SWITZERLAND	7	570 394	26	153 975
NO	NORWAY	7	4 591 403	19	1 702 265

The average size of NUTS2 regions vary from country to country (see Table 2). There are countries where NUTS2 regions correspond to single CGMS 50 km x 50 km grid cells (Netherlands, Belgium) but it is not an exception to have NUTS2 regions covering more than 10 CGMS grid cells (France, Spain, Romania, Sweden, Finland, Norway, Ireland, Turkey). This ratio is even much bigger for countries not using

NUTS2 division at all (Denmark, Estonia, Lithuania and Latvia).

For the NUTS 3 data, which is especially important for the MCYFS for the crop mask production the situation is quite diverse not only from country to country but in some cases also within the country (e.g. Germany). Collection and administration of crop statistical data related to NUTS3+ regions are not always the responsibility of the central statistical office (or a similar institution) but this activity can be regionally distributed. Nevertheless a huge amount of crop acreage data at NUTS 3 level or even higher is available on-line but complete spatial and thematic coverage can hardly be achieved without a formal procedure of data collection and harmonization throughout the Member States.

In general the creation based on NUTS3 statistics should be favoured due to the large variation in size of the NUTS2 regions and the decreasing grid size of the MARS system (25 km x 25 km) in the future.

4. RESULTING MARS CROP MASKS

For the crops soft wheat, durum wheat, wheat total, barley, rye, grain maize, rape, sunflower, potato, sugar beet and rice crop masks based on NUTS 2 statistics (average area 2000 – 2003) for 50 km and 25 km grid cells have been created. An example is given in Figure 1. These crop masks are mainly used by the experts to focus the analysis of the crops. So far only for two selected countries crop masks using NUTS 3 statistics have been created.

Figure 1: MARS crop mask total wheat
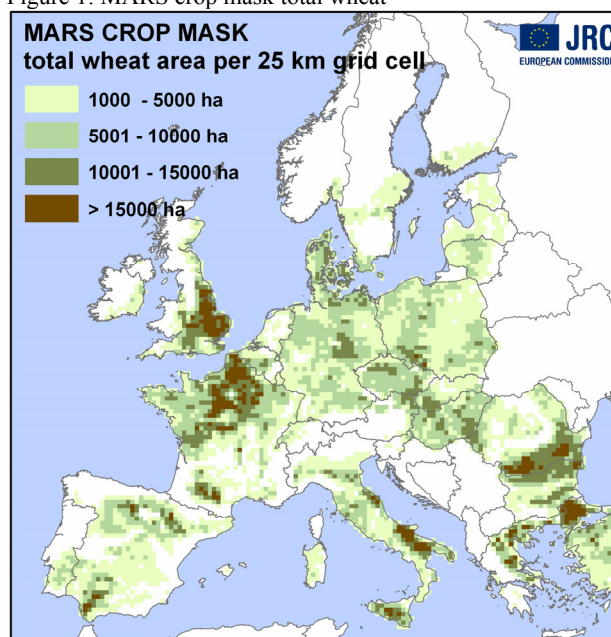
5. SUMMARY

The selected approach is a basic approach relying only on two information layers – a land cover map and regional acreage statistics. Disaggregation is performed under the basic assumption that the crops are spatial equally distributed within an administrative region. Errors introduced by this assumption are partly compensated if the administrative regions are small enough to reflect also particular situations. An advantage of the

approach is the fact that the masks are easy to update if new input data is available and quickly inserted into our system.

As long as a general coverage with NUTS 3 crop acreage statistics can not be achieved the crop masks data will not be used in the CGMS aggregation approach, but used by the experts for a focused analysis and for extraction purposes in generating agricultural specific remote sensing data products.

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GENERALIZED SOFTWARE TOOLS FOR CROP AREA ESTIMATES AND YIELD FORECAST

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Commission VIII, WG VIII/10

ABSTRACT:

The procedure that leads to the estimates of the variables of interest, such as land use and crop yield and their sampling standard deviations, is rather tedious and complex, till to make necessary for a statistician to have a stable and generalized computational systems available. The SAS is often the ideal instrument to face with these needs, because it permits the handling of data effectively and provides all the necessary functions to manage easily surveys with thousands of micro-data.

This paper focus on the use of this system in different *steps* of the survey: sample design, data editing and estimation. The information produced is, however, available for one user only, the manager of the survey.

Our idea is to reduce the time needed to process the collected data and to reduce the inefficiencies which unfortunately characterize the management and dissemination of aggregated information, without loosing the stability of the SAS and at the same time increasing the informative content of the survey. For this reason we developed a user oriented Visual Basic (VB) software, whose aim is the production of *reports* based on the data coming from the SAS central system, capable of meeting the user needs of private and public agencies involved in this sector. If SAS is excellent for large scale data processing and has a very rich function set, VB 2005 helped us develop a high quality graphical interface that make possible to personalize estimations. Particularly, in this type of survey, we may be asked to provide estimates not only at the national level, but also at provincial and local levels, in other terms we may be interested at the *estimation for domains*: VB software support the definition of a priori domains.

We feel that through the use of this two integrated systems we could help researchers and institutions working on remote sensing in agriculture in growing their interest in this kind of large scale surveys.

1. INTRODUCTION

Information is an instrument of knowledge, and learning new information means raising the level of knowledge. Information becomes "statistical" if it is the result of a survey whose aim is to respond to well-defined cognitive needs.

An informative system is a system that organizes and administers competently and efficiently the information which is necessary to pursue one or more aims.

A statistical informative system aims at rationalizing the production and the spreading of statistical information through the use of some categories of data which, as already stated, is gathered through a survey. This system is characterized by the treatment of aggregates "macro-data" and through particular attention given to meta-data and to meta-information.

Therefore the task of the statistical informative system is:

- ➢ Data collection;
- ➢ Keeping collected data by archiving it;
- ➢ Data processing by transforming it into information;
- ➢ Dissemination of information.

To do this, the informative system can make use of technological data processing. Thus, the aim of our work is the creation of a modern informative system, which can develop efficiently, through the integrated use of statistical methods for the analysis of frames of extensive dimensions (data mining), the valuable information collected and elaborated in the field of agricultural surveys.

The system we are presenting foresees the integrated use of two software appliances (figure 1): the former developed by SAS, one of the most used systems of administering information,

which deals with data-filing, sample design, data editing and estimation; whereas, the latter, developed in Visual Basic (VB), will help to administer the publication of the results and use the technique of domain estimation.
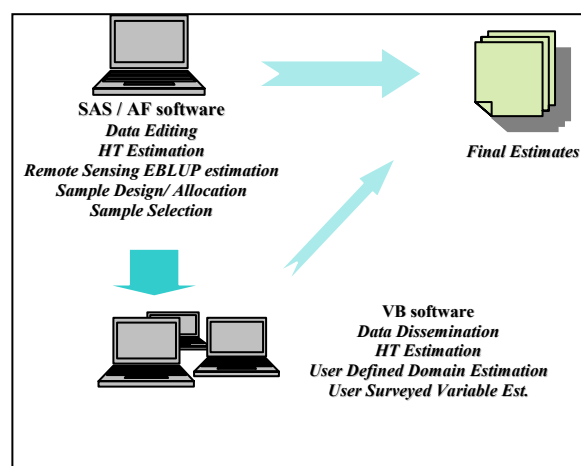
Figure1: Integrated use of two software developed by SAS and Visual Basic 2005.

In section 2 we will describe the way in which we collect data, in section 3 the problem of sampling design (Bethel, 1989), using the procedure of multivariate allocation and the technique of the *permanent random numbers* (Ohlsson, 1995) for the data mining are considered. In section 4 we will describe the problem of identification and correction of errors (data editing). In section 5 the way in which we estimate the variables of

interest will be described and in the last one the phase of data dissemination.

2. DATA COLLECTION

In this section, we will describe the way in which we have carried out a physical integration, in a single relational database, of all the information coming from the periodic surveying done on Italian national territory in the field of agriculture.

In particular, for each survey included in the system, two types of information are produced: data and meta-data.

The relational database, which we have carried out, contains an frame of points, identified univocally by a numeric code.

The frame is associated or combined with one or more classifications. In the present project the data is registered and classified by: region, province and strata. Besides the identified codes of the units, the frame contains information about their geographical location and other information that can be used for sampling as well as producing estimations of certain basic characteristics as simple aggregations and tabulations.

The survey in question is the sampling type and for this reason the database contains, besides the frame, also the sample on which the surveys were carried out.

The operations on the database are carried out through the Import Section of the SAS software.

3. SAMPLING DESIGN

For this survey we used the technique of stratified sampling and the procedure of multivariate allocation, whose development (Bethel, 1989) requires a generalization of the classical formulas of calculation of the optimal size of Neyman (Neyman, 1934; Cochran, 1977).

The stratified random selection without replacement of the units is make through the use of the well known technique of the *permanent random numbers* (Ohlsson, 1995) in which, for every unit i of the frame of N dimension is associated, independently by the others, a meaning *pseudo-random* (*pseudo* because it is generated by a *computer*) by a rectangular variable r_i. The stratified simple random sample of a survey is obtained sorting the units for strata and *random number* so that we obtain a random permutation of the units and we can select for every strata h the first units (or the last) n_h.

This technique, particularly easy to develop, assure that, after sorting the frame, every selection of adjacent units represents a random sample with inclusion probability equal to n_h/N_h.

The sample design is carried out through the Sample-Bethel section of the SAS software (figure 2).
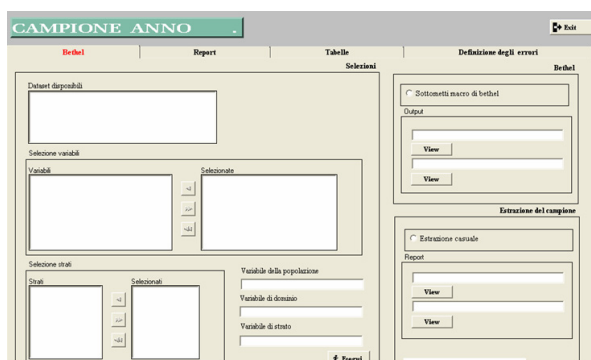
Figure 2: Section Sample-Bethel

4. DATA EDITING

For every survey of sampling or census, the problem of identification and correction of errors present in the information taken comes up.

Although there is no real agreement on the necessity of intervening automatically on the possible errors or on reconstructing the missing information, it is necessary to make the problem of coherence and completeness as automatic is possible and this means a reduction in the time necessary for the elaboration of said data as well as an improvement in the quality of the final information produced.

This last point takes on a remarkable importance if it is considered that the units in which the errors are found rarely constitute a random sub-sample of the population referred to.

Very often even a restricted number of errors can produce a wide impact on the estimation when the said number is localized in the most important units. In such a case, therefore, it is important to make sure that the errors in the units in question are found and eliminated in the most accurate way possible.

Before going ahead it is necessary to state that, according to us, the main problem is not so much in the particular system of correction adopted as in the identification of the errors.

Once the errors have been localized, the fields taken into account are transformed into missing data and, only at this stage can the phase of more or less sophisticated reconstruction of the missing information be activated. As in many surveys the partial missing information is practically inexistent, it is opportune to point out that the problem of missing data to be estimated is often generated after the identification of the errors.

The SAS section that allows data editing is structured in such a way as to allow access to six modules:

The first two are destined to find *outliers* through observation of the variable in question in two different periods of time, using *scatter* and *histograms* (figure 3);

The third allows the crossing of several variables in a set period and the finding of *outliers*;

The fourth module applies to the operations of *macro-editing* based on a manual or automatic type of correction;

The fifth allows the definition of rules concerning the compatibility plan.

The sixth applies to the correction of data and is made up of a table, which can be modified, where doubtful fields, found in preceding modules, are shown.
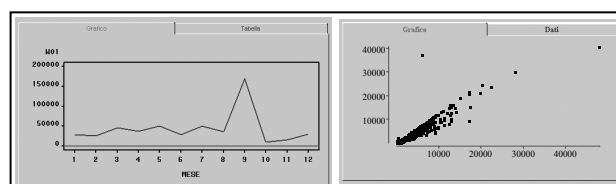
Figure 3: An example for data editing

5. ESTIMATION

Let us consider $s=\{1, \ldots, i, \ldots, n\}$ a sample consisting of n points, randomly selected by a population Ω, through the sample design which assigns to s the probability $p(s)$ to be selected. Analogically at the population, the sample s is divided in $s_1, s_2, \ldots, s_h, \ldots, s_H$. Let us consider $y = \{y_1, y_2, \ldots, y_j, \ldots, y_J\}$ a vector of the J variables of interest and $\pi_i = \sum_{i \subset s} p(s)$ the inclusion probability in the sample for the generic unit $i \in \Omega$.

Suppose that an estimate is needed for the population total of every interest variable J.

If we have no good auxiliary data or missing data, an unbiased estimator of the total $Y_j = \sum_{i \subset \Omega} y_{j,i}$ for the j variable in the population is represented, as known, by the Horvitz-Thompson estimator (Horvitz e Thompson, 1952):

$$\hat{Y}_{j,HT} = \sum_{i \subset s} d_i y_{j,i} = \sum_{i \subset s} \frac{N_h}{n_h} y_{j,i}$$

with the variance:

$$\hat{V}(\hat{Y}_{j,HT}) = \sum_{i \subset s} \sum_{z \subset s} \frac{\pi_{iz} - \pi_i \pi_z}{\pi_{iz}} d_i y_{j,i} d_z y_{j,z} =$$

$$= \sum_{h=1}^{H} d_h (N_h - n_h) S_{y_j h}^2$$

where $S_{y_j h}^2$ is the sample variance of y_j in the strata h in which the unit i is included.

π_i is the first order inclusion probability and $d_i = 1/\pi_i$.

π_{iz} denote the probability that both of the elements i and z will be included.

The estimates of the variables land use and crop yield at regional and provincial level apart from the national one, take us employing an instrument which considers these needs. The *SURVEYMEANS* procedure allows carrying out sub-populations or domains estimations (Cochran, 1977; Rao, 2003) apart from the population. In particular, for the estimates of the land use, we use *SURVEYMEANS* for totals, instead, for yield forecast we use *SURVEYMEANS* for means.

SURVEYMEANS uses the Taylor series expansion theory to estimate the variance of the mean $\hat{\bar{Y}}$ (SAS manual). The procedure computes the estimated mean as

$$\hat{\bar{Y}} = \left(\sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} \omega_{hij} y_{hij} \right) / \omega...$$

$$\omega... = \sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} \omega_{hij}$$

and the estimated variance of $\hat{\bar{Y}}$ as

$$\hat{V}\left(\hat{\bar{Y}} \right) = \sum_{h=1}^{H} \hat{V}\left(\hat{\bar{Y}} \right)$$

where if $n_h > 1$,

$$\hat{V}\left(\hat{\bar{Y}} \right) = \frac{n_h(1 - f_h)}{n_h - 1} \sum_{i=1}^{n_h} (e_{hi}. - \bar{e}_h..)^2$$

$$e_{hi}. = \left(\sum_{j=1}^{m_{hi}} \omega_{hij} \left(y_{hij} - \hat{\bar{Y}} \right) \right) / \omega...$$

$$e_h.. = \left(\sum_{j=1}^{n_h} e_{hi}. \right) / n_h$$

and if $n_h = 1$,

$$\hat{V}\left(\hat{\bar{Y}} \right) = \begin{cases} \text{missing if } n_h = 1 \text{ for } h = 1,2,...,H \\ 0 \quad \text{if } n_h = 1 \text{ for some } 1 < h < H \end{cases}$$

The estimation of the total is the weighted sum over the sample:

$$\hat{Y} = \left(\sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} \omega_{hij} y_{hij} \right)$$

and the estimated variance of $\hat{Y}$ is: (5.2)

$$\hat{V}(\hat{Y}) = \sum_{h=1}^{H} \hat{V}(\hat{Y})$$

where if $n_h > 1$, (5.3)

$$\hat{V}\left(\hat{\bar{Y}} \right) = \frac{n_h(1 - f_h)}{n_h - 1} \sum_{i=1}^{n_h} (y_{hi}. - \bar{y}_h..)^2$$

$$y_{hi}. = \sum_{j=1}^{m_{hi}} \omega_{hij} y_{hij}$$

$$\bar{y}_h.. = \left(\sum_{i=1}^{n_h} y_{hi}. \right) / n_h$$

and if $n_h = 1$,

$$\hat{V}\left(\hat{\bar{Y}} \right) = \begin{cases} \text{missing if } n_h = 1 \text{ for } h = 1,2,...,H \\ 0 \quad \text{if } n_h = 1 \text{ for some } 1 < h < H \end{cases}$$

where $h = 1, 2, ... , H$ is the stratum number, with a total of H strata

$i = 1, 2, ... , n_h$ is the cluster number within stratum h, with a total of n_h clusters

$j = 1, 2, ... , m_{hi}$ is the unit number within cluster i of stratum h, with a total of m_{hi} units

$n = \sum_{h=1}^{H} \sum_{i=1}^{n_h} m_{hi}$ is the total number of observations in the sample

w_{hij} denotes the sampling weight for observation j in cluster i of stratum h

$\mathbf{y}_{hij} = (y_{hij}^{(1)}, y_{hij}^{(2)}, ... , y_{hij}^{(P)})$ are the observed values of the analysis variables for observation j in cluster i of stratum h, including both the values of numerical variables and the values of indicator variables for levels of categorical variables.

The standard error of the mean is the square root of the estimated variance.

We can show that, not considering the clusters, the results arising by the *SURVEYMEANS* are those achieved by the formulas proposed by Horvitz e Thompson in the 1952.

After the phase of sample selection and the data-editing with the SAS, it generate a database composed by the samples for the estimates of the variables land use and crop yield. This database will be imported in the VB software, which, allows to execute the *SURVEYMEANS*. In other words, it allows to personalize the estimates, for domains: Province and Region or directly defined by the user.

6. DATA DISSEMINATION

Protection of the data contained in the database is very important. Safety, in fact, is at the basis of any project that foresees investments on data of various kinds and in particular

on data considered by the law to be "sensitive". Regarding surveys in agriculture, there is no contact with data strictly sensitive, but in our case we have preferred to deal with basic data as such. In particular, the database is protected in such a way that access can come about exclusively through software interface. In addition, access is reserved only for aggregated data or a database compiled directly by the user. Besides access to the system can come about only through the insertion of a user name and a password.

In the phase of developing the system we pre-established the attainment of certain well-defined objectives. In particular, if the SAS software whose to have bettered the organization of agricultural surveys and lead to a reduction of calculation times, the VB software should have augmented the informative capacity of such surveys.

The inspiring principle which accompanied us during the phase of the development of the software in Visual Basic 2005 was that of the simplicity of use thanks to a strong intuitive interface.
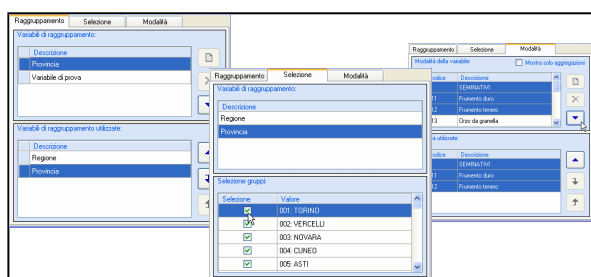
Figure 4: Settings for estimation

The result is a software that in a few clicks allows the carrying out and the personalising of crop yield estimation and land use at different levels of aggregation.

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EBLUP ESTIMATES BY USING REMOTELY SENSED DATA

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ABSTRACT:

The knowledge of auxiliary variables for entire population is a necessary task in many agricultural applications; for example a method widely applied to improve the efficiency of crop area estimations is the regression estimator (Cochran, 1977), that exploit the correlation between classified satellite images (auxiliary information) and ground surveys' data. The regression analysis offer a lot of advantages, even if it's highly affected by two main problems: the presence of outliers which usually implies instability in the regression parameters estimates and the so called scale problem (MAUP) that is the use of aggregated data increase artificially the amount of correlation between variables (Openshaw e Taylor, 1979). According to the aforesaid problems and considering that generally the final goal is to obtain crop area estimations at small area level (usually districts/provinces), the idea is to improve the direct estimator using small area models that relate the small area surface to area specific auxiliary variables, instead of using regression analysis on the sampled point (which generally represent a very small portion of the territory). Generally the linking models based on random area-effects that account for between area variations other than the variation explained by auxiliary variables are called small area models and the indirect estimator based on small area models will be called "model-based estimators".
The aim of this work is to produce area estimates of the main crops at a provincial, regional and national level, using as sampling design a stratified two-phase sampling. We improve the direct Horwitz-Thompson estimator whit the two stage model of Fay and Herriot (1979) and the EBLUP (Empirical Best Linear Unbiased Predictors) estimators (Rao, 2003).
A spatial autocorrelation amongst the small area units has been also considered to improve the small area efficiency. Spatial models are a special case of a mixed linear model and therefore EBLUP estimator con be easily obtained.
Moreover, we have valuated the importance of good auxiliary data for the success of model-based methods. In fact, cloudy whether is usually the main source of missing data in satellite images. All the missing data and outliers (considered as missing) have been imputed, whit a technique called Multiple Imputation (MI - Rubin, 1987). In the MI instead of imputing a single value for each missing value, m value are drawn from the predictive distribution $P(Y_{miss} / Y_{obs})$ and then complete data analysis is repeated a given number of times, say h.
We confirmed that the combination of small area model whit the technique of spatial autocorrelation and Multiple Imputation improve the crop area estimations compared with direct estimations. To illustrate the proposed approach, we applied the spatial EBLUP estimation and the MI method for missing covariates to the AGRIT 2005 data.

1. INTRODUCTION

The regression estimator is a classical technique used to improve the precision of a sample estimation when an auxiliary variable is available for entire the population. This technique has been widely applied to improve the efficiency of crop area estimations when classified satellite images are available as auxiliary information. The collocation inaccuracy between the ground survey and satellite images, and the difficulties to improve the positioning through geometrical correction have been considered the main problem of this technique. However, the lack of gain in efficiency when remote sensing information are linked to the ground observations is mainly due to the statistical methodology used. In particular, the regression analysis is highly affected (i) by the presence of outliers, and (ii) by the scale problem (MAUP), that is the use of aggregated data increase the amount of correlation between variables. According to (i) and (ii) and considering that usually the final goal is to obtain crop area estimations at small area level (usually districts/provinces), the idea is to improve the direct estimator using small area models that relate the small area surface to area specific auxiliary variables, instead of using regression analysis on the sampled point (which generally represent a very small portion of the territory). The scope of the present work is to produce conjectural area estimates of the main crops at a provincial, regional and national level. The direct estimator is

obtained using the Horwitz-Thompson estimator, where the sampling design is a stratified two-phase stratified sampling (i.e. the phase 1 is a stratification of the national frame using digital photo interpretation and the phase 2 is a field data collection on physical points sampled from the strata). In section 2 is described the area specific model used which is the two stage model of Fay Herriot (1979) and the EBLUP (Empirical Best Linear Unbiased Predictors) estimators. Spatial autocorrelation amongst the small area units has been also considered for improving the small area estimators. In section 3 is considered the problem of missing values and outliers in the auxiliary variable and a multiple imputation (Rubin 1976, 1987) has been used to fill-in the missing information. Finally, in the last section of the paper are discussed some results.

2. SMALL AREA ESTIMATION

Linking models based on random area-effects that account for between area variation other than the variation explained by auxiliary variables are called small area models. Indirect estimator based on small area models will be called "model-based estimators". Rao (2003) classifies the small area models in two types: (i) Basic area level models, that relates the small area direct estimators to area-specific covariates; (ii) basic units level models, that relate the unit values of a study variables to units specific covariates. Here, according to what has been

discussed earlier, a basic area level model is used. The two stage model of Fay and Herriot (1979) can be expressed as:

$$\theta_i = z_i^T \beta + b_i v_i , \qquad (1)$$

$$\hat{\theta}_i = \theta_i + \varepsilon_i , \ i = 1,...,m \qquad (2)$$

where θ_i is the characteristic under study in the small area i, related to a specific auxiliary data $z_i = (z_{1i},...,z_{pi})$, $\hat{\theta}_i$ is the direct survey estimator of θ_i, b_i 's are known positive constants , β is a $(p \times 1)$ vector of regression parameters; the v_i are the area random effect assumed to be independent and identically distributed with $E(v_i) = 0$, $Var(v_i) = \sigma_v^2$ $i = 1,...,m$ (3) and the ε_i are the independent sampling errors with $E(\varepsilon_i / \theta_i) = \psi_i$, $i = 1,...,m$ (4), where ψ_i are the sampling variance usually assumed as known. The equation (1) is the design model while the equation (2) is the linking model; combining (1) e (2) we obtain the model

$$\theta_i = z_i^T \beta + b_i v_i + \varepsilon_i , \ i = 1,...,m \qquad (5)$$

which involves the design error v_i and the model error ε_i, assumed to be independent.

The model (5) is a special case of a linear mixed model; from the linear mixed model theory the best linear unbiased predictor (BLUP) estimator can be easily obtain to θ_i and the MSE of the BLUP estimator as measure of variability. Then, if the matrix of variance and covariance of v_i and ε_i are given by (3) and (4), the BLUP estimator of θ_i is a weighted average of the direct survey estimator $\hat{\theta}_i$ and the regression estimator $z_i^T \beta$, that is $\widetilde{\theta}_i = \gamma_i \hat{\theta}_i + (1 - \gamma_i) z_i^T \widetilde{\beta}$ where $\gamma_i = \sigma_v^2 b_i /(\psi_i + \sigma_v^2 b_i^2)$ The MSE of the BLUP estimator is given by: $MSE(\widetilde{\theta}_i) = g_{1i}(\sigma_v^2) + g_{2i}(\sigma_v^2)$ where $g_{1i}(\sigma_v^2) = \gamma_i \psi_i$ and $g_{2i}(\sigma_v^2) = (1 - \gamma_i) z_i^T \left[\sum_i z_i z_i^T /(\psi_i + \sigma_v^2 b_i^2) \right]^{-1} z_i$. Comparing the leading term $\gamma_i \psi_i$ with ψ_i, the MSE of the direct estimator, it is clear that $\widetilde{\theta}_i$ gains in efficiency when γ_i is small, that is when the variability of the model error is small relative to the total variability. The BLUP estimator and the relative MSE depend on the variance component σ_v^2 which is unknown. Various methods have been proposed to estimate the variance component in a linear mixed model. By replacing σ_v^2 with an asymptotically consistent estimator $\hat{\sigma}_v^2$, it is possible to obtain the empirical best linear unbiased predictor (EBLUP) and the MSE estimation. The model (5) assume iid small area effects v_i. In this paper, to improve the efficiency of small area estimators, a spatial autocorrelation amongst the small area v_i has been considered. The covariance matrix of the v_i, earlier set equal to $G = \sigma_v^2 I_m$, is now given by $G = \sigma_v^2 (I - \rho W)$. The elements of W have been defined as binary values that is $W_{ij} = 1$ if the small area i is physically continuous to the small

area j and $W_{ij} = 0$ otherwise and the constant ρ is a measure of the level of spatial autocorrelation. Spatial models are a spatial case of a general linear model and therefore EBLUP estimator con be easily obtained.

3. IMPUTATION OF THE MISSING AUXILIARY VARIABLE

Availability of good auxiliary data are crucial for the success of any model-based methods and therefore attention have been given to their control. Missing data or outliers in satellite images are mainly due to cloudy whether and their detection have been carried out using graphical tools. All the missing data and outliers (considered as missing) have been imputed. In order to take into account, in the complete data standard errors, the error generated by the imputation, a multiple imputation (MI) has been carried on. In the MI instead of imputing a single value for each missing value, m value are drawn from the predictive distribution $P(Y_{miss} / Y_{obs})$ and then complete data analysis are repeated m times, once for each imputation. Important is the choice of the imputation model. If Y_1 is a fully observed variable, Y_2 given the observed Y_2 is high then better imputation can be obtained by using Y_1 and the observed Y_2 for the imputation; this means that an imputation model should preserve the relationships among variables measured on a subject and therefore a full parametric model for $Y = (Y_1, Y_2)$ to impute for non-response should be used.

Here, to impute missing values in the explanatory variables z_i, it is assumed that $y_i = (z_i, \hat{\theta}_i)$, $i = 1,...,m$ are independent realizations of a random vector $Y = (Z, \hat{\theta})$ with a multivariate normal distribution; that is $(z_i, \hat{\theta}_i)$, $i = 1,...,n /(\mu, \Sigma) \sim$ iid $N(\mu, \Sigma)$, where (μ, Σ) are the unknown parameters. Considering that are not available information about (μ, Σ) an improper prior is applied. MCMC method are then used to obtain m independent drawn from the predictive distribution $P(Y_{miss} / Y_{obs})$.

4. RESULTS

To apply the EBLUP estimators it is necessary to know the direct estimators and the relative sampling errors of the main crops at a province level. Moreover, σ_v^2 or (σ_v^2, ρ). if a spatial autocorrelation among the small areas is considered, need to be estimate. Here, σ_v^2 and (σ_v^2, ρ) have been estimate using REML; the EBUP estimators and RMSE have been calculated using the linear mixed models formulas. For all the crops both models (with/without spatial autocorrelation) have been fitted and the one with a larger variance reduction has been chosen.

Before fitting the linear mixed model, provinces with missing value or outliers (mainly due to cloudy whether) in the auxiliary variable, have been detected. All the outliers have been considered as missing and the unknown missing data have been replaced with m=100 simulate values.

Crop	A	B	R^2	Spatial Correlation	% missing	% missing outlier	% Variance reduction
Hard wheat	1934	0,099	0,9851	No	6,63	6,63	28,16
Wheat	407	0,097	0,93051	No	3,70	3,70	15,79
Barley	124	0,090	0,98269	No	30,81	30,81	34,47
Maize	439	0,083	0,98669	Yes	1,57	18,16	32,69
Sun-flawer	69	0,109	0,96738	Yes	16,56	37,79	30,83
Soya	-69	0,114	0,95965	Yes	0,32	17,43	38,99
Sugar beet	405	0,121	0,87175	No	7,92	16,81	18,37
Tomato	315	0,081	0,72850	No	40,15	60,64	14,97

Table 1: Estimates of Parameters for Small Area Estimation.

Some of the results have been summarized in the table 1. Here for each crop are shown the estimates of the parameters for small area estimation, the value of the correlation coefficient between the direct estimator and the auxiliary variable, the % of missing values and the reduction of the variance. The variance reduction in table 1 have been calculated as a national average, of course bigger variance reduction have been obtained for some province. However, the models for all the crops improve the direct survey. The spatial model further improves the estimates for three crop (maize, sunflower, soya).

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INTRODUCTION OF CHINA CROPWATCH SYSTEM WITH REMOTE SENSING

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KEY WORDS: Crop Monitoring, Remote Sensing, China, System

ABSTRACT:

This paper introduces the progress of China Crop Watch System with Remote Sensing (CCWS). Crop-relevant information is important for the national economy and the people's livelihood. It is also beneficial information for grain trade and agricultural production. With about 20-years' researching experiences, China CropWatch System was developed by Institute of remote sensing applications (IRSA), Chinese Academy of Sciences (CAS) in 1998 and operated since then. The CCWS covers the entire China and 46 main grain growing countries in the world. The monitoring contents are crop growing condition, crop production, drought, crop plantation structure and cropping index. In line with 9 years' operation and improvement, the CCWS publishes 7 month bulletins and 20 newsletters every year, which had become important information sources of government bodies.

1. INTRODUCTION

Crop-specific information is collected mainly through surveys of standing crops in agricultural research stations and agro-meteorological stations. The method mainly consists of on-the-spot visual assessment. However, the number of such stations is limited because of the high cost of maintaining them. Also, spatial variation in physi-chemical properties of soil and farming practices makes it difficult to extrapolate the data from one station to represent a larger area. Therefore, it is necessary to have a better method of collecting crop-specific information.

Remote sensing technology can obtain both the macro and the micro information about the monitoring target (Sun Jiulin, 1996). The large-scale crop information can be monitored by using remote sensing technology (Chen Shupeng, 1990). In past 30 years, it has seen commendable progress in the use of remote sensing to monitor crops and remote sensing has made it possible to obtain quantitative crop-specific information on a regional scale or global scale. The China CropWatch System (CCWS) has been a success application of remote sensing technology in crop monitoring. With about 20 years' of research experience behind it, the Institute of Remote Sensing Applications (IRSA) of the Chinese Academy of Sciences (CAS) developed the system in 1998 and has kept it into operation ever since. CCWS covers entire China and 46 major grain-growing countries of the world. The system served more than 20 departments in China.

The structure, monitoring contents, operation, progress and future activities of the system were described in detail in the paper.

2. SYSTEM CONTENTS

CCWS consists of seven models: crop growth monitoring, drought monitoring, grain production estimation, crop production prediction, crop planting structure inventory, cropping index monitoring, and grain supply–demand balance and early-warning (Figure 1). The monitoring can be carried out on different scales or levels ranging from a county through a province and the whole country to the main producing countries in the world.
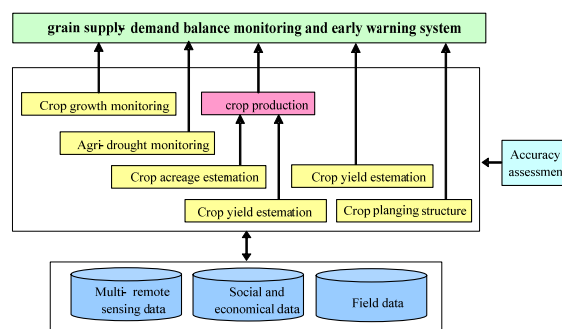
Figure 1. Contents of China crop watch system using remote sensing

2.1 Crop growth Monitoring

Crop growth reflects the growth of seedlings, an early stage in a crop's growth, as well as the metaphase and the anaphase of each crop as it matures and the changing trends in its yield. Monitoring crop condition with remote sensing can get the condition of cereal crop seedlings, as well as the status and trend of their growth. It also helps to acquire the crop production information (RAO M. V. K, Ayyangar R. S, 1982).

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CCWS monitors crop growth with two methods: real-time monitoring and crop-growing process monitoring. In real-time monitoring, maps of the crop condition are generated from the difference between the vegetation index of the previous year and the current year (Wu B F, 2000). The map shows different grads of crop growth, each in a different colour. Spatial difference in crop growth can easily be seen from the map. AVHRR and MODIS data are used, large coverage makes it possible to monitor the crop continuously and dynamically. In crop growing process monitoring, growing profile of crops can be generate by collocate the remote sensed data along time; it can reflect the change of crop parameters from planting, seedling, tassel, to maturation and harvest (Zhang F, 2004; S. M. E. Groten, 1993). Normalized difference vegetation index (NDVI), Leaf area index (LAI) and net primary productivity (NPP) are used to monitor the crop growth in different period during the crop-growing season. Different regions has different indicator, NDVI, LAI or NPP.

2.2 Drought Monitoring

Agricultural drought is a natural disaster when water supply cannot meet the needs of the growing crop. China is one of the countries in the world that suffer from serious droughts, which reduce the country's grain production considerably. CCWS monitors the drought by computing indices from satellite data, which have strong relationship with drought, and then building drought model with these indices. Regular monitoring can not only predict droughts but also estimate their severity. The prediction and estimation of the drought development can be realized by monitoring the crop drought continuously.

2.3 Crop production Prediction

By monitoring the crop planting area and predicting the yield, CCWS can make a crop production prediction one month before the harvest. Eight crops, including winter wheat, spring wheat, early rice, semi-late rice, late rice, spring maize, summer maize and soybean are covered in the activity.

2.3.1 Yield prediction: CCWS adopts four models for yield prediction, namely the agro-meteorological model (Meng Q Y, 2004), the remote sensing index model (Cook, Paul W, 1995), a combination of both, and the biomass model. The biomass model combines inputs from three models, namely the photosynthetically active radiation (PAR) model, the light use efficiency model, and the land surface energy balance model, along with AVHRR/TM data from remote sensing to calculate regional total crop biomass; that value is then used in conjunction with the harvest index. CCWS generates the first crop yield prediction a month before the harvest and the second estimation one month after harvest.

2.3.2 Crop planting area monitoring: A method based on two independent sampling frames is proposed for estimating the area using remote sensing technology together with sampling on the ground. By stratifying the main crop-growing areas into regions and applying stratified cluster sampling frames to the data from remote sensing, crop planting ratio (that is, the proportion of the total area sown to the total arable land area) are monitored, and the transect sampling frames and GVG (integration of GPS, Video and GIS) sampling system are used to estimate each crop's planting ratio (that is, the proportion of area under a given crop to the total sown area). Using these two ratios, the total sown area under each crop can be estimated.

2.3.3 Production prediction: On the basis of the estimation of areas and yield per unit area), CCWS predicts the total yield of each of the eight crops in China. Besides, it makes it feasible to carry out the grain supply–demand analysis on different spatial scales. The model provides the results of such analyses, and an early warning when needed, to users. As with other models, this model too can provide information for any specific area or region specified by the user.

3. OPERATION AND APPLICATION

China CropWatch System has been put into operation since 1998. Every year, 7 monthly bulletins and 20 newsletters are released, covering crop condition, crop acreage and yield, drought, agro-meteorology, cropping index and crop planting structure, as well as grain production. The results of monitoring were also initially made available on the intranet of the government and later on the Internet as well.

In its 9 years' operation, the CCWS has published more than 60 monthly bulletins and over 160 newsletters, which had become a important information source for government bodies. A highlight of the part played by CCWS is its accurate prediction that domestic grain production in 2000 would decrease by 3% and that in 2001 would remain at the same level as that of the previous year, which proved immensely useful to decision-makers involved in macro control.

4. VALIDATION

CCWS has its own validation program. Each year, a few validation sites have been selected to do the field measurement for verifying specific results. The crop LAI every 10 days and crop type proportion have been measured to verify the crop condition and crop acreage. Validation shows that the accuracy is up to 97% for plant proportion and 95% for crop type proportion (He L H, 2004; Li Q Z, 2004).

After comprehensive validation work have been done in different area of China during the last 9 years, the accuracy of each monitoring item for all monitoring content in CCWS is proved to be higher than 95%, which can meet the users' requirement on accuracy for the system (Wu B F, 2004; Li Q Z, 2004).

5. PROGRESS

CCWS has been making great progress in terms of content, quality, range, and frequency each year since 1998.

5.1 Monitoring Area

The CCWS continuously expands its monitoring area. From 1998 to 2006, its monitoring area has expanded from east China to national wide, to north and South America, to Australia and Thailand. Now, almost all the main grain producing countries in the world are monitored by CCWS. Meanwhile, the CCWS continuously expands its monitoring contents, from crop condition monitoring, crop acreage estimation and crop yield prediction, to grain production, crop structure, cropping index, etc (Wu B F, 2004).

5.2 Data Source

NOAA/AVHRR, SPOT/VGT, Landsat TM used to be the main data source of the system. But now CCWS is converting its main data source to MODIS, IRS P6 and RadarSat. IRS data can cover a large area than TM at the same expense. Experiments and analyses were carried to evaluate the applicability of a new remote sensing data before it is used in the system. Corresponding data pre-processing systems were developed to process these data which can also guarantee the data quality.

5.3 Methodology

CCWS has been continually improving its methods on the following aspects in the last 9 years:

5.3.1 Crop yield prediction: There are four models for the prediction of yield per unit area within CCWS, including agro-meteorological model, remote sensing index model, a combination model of the above two and the biomass model. Each model has its own value. Four models are integrated into one value based on the ground observation data and for different regions. The zonal suitability of different models was also discussed (Xu Xingang, 2007).

5.3.2 Drought monitoring: Vegetation Condition Index and Temperature Condition Index from remote sensing data are used to calculate Vegetation Health Index, with different weight coefficients. Weight coefficients are based on the relation analysis of two indices and soil moisture from ground observation for each drought zone of China (Mu Lingli, 2006). Vegetation Health Index has been used to monitor drought since March 2005.

5.3.3 Crop growth monitoring: Taking the main food crops as monitoring target, CCWS studied the suitability and validity of six remote sensing indices in different zones, for different crops and at different growing periods both in real-time monitoring and crop growing process monitoring. The six remote sensing indices used in the study are NDVI, LAI, NPP, TCI, VCI and NDWI. It found that NDVI, LAI and NPP are good indices. The country scale index collection for crop growth monitoring with remote sensing were build after research (Meng jihua, 2006).

5.4 Systematization

While continuously researching and applying new methods and models to the system, CCWS also improve the systematization of the system. Systems and models are developed for different purposes of monitoring. Systematization helped the system to generate standard monitoring result, which can also help to increase the efficiency of the system by reducing its production time.

6. FUTURE ACTIVITIES

To improve its services, CCWS development are focusing on the following aspects: (1) Reduce the operational expense by reducing the ground survey and increase the use of remote sensing data in the system. (2) Develop a new serving method for delivering crop relevant information to clients. (3) Improve the quality of existing products. (4) Improve the systematization degree of the system.

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CROP AREA ESTIMATES WITH MERIS DATA ON BELGIUM AND POLAND

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ABSTRACT:

In the framework of Geoland, Infoterra France has mapped with MERIS the distribution of annual crops surfaces in Belgium, Poland and Russia (Rostov oblast). The maps provided are the acreages of main groups of crops per administrative or agricultural circumscriptions unit. The groups are winter, spring and root crops (sugar beet, potatoes). The method for mapping exploits the MERIS capability to monitor large areas (~30 000 km2 to 300 000 km²) and to measure frequently, twice per month as an average, the Fraction of Green Vegetation covering the soil. The temporal series of fraction of cover observed along the vegetation season is then compared to crops phenological models of the various groups of crops. An inversion based process calculates the proportion of the various groups of crops on the unit that covered by arable land. The produced maps have been evaluated with national agricultural statistics for the various covered area. The results obtained both on Poland and Belgium are presented here and are in general satisfactory. The methodology is relevant when agricultural conditions correspond to a bit of major crops within dominant agricultural areas. The only present limitation is the underestimation of Maize crops on Belgian case. However this performance should be tentatively improved in future versions of the processing chain.

1. INTRODUCTION

In the framework of Geoland, the Observatory for Food Security and Crop Monitoring (OFM) aims to contribute to the establishment of an independent pre-operational capability to provide near-real time information on crop conditions and cultivated areas in support of the assessment of local food security and global market prospects. In this context, the product that Infoterra France has developed and proposed is intended to serve estimation of major crops areas in region of the world where there is limited information available (Asia, Eastern Europe, Africa).

The maps of annual crop acreages serve two other main domains of applications: (i) the compliance with European Directives in relation with agriculture and agri-environment, namely the Water Framework Directive, the Nitrates Directive, the new agri-environmental pillar of the Common Agricultural Policy, and in the future the Strategy for Soil Protection, (ii) it is a valuable input for crop surface inventories required by administrations and for commercial purposes.

In the first case, the maps of annual crop acreages are used as inputs of scientific models to assess the impact of agriculture on the environment. This application has already been made with two water related models.

The service 'Regional maps of annual crop acreages' has been designed since year 2004, in collaboration with regional and national end-users, with the aim to support their obligation to fulfill European Environmental Directives and the Common Agricultural Policy (PAC). This methodology has been applied successfully for the estimation of irrigated areas for water management applications in other countries (France, Spain). The development has involved users from Spain (Ebro Catchment Authority, Ministry of Agriculture), three water

agencies from France (Adour Garonne, Seine Normandie, Rhin Meuse), the French Institute for Environment (IFEN),

German Landers (Saar and Rhein Pfalz) and finally the International Commissions for the Saar and Mosel.

Furthermore, Infoterra France has mapped in the year 2006 the distribution of annual crops surfaces on a total area of 700000 km². This Meris based application can be exemplified as a pre-operational GMES service.

The developments of the service have been mainly funded in the frame of GMES by ESA, and the EC, complemented by national French programmes.

2. DEFINITION OF THE PRODUCTS AND SERVICE

The service provides the information of acreage covered by different crops categories. A figure (in ha) is provided per administrative or hydrographical unit of an average 10 km² size.

The categories of annual crops that can be mapped are the ones that can be separated thanks to their distinguishable development profiles. Examples are the winter crops, spring crops, summer crops, the pastures and also the "intermediate crops". This latter category refers to the crops cultivated in autumn and winter to absorb nitrogen surpluses left in soils and prevent their leaking to rivers.

Examples of maps are presented on Figure 1 and on Figure 2. The colour code indicates the range of acreages in the agro-circumscription or hydrological unit respectively. In order to show where arable acreages are, colours are applied solely to the mask of "arable land" Corine Land Cover (CLC) objects (classes 2.1.1 and 2.1.2). None "arable land" CLC objects are left in blank.

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This service is made to be delivered annually, either as a finalised product at the end of the crop season or as progressively refined maps at key dates during the growing season. The latter (figure 2) applies particularly for regions where summer irrigation is important and where water managers need to know the irrigated acreages during the irrigation campaign.

The product is generated from medium-resolution MERIS data by an operational and automatic production chain.

The MERIS sensor is very well adapted to covering large areas, which is the user's expectation. Thus the maps may cover a whole country, a basin or a sub-basin, i.e. an extent ranging typically from 7.000 to 300.000 km2. The elementary spatial unit of application (administrative or hydrographical) must be larger than 3 km² due to methodological constraints.

The small scale maps generated with MERIS are complementary to the large scale maps, classically obtained with high resolution sensors (SPOT, Landsat) and that identify crops within field boundaries.
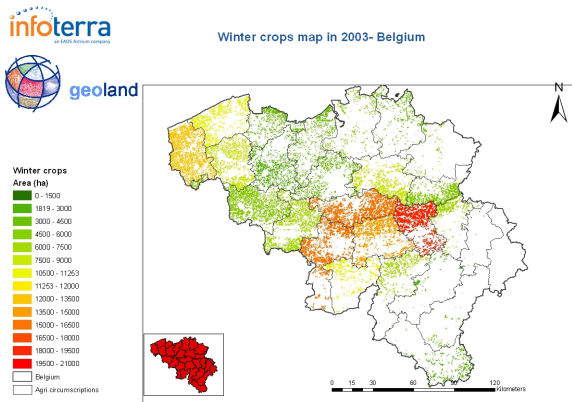
Figure 1. Winter crops acreage maps per agri-circumscription unit in Belgium in 2003.
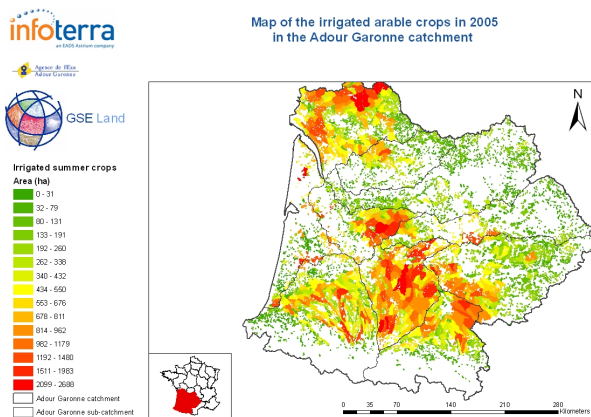
Figure 2. Irrigated summer crops acreage maps per hydrological unit in the Adour Garonne district in 2005.

3. METHODOLOGY AND PROCESSING CHAIN

The method exploits the MERIS capability to measure frequently, twice per month as an average, the Fraction of Green Vegetation (GLCV) covering the soil as well as the variance of this GLCV within each MERIS pixel, considered as a composite of vegetation and soil patches (variance : GCVV). The temporal series of GLCV, such as the one illustrated on Figure 3 on the Beauce region in France, and GCVV observed along the vegetation season, are averaged at

the scale of administrative or hydrographical unit, and are then compared to a model.
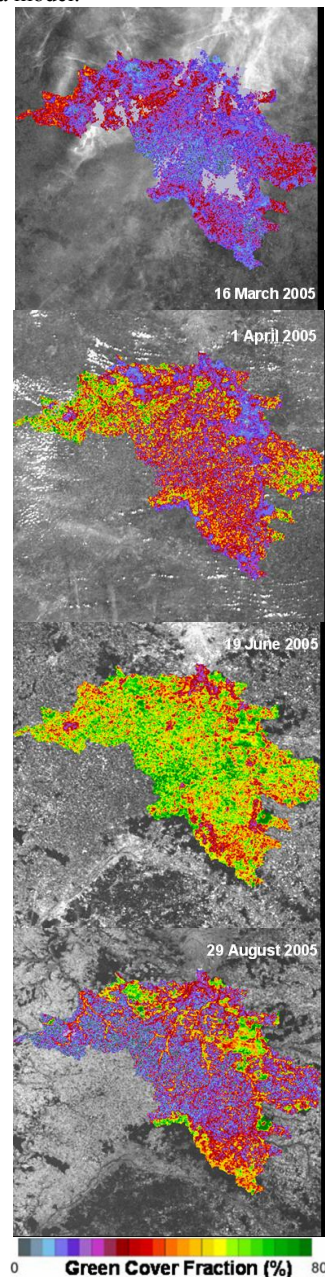
Figure 3. Evolution of GLCV in 2005 over the Beauce region (France)

From the set of biophysical images, we can see the evolution of GLCV along the seasonal campaign:
- Winter crops start developing highlighted in red (16th March),
- Winter crops development is speeding up, even areas less dense in crops are reddish (1st April),
- Winter crops reach their maximum greenness, summer crops start developing (19th June),
- Winter crops ripen (back to blue) whereas summer crops reach their maximum (29th August).

This model combines the phenological development models of the various groups of crops. This combination is illustrated on the Figure 4.

The models are driven by the meteorological conditions along the vegetation season, which therefore need to be provided.

Finally an inversion based process calculates the proportions of the various groups of crops in the unit that produce the best fit between the observed and modelled temporal composite profiles of GLCV and GCVV. In order to avoid mixing signals from the target (arable land) and from other types of covers (urban, forests, natural areas), the process is applied to the only MERIS pixels covered by arable land. An arable land mask is derived from a land cover information that can be Corine or a more detailed data base produced in the frame of GMES projects (GSE land or Geoland).

An operational processing chain has been developed in Infoterra France to process sets of MERIS data on regional scale. This chain includes the OVERLAND™ software for the generation of GLCV and GCVV. It is fully automatic and is based on the implementation of algorithms programmed with IDL and MATLAB languages, which guarantees the perfect reproducibility of the results. The processing chain has been certified by an external audit in the frame of the GSE land project.
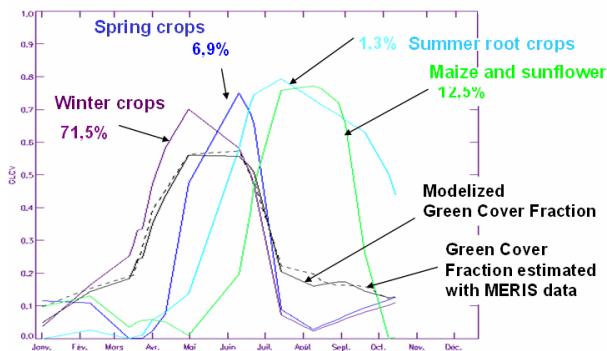
Figure 4. On a given administrative or hydrographical unit:
1) Individual modelled plots of GLCV's of various crop categories (winter, spring, summer root crop = sugar beet and potatoes, maize and sunflower). 2) The modelled plot of GLCV obtained by combining the individual models with given proportions of crops in the unit (winter crops 71.5 %, spring crops : 6.9 %, etc.). 3) The GLCV average profile estimated (observed) with MERIS represented in dotted line. The inversion process tunes the crop acreage percentages so that the modelled GLCV (crops combination) fits the observed one.

4. RESULTS

The products on Belgium and Poland are illustrated on the figure 5-1 and figure 5-2 respectively. They are directly provided in GIS format. The spatial unit for Belgium and Poland corresponds to the agricultural circumscription units and administrative units (NUTS2) respectively. The surfaces are expressed in hectares. The arable acreages maps are illustrated by one colour per administrative (Poland case) and per agricultural circumscription (Belgium case) unit, spatialized thanks to the CLC mask of arable land. The three "Arable acreages maps" groups of classes discriminated by MERIS are (i) for the Belgian case, Winter (and Spring included) crops, Maize (and assimilated) and Root (sugar beet and potatoes) crops and (ii) for the Polish case, Winter crops, Spring crops, and Root (sugar beet and potatoes) crops.
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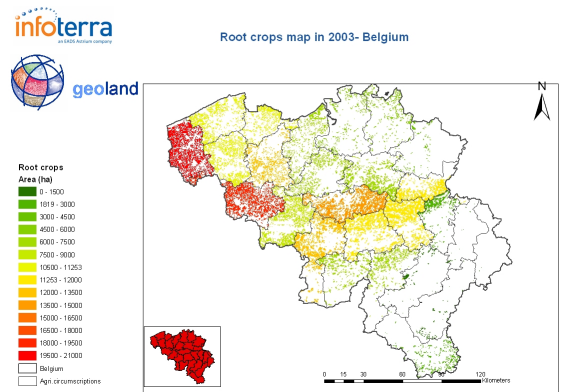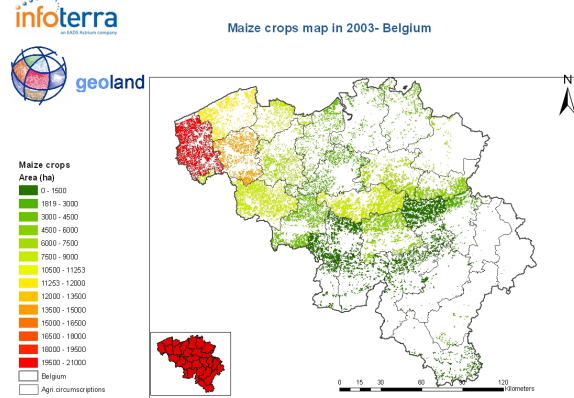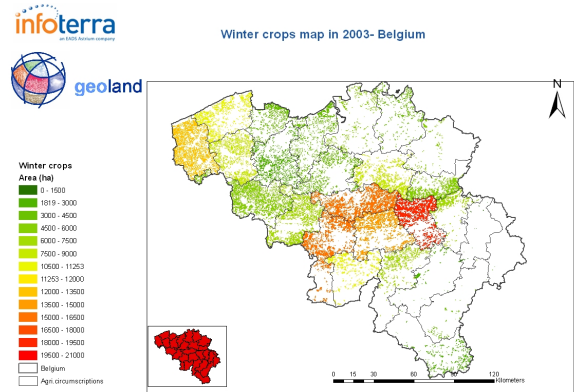
Figure 5-1. Illustration of arable acreages maps on the whole of Belgium in 2003: Winter crops, -Maize crops and Root (sugar beet and potatoes) crops.
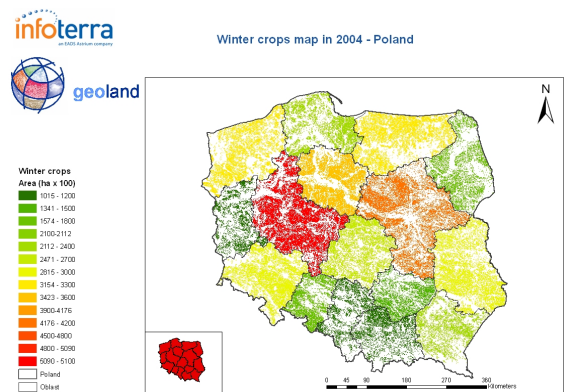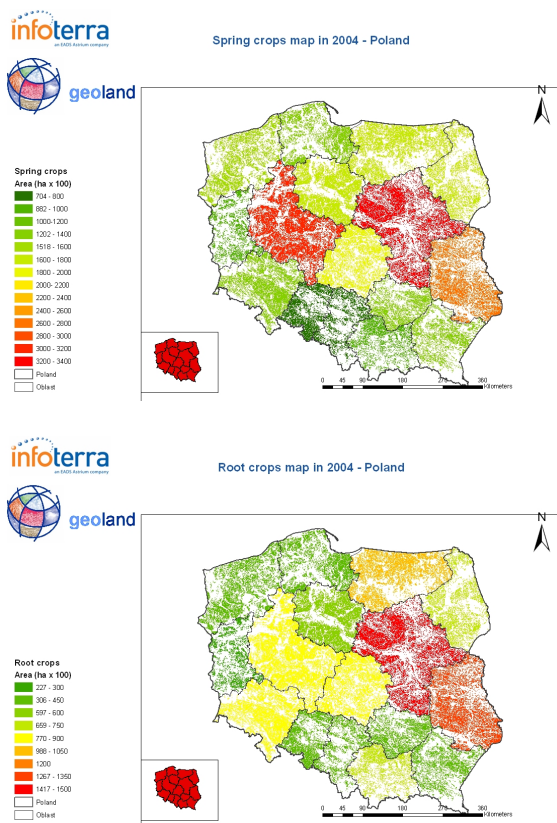
Figure 5-2. Illustration of arable acreages maps on the whole of Poland in 2004: Winter crops -Spring crops and Root (Sugar beet and potatoes) crops

4.1 Criteria of validation

The evaluation of the results has been carried out by comparing them to one reference data base:
- Agricultural statistic database from IACS (Belgium case) and from IGIK (Poland case).

For the Belgian case, the types of crops distinguished in the "Arable acreages maps" product do not correspond to the crops identified in IACS database which is very detailed. Hence it has been necessary to group the latter types of crops in macro-classes that are identical to the three "Arable acreages maps" groups of classes: Winter / Spring crops, Maize (and assimilated) and Root (sugar beet and potatoes) crops.

Concerning the polish case, major crops (sugar beet, oats, rye and winter barley) acreages information is missing the Agricultural statistic database provided by IGIK. Consequently, the validation had to perform from information at national scale (provided by MOCA study-JRC).

4.1.1 The average error on the complete area covered

The relative error, compared to agricultural data bases, is provided in the following table for the different cases that have been processed. The relative error equals to:

$$1 - \frac{\sum SIMULATION}{\sum DATA} \qquad (1)$$

where $SIMULATION$ and $DATA$ are , for each of the three "Arable acreages maps" classes, the estimated

surface on the overall area and the surface reported by the reference databases respectively.

4.1.2 The errors observed on the various spatial units of analysis

The performance of the product "Arable acreages maps" is evaluated through a statistic indicator (T): The T statistic is defined as:

$$T = 1 - \frac{\sum (DATA - SIMULATION)^2}{\sum (DATA - \overline{DATA})^2} \qquad (2)$$

where $SIMULATION$ and $DATA$ are, for each of the three "Arable acreages maps" classes and per administrative (Poland case) or agricultural circumscription unit (Belgium case), the estimated surfaces and the statistical database respectively. $\overline{DATA}$ is, for each of the three "Arable acreages maps" classes, the average value of the acreage on the whole population of units.

The T statistic characterizes the equality of two variables and measures the scattering around the 1:1 line. A good performance of estimation is associated to T values close to 1.0. Conversely, poor performance will show low T values.

4.2. Belgium case

The results in terms of errors are provided in the table 1. The T statistic and relative errors are presented hereunder:

Comparison with IACS database	Winter crops	Maize crops	Root crops
Relative error (%) (eq 1)	24	3.8	0.68
Relative error (%/total circumscription unit)	45	4.3	0.12
T calculated on the agri-circumscription unit (eq 2)	23	2.4	0.76

Table 1. Relative errors and T values characterizing the performance of Winter-Spring crops, Maize crops and Root crops (Sugar beet and Potatoes) from IACS database.

The error relative is then calculated from theses values and reported in the table 1 (line 2).

The T values reach 0.76 and 0.68 (Table 1) for Root (Sugar beet and potatoes) crops and Winter Spring crops respectively, except the case of Maize crops (0.12). The relative errors are satisfactory for both Winter Spring and Root crops.

The results for the Maize crops are not as satisfactory as the other crops. The low value of T observed for Maize crops is due to underestimation of Maize for some high values (not shown). These errors might be explained by major factors:

The arable land area provided by Corine Land Cover is less important than this one provided by the agricultural statistic database in the districts where the maize fields are dominant (North-West of Belgium). Consequently, the surfaces estimated from MERIS are inferior to those estimated from agricultural statistic. In particularly, this difference between Corine Land Cover and agricultural statistic database is found in the Maize class.

In addition, from a crop development point of view which is analysed with Meris, the patterns of the maize crops appear as similar to pastures. Indeed, a parallel study has shown that from high resolution satellite data, a drop of the GLCV signal on maize fields is observed after flowering phase. This effect has been emphasized due to the severe drought in 2003. Maize

crops may be identified like natural vegetation or/and pastures. Consequently, the distinction between these two classes of "crops" is difficult and the process tends to underestimate the Maize crops.

4.3 Poland case

Major crops (sugar beet, oats, rye and winter barley) acreages information is missing the Agricultural statistic database provided by IGIK. Due to this data gaps, it has been impossible so far to produce meaningful figures of acreages accuracy at administrative scale. In spite of this lack of data, the repartition between the groups of crops is respected and adequate (Figure 6). Otherwise, we obtain good results at national level (relative errors for each group of crops are very low, see table 2 and figure 7). The information at national scale is provided by MOCA study (JRC).
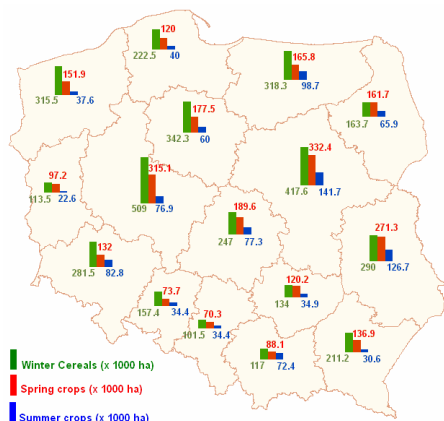
Figure 6. Repartition of three components of Arable acreages maps in 2004. Spring crops, Spring crops and Root crops (Sugar beet and Potatoes) are represented in green, in red and in blue respectively.

Table 2. T, Relative errors characterizing the performance of Winter crops, Spring crops and Root crops (Sugar beet and Potatoes) from MOCA database at national scale. T cannot be calculated due to the lack of data at administrative scale (IGIK database).
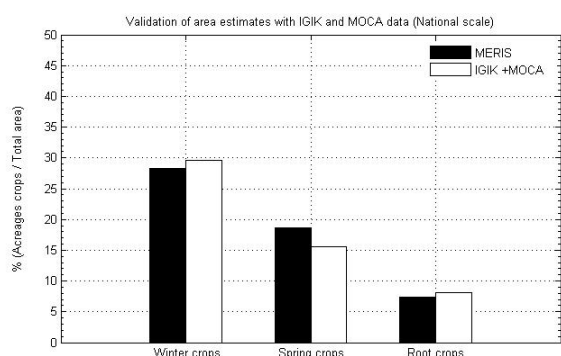
Figure 7. Proportion per crop (surface aggregated on the whole of Poland). In black bar is represented the values from MERIS and in white bar the statistical values mixed of IGIK and MOCA data. MOCA data are available at national scale.

5. DISCUSSIONS

The only problem for validation is the availability of reference data bases at administrative level (Poland case). In addition, the link between the agricultural statistic database and GIS compatible map of the agricultural circumscription units may not be 100% reliable (Belgian case).These limitations are always to be kept in mind in the process of validation.

The results that have been obtained are in general satisfactory and compliant with the specifications of the products. However two points need to be better understood through further developments:

Though this lesser performance (Belgian case) is not critical, this point needs to be improved in further developments. The performance improvement could be expected when the MERIS geometry problems are solved. The provision of upgraded 1P product by ESA is expected in the immediate future.

The difference between estimated surface and statistic data base is high for certain zones (North of Belgium) for the Maize crops. This can be explained on one hand, by a large difference between CLC and agricultural statistical databases and on the other hand by confusion between the temporal profile of maize crops and pastures emphasized by the drought in 2003.

This study demonstrates that the approach used is relevant when condition context corresponds to a dominant agricultural area with a bit of dominant crops. In return, the approach is limited when condition context is rendered difficult when land cover is fragmented and there are a lot of minor contributions of classes and crops. On the other hand, the results obtained on Poland demonstrate that the product developed and proposed is able to serve estimation of major crops areas in region of the world where there is limited information available like for example in Eastern Europe, in Asia and in Africa.

6. OPERATIONS CARRIED OUT IN 2006

comparison with MOCA database	Winter crops	Spring crops	Root crops
Relative error (%) (eq 1)	4	15	8
T calculated on the administrative unit	NA	NA	NA

In 2006, a large set of maps was produced in the frame of several GMES projects (GSE land funded by ESA, geoland funded by the EC, AGRIMOD funded by French Space Agency CNES). These maps, covering a surface of 700.000 km² and sketched on Figure 8 have been produced in Spain, France, Belgium, Germany, Luxemburg, Poland and Russia. This performance demonstrates the operational capacity of the production facilities.
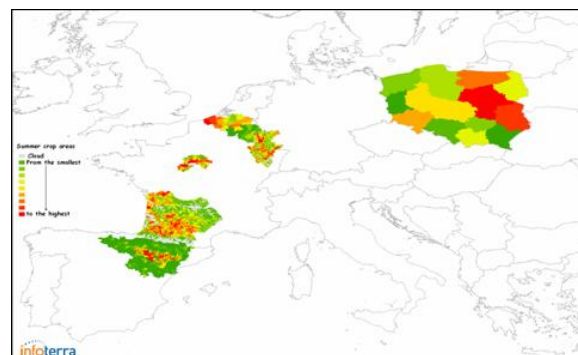
Figure 8. Annual crop maps produced in the projects of year 2006 for various types of users.

7. CONCLUSION AND PERSPECTIVES

Through the variety of regions covered in Europe and Russia, it has been demonstrated that the product is applicable to many types of climatic and phenological conditions and is therefore a truly pan-European product.

The annual crop maps generated with MERIS are complementary to the large scale maps, obtained with high resolution sensors (SPOT, Landsat) and that identify crops within field boundaries. The annual maps provide exhaustive spatial information and can then drive more detailed monitoring exercises that require high resolution sensors.

They provide also complementary information to the crops acreage maps obtained by Area Frame Sampling (AFS) statistics methods.

Finally these maps are produced at affordable and therefore attractive costs, around 0.5 €/km2, the cost of MERIS data being non significant in that amount.

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CROPMON: HUNGARIAN CROP PRODUCTION FORECAST BY REMOTE SENSING

G. Csornai, Cs. Wirnhardt, Zs. Suba, G. Nádor, L. Tikász, dr. L. Martinovich, A. Kocsis, Gy. Zelei, I. László, E. Bognár

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ABSTRACT:

The Hungarian Agricultural Remote Sensing Program led to a concise methodology that could further be applied operationally. First the main results of a substantial R&D investment and methodology plus validation results are summarized. The crops area assessment, through the processing of multitemporal Landsat and IRS-1C/1D data proved to be efficient at county level because of the accuracy of thematic classification. The novel combined high resolution images + NOAA AVHRR series based crop yield forecast methodology performed well for the major crops (8) at county level. Based on the experiences of the first 5 operational years (from 1997) a general evaluation on the Operational Crop Monitoring and Production Forecast Program (CROPMON) is given. The CROPMON system is a good platform for additional projects implementation as in the case of a serious waterlog assessment and impact analysis in spring, 1999 or flood monitoring in 2000, and the remote sensing control of area-based agricultural subsidies (CwRS), that is carried out operationally for the eight year in 2007 in Hungary.

1. BACKGROUND

Up to 1990 the crop production was based on some 1400 co-operative or state farms in Hungary. The crop information and production forecast system used their reports that were obligatory by law. This information system worked fairly well. Because of the dramatic changes in the Hungarian economy and also in the agriculture, the former crop information system became inadequate. The land privatisation brought dramatic changes in the holdings and parcel sizes, the number of farm owners or operators, the agricultural technology and also in the investment structure. In this very quick transition, the need for an efficient information system became even more imperative.

The priority Hungarian Agricultural Remote Sensing Program (HARSP) was launched in 1980 and has been implemented by FÖMI Remote Sensing Centre (FÖMI RSC). The final objective of the program was to introduce remote sensing to the operational agro information system in Hungary. In the beginning of HARSP (Fig. 1.), the satellite image analysis methods development and validation were the most important (1980-85). As early as in 1984 the reviews of the yield models showed, that the research for a direct relationship between the crop development, the expected yield and the crop canopy - that can be observed by satellite data – could be a good alternative. Despite of the first results in canopy development assessment by satellite data we studied the capabilities of agromet models (WOFOST-MERA, Csornai et al., 1996), but FÖMI put a real emphasis to the remote sensing based model.

The operational system was expected to be capable to monitor crops in the entire country, providing accurate, timely and reliable information on the area of the major crops, their development quantitatively. This should be accompanied by problems areas delineation focusing to drought assessment plus the provision of reliable yield forecast and final yield estimates. These data are to be available at the country as well as the counties

(19) levels. The main user of the information included, primarily the Ministry of Agriculture and Rural Development (MARD) and has been indirectly gradually the grain processing and trading companies and associations, the farmers and their different organisations, associations. After a seven year of continuous operations (1997-2003) and having a lot of experience to meet the strict accuracy and deadline requirements there has been a continuous improvement in the technology applied. This led to a number of additional applications offered by this system. Although the CROPMON has been suspended to operate from 2004 because of the national resources are directed to EU memberstate obligations, in more recent cases, definite demand appeared for its revitalization.

2. THE TWO MAIN PERIODS OF THE PROGRAM

The HARSP (1980-) program can be divided into two main periods (Fig.1.):
− the development of the methodology basis, the crop mapping and area assessment methods plus the yield forecast models and validation (1980-96) and
− the operational period (1997-2003).
The final, most intensive period (1993-96) was the breakthrough in the development. This resulted in an operationally ready to use technology that had been validated prior to the operational phase on a 16 counties sample from quite a diverse crop years period: 1991-96 (Csornai et. al., 1998).

2.1. The operational crop area assessment method

The method was developed by FÖMI RSC. It applies high resolution satellite data series (e.g. Landsat, IRS-1C/1D, SPOT) in a multitemporal digital image analysis procedure for the crop identification and area estimation (Csornai et al., 1983). This approach was thoroughly tested by 1990 up to 3 counties region

(Csornai et. al., 1990). It was found that the traditional agro information system in Hungary, can only be surpassed in accuracy if advanced digital image analysis was used (Csornai et. al., 1997). This approach also provides reliable crop maps, which are necessary to the crop development monitoring and production forecast models.

The performance of this approach in crop area assessment proved to meet the strict requirements (Figs. 3.a.b.) both for the validation period (1991-96) and in the operational one. The strong relationship in the Landsat TM derived (FÖMI RSC) and Central Statistical Office, Hungary (CSOH) data for the major crops proved, that this method was independent from the given year or the area, the different terrain and complexity of the counties.

The crop maps, made of high resolution satellite data were supported by a carefully selected area and farms sample. Annually, some 100-200 sets of agricultural fields associations, farms or parts of farms ground data were analysed, checked and got built in to train the classifiers or – on a disjoint subset – to validate the accuracy of the derived maps. Thorough on the spot studies revealed, that 85-95% of the confusion values in the accuracy assessment tables come from existing inhomogeneities on the ground.

This means that the confusion tables incorporate information relevant to the nonuniform development character of the crops. The raw confusion tables and measures showed steady 85-97% overall agreement before the compensation techniques application. Global estimation handled the empirical confusion matrices values (per stratum) that were spatially balanced.
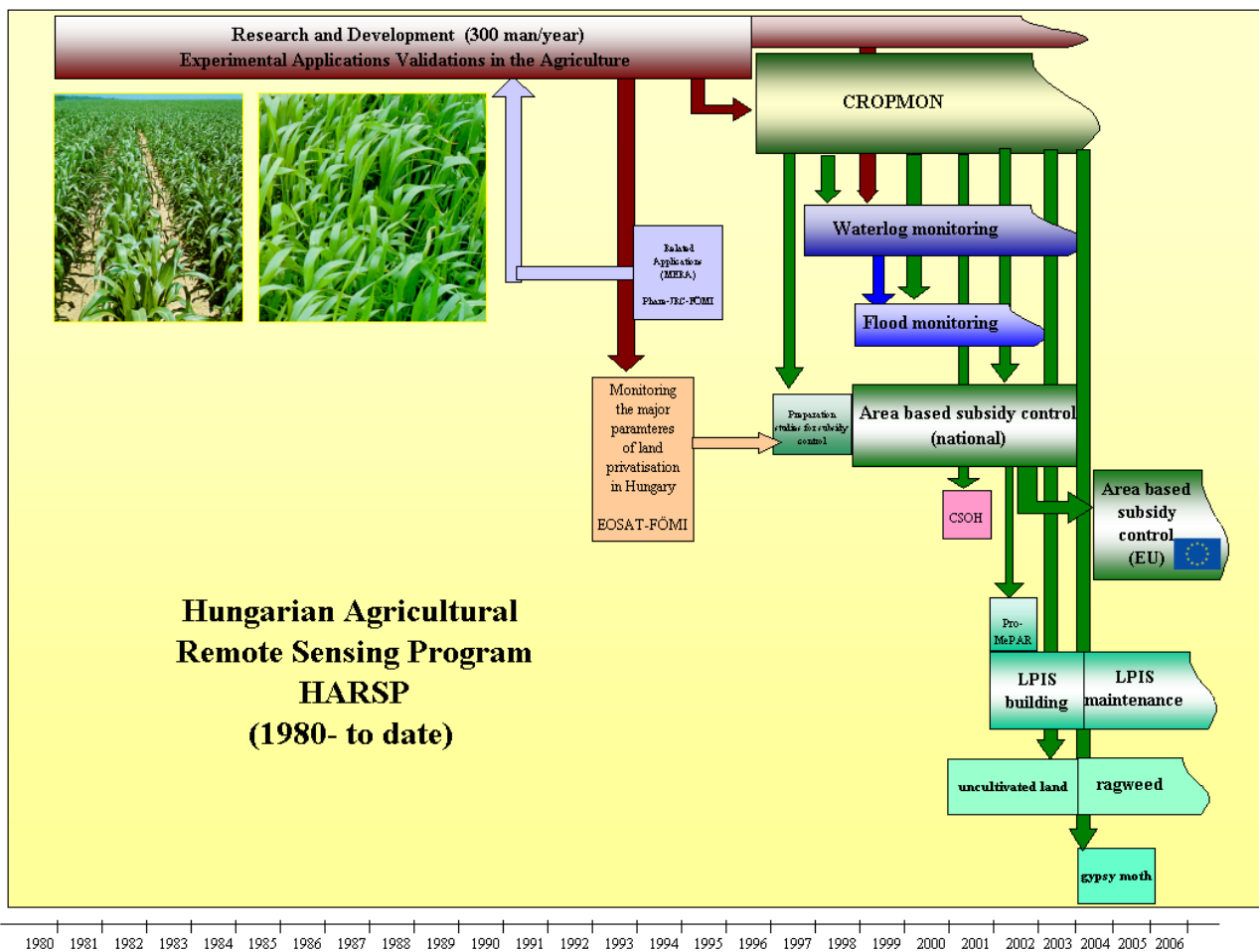
Figure 1. The background and history of remote sensing based agricultural applications in FÖMI RSC, Hungary

2.2. Crop monitoring and yield estimation methods

The novel results of HARSP are the purely remote sensing based crop monitoring and yield forecast models. The models were developed by FÖMI RSC. They integrated NOAA AVHRR and high-resolution satellite data (e.g. Landsat, IRS-1C/D, SPOT). The models combine the benefits of both data sources: the frequency of NOAA AVHRR data and spatial resolution of high resolution images. This approach requires fairly accurate crop maps. Using these crop maps and pre-processed NOAA AVHRR time series a crop development assessment and

quantitative yield forecast model was developed. This relies on crop specific AVHRR indices. The model was calibrated at the spatial units level of 400-500 ha. This was the second area where the sample of farms could help. That is the guarantee for its good performance at the counties level (approx. 0,5 million hectare each, in Hungary) and further. That is also why it can produce a crop yield distribution map. The county wheat and maize yields predicted by the model compared favourably to the official data (Figs. 4.a.b.) both in the pre-validation period (1991-96) and in the operational one (1997-2003) as well. The structure of the model is similar for different crops and it does not depend on the area and the given year's weather. It was also

found that the timeliness requirement can be met by the yield forecast model.

There was a clear emphasis and determination in the design of our methodology and later system not to get validated by the

CSOH county average yield data. We wanted to build an independent crop production model that covers the entire cropland.
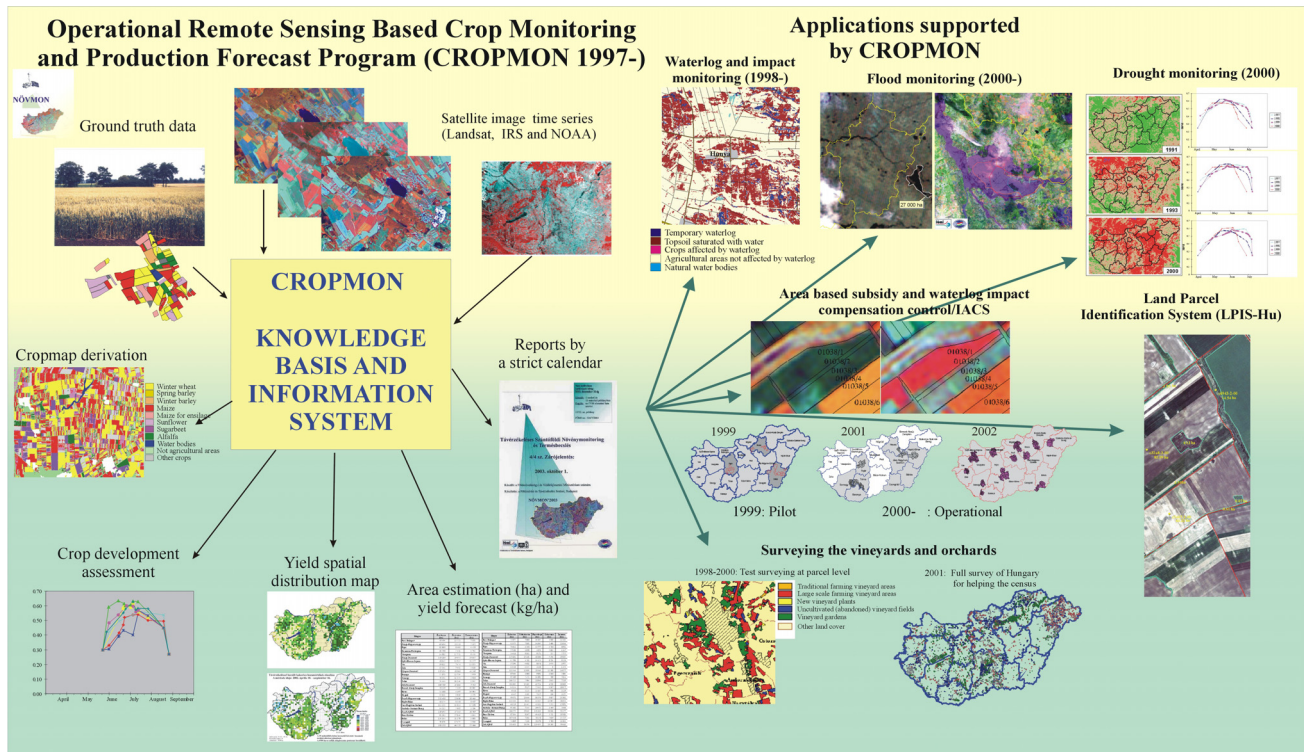
Figure 2. The overall structure of CROPMON and the application supported by it

3. OPERATIONAL CROP PRODUCTION: AREA ASSESSMENT AND YIELD FORECAST FROM 1997-

The substantial R&D and validation provided a firm basis to move forward to an operational program: Crop Monitoring and Production Forecast Program (CROPMON 1997-2003). The crop data-reporting calendar was set by the customer, the Ministry of Agriculture and Rural Development.

It consists of five dates from July 5 to October 1 in harmony with the existing traditional production forecast system of MARD. The area covered directly have been a characteristic subsample (6-9) of all the counties (19). This 40-57 % of the total cropland in Hungary was directly monitored, by remote sensing, while appropriate area and yield estimates for the non covered counties were computed by a historical spatial correlation of these values. This relationship was found quite strong suggesting an $R^2 \sim 0.9$ or better fit. Confidence values were also reported. From 2002 the whole country was covered by direct remote sensing measurements. The eight main crops monitored are winter wheat, winter and spring barley, maize, sugar beet, sunflower, alfalfa and maize to ensilage. These crops together represent the 78-82 % of the entire Hungarian cropland.

The crops area assessment is based on the quantitative analysis of multitemporal high resolution images (Landsat TM and IRS-1C/1D LISS III.) from early April (or earlier sometimes) through August, to compensate for the cloudiness. The comparison of the remote sensing results with CSOH data is obviously an indication only. The differences cannot be interpreted, by any means, as errors of the remote sensing technology. On the contrary, the area estimation bases, the crop maps were always thoroughly checked at some pixels detail.

The difference of crop areas estimates of FÖMI RSC and the Central Statistical Office, Hungary (CSOH) is in the range of 0.8-3.7 % for the entire cropland in Hungary. The county crop area differences occurred in the interval of 1.5-21 % depending on the crop and county. However the area weighted average difference was 4.08 %.

This partially can be explained by the main differences in definitions, that is the ownership based sampling of CSOH and the administrative boundary based total coverage of cropland by the satellite images (FÖMI RSC). The actual standard crop maps derived were also provided to MARD.

The crop yield forecast was accomplished by the application of FÖMI RSC developed model which combines high-resolution satellite (Landsat TM and IRS-1C/1D LISS III. or SPOT) data and NOAA AVHRR time series. The reporting dates corresponded to those of the operative Production Forecast System of the Ministry of Agriculture and Rural Development. Both appeared prior to the harvest. The earliest official production data estimates are available after the harvest: by the end of August for wheat and barley and in December (January) for the rest. Until 2002 FÖMI RSC provided yield estimates for the counties (6-9) and expanded these measurements to Hungary using a regional-historical correlation scheme. From 2002 all the 19 counties were covered directly, so there was no need for extrapolation any more. The country average yield data compare favourably with CSOH preliminary values, that appear six weeks later. The differences are less than 1 % for wheat and 4.5 % for maize average yields in Hungary. The differences at county level averages are somewhat bigger. Because of the method applied, yield spatial distribution maps could also be reported for the major crops.
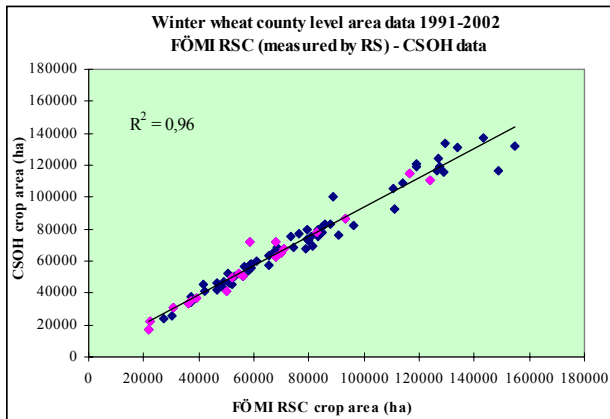
Figure 3.a. The area estimation for winter wheat shows a strong relationship between the traditional (questionnaire) method and the remote sensing one
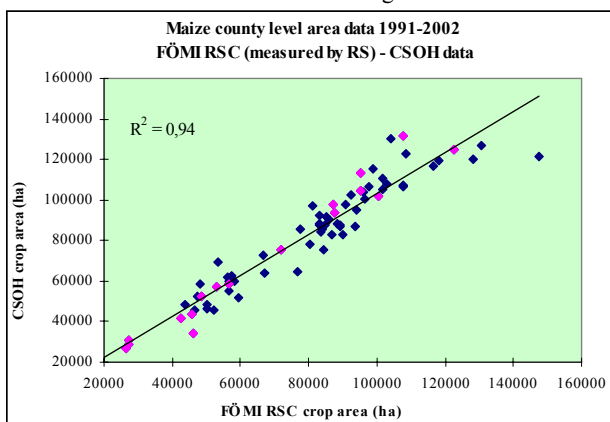
Figure 3.b. The figures compare similarly to those of wheat. The relationship is somewhat affected by the practice and statistics of maize for silage
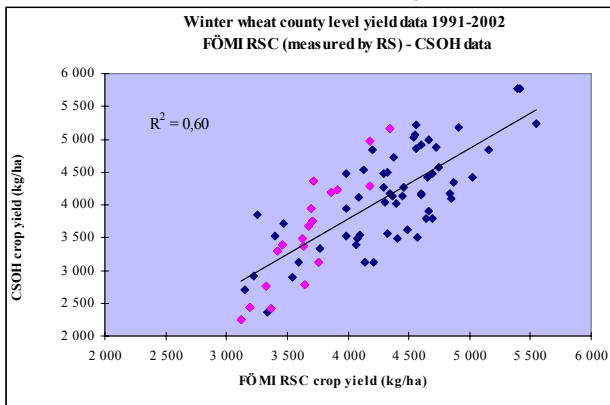
Figure 4.a. The wheat yields can be predicted by remote sensing prior to the harvest. The years covered comprise good and extreme bad ones as well
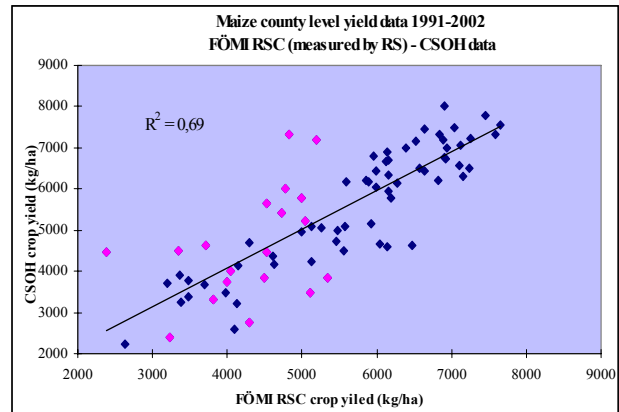
Figure 4.b. The maize yields can be predicted early prior to the harvest. The sample comprises diverse years. No CSOH yield data are available to date for 2001

Beyond the accuracy control built in the area estimation getting helped by the 2-4% ground sample and also the comparative analysis of the CROPMON predicted yield values and the respective farms after harvest data, the comparison to the final CSOH data is meaningful (Figs. 3. and 4.). These comparisons of the county area and CROPMON predicted – CSOH after harvest yields were done by crop. Around 180 data pairs were available either for area or yield to compare in the 1987-2003 period. The differences and R^2 –s should carefully be interpreted!

The inherent advantages and limitations of the traditional and remote sensing methodology suggest the handling of these data. The Ministry of Agriculture and Rural Development selected our data from the second year when there was a conflict.

4. APPLICATION OF THE YIELD MODEL FOR PARCELS AND FARMS

The crop development assessment plus yield prediction model performance suggested a step forward to the parcel level. In 1999 two large farms were studied. IRS WiFS 3,6 ha resolution data were used similarly in a 35 ha average field size environment. The two major crops were estimated: winter wheat and maize. The model seemed to work in this study providing some 3-5% difference between the remote sensing predicted and harvested yield after one year calibration. This could be achieved only to the farm total estimation only. The model may perform definitely better or at least as well in the operational way with a more appropriate field size/pixel ratio. Also, it was suggested that the individual fields' yield (production) values were not very accurate unlike those of the farm totals. This was characteristic in that period.

5. DROUGHT MONITORING AND YIELD LOSS ASSESSMENT (2000-)

The basic idea behind drought monitoring is the comparison of actual year's vegetation index maps (NDVI, MGVI) with the maps representing a mean of the vegetation index maps derived from the maximum value composites (MVC) of a reference period. This is the approach, that is most studies or systems pursue. FÖMI also explored and applied this approach, but having a strong yield prediction model, developed that performed well it was straightforward to use it for drought assessment and alarm. Beyond the widely used methods that apply NDVI or similar indices or their maximum values in a period to indicate the categories of drought or yield losses FÖMI utilized the yield

model for this purpose. The quantitative yield model was used to the characterization the strength and spatial distribution of drought. This is quantitative and provides the expected yield for that particular area. To this not only the compared period – usually 1-3 weeks – but the whole growing season is compared by the model output in the different years.

In the frame of FÖMI-ESA co-operational programs (see 6.) the CROPMON based drought monitoring, crop development and yield loss assessment (2000-2003) activities based on NOAA AVHRR data received at FÖMI satellite station were also continued and developed further (2003-). Other available satellite data (SPOT VEGETATION, IRS WiFS, AWiFS and ENVISAT MERIS) were integrated into the regional drought monitoring model to detect the extension and intensity of the drought at regional or country level (2003-2006).

6. WATERLOG/FLOOD AND IMPACT MONITORING, RAGWEED MONITORING AND CONTROL PROGRAM

As a component of CROPMON, further additional extension of remote sensing based operational applications were launched to extract information about those most significant factors, extreme natural disasters which occur on large areas and produce negative effects on crop development and crop production. Thus, satellite based waterlog/flood and impact monitoring (1998-), and recently ragweed monitoring and control program (2004-) were all growing out from the CROPMON methodology and technology basis.

Waterlog and impact monitoring program was initially launched for MARD, that covered the most affected 4 (in 1998) and 7 (in 1999) counties of about 4 million hectares. Reliable waterlog/flood maps and derived areal measures reflected the static status assessment of the areas under water or having saturated soil. Beyond this, temporal evaluation of waterlog/flood affected areas, impact analysis on the crops and the dynamism of changes could also be monitored quantitatively. During the combats against flood, when serious flood events occurred on Hungary's largest rivers, the Körös and Tisza, in April 2000 and March 2001, FÖMI RSC provided real time satellite data and flood maps for the disaster areas. The extent of flooded areas was evaluated and high-, low- and medium resolution flood maps were forwarded to the central and local management authorities through electronic transmission (Lelkes et. al, 2001). These effectively helped the local water management authorities in planning the necessary steps and managing the fight against the flood. Further improvements of the models to map and monitor waterlog and flood affected areas were also carried out in the frame of FÖMI-ESA co-operational R+D programs (Prodex[*]: 2000-2004, PECS[**]: 2004-2007, Csornai et. al 2004, 2007). Yearly monitoring tasks were performed at regional level in 2005-2006 for waterlog and flood assessment using also integrated radar (ERS, Radarsat, ENVISAT ASAR) and optical (IRS WiFS, AWiFS, ENVISAT MERIS Landsat/IRS LISS) satellite data sets.

The technique developed for ragweed monitoring and control (2004-) is based on the methods that had been used in CROPMON. However, the remote sensing identification of the areas contaminated by ragweed is much more difficult than the crop identification. About 80% of ragweed infected areas (of a total of 500.000 – 700.000 hectares) can be pinpointed by remote sensing on the arable land. The reconnaissance of ragweed spots are substantially helped by remote sensing as well as the ground

measurement and record by GPS plus integrated GIS tools. The temporal development assessment of ragweed has fundamental importance. FÖMI RSC produces a countrywide ragweed risk map focusing to the most heavily infected croplands. These ragweed risk maps are derived from time series of medium and high-resolution satellite images. In 2005, FÖMI RSC detected about 20 000 heavily infected spots (60 000 hectare) in the country. Applying the procedure of four high tech (two space technology related) areas, the whole system is 4-12 times more efficient than the former ground based one, concerning different parameters.

7. AREA-BASED SUBSIDY CONTROL WITH REMOTE SENSING (CWRS, 1999-)

The methodology and technology basis of CROPMON can be used also to extract information on the agricultural areas at parcel level, thus to control of the agricultural subsidy claims with the use of satellite images. After controlling a 3 counties sample for MARD in a pilot project in 1999, FÖMI extended the remote sensing control of national area-based subsidies to the sample of 4-6% of all the dossiers (160-180 000) between 2000 and 2003. The CROPMON based digital crop maps were very effective tools to access the automatic control of the parcels and were an important part of CwRS technique in Hungary. Since 2004, in the EU system, FÖMI's CwRS control ran on the newly built and updated Hungarian Land Parcel Identification System (LPIS-Hu, 2004-). The total number of submitted claims in Hungary grew to about 200 000 – 210 000. The successful control of the amounts of dossiers (4-6%) within a very short period of time could proved that the only feasible solution to carry out on-the-spot checks is the use of remote sensing and GIS techniques for the majority of the claims.

8. CONCLUSION

Both the validation of the developed remote sensing based crop area assessment and yield forecast methods plus the first Operational Crop Monitoring and Production Forecast Program (CROPMON 1997-2003) in Hungary clearly demonstrated that these methods can be efficiently applied for the entire cropland. Substantial background and investment were certainly needed. About 300 man/year was invested by FÖMI RSC in the framework of the Hungarian Agricultural Remote Sensing Program (1980 to date). The CROPMON reporting calendar was very strictly set up by the Ministry of Agriculture and Rural Development, Hungary, to be in synchron with its existing farms' reports based operational production forecast and monitoring system. The 8 most important crops were covered and monitored merely by remote sensing methods and technology. The CROPMON is objective and validated in a series of years and for very different areas.

Remote sensing could be very efficiently used for precise crop area estimation and provision of crop maps. The results suggest that the necessary classification performance can be obtained in most of the cases, therefore the analysis could be cost effective. The investment to achieve this seems to be worthwhile.

The new primary quantitative crop development assessment and yield prediction model works on the basis of a combined AVHRR and high resolution images based crop monitoring. The quantitative yield prediction model performed properly and efficiently in a more counties' area application and also for the entire country. This model produces spatial distribution map for the predicted yields.

CROPMON was extended into different directions. The model could be adapted to IRS WiFS data applications to farms. Also, CROPMON provided a tool for going far beyond the qualitative

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[*] Prodex= Scientific Experiment Development Programme
[**] PECS= Plan for European Co-operating States

comparisons of vegetation periods through non crop specific NDVI-values and provided potential yield estimates to characterize the extent of drought.

Parallel to these, many other applications could efficiently be added similarly to the waterlog assessment and ragweed monitoring and the remote sensing control of national area-based agricultural subsidies.

ACKNOWLEDGEMENT

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AGROPHENOLOGY INDICATORS FROM REMOTE SENSING:
STATE OF THE ART

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ABSTRACT:

Monitoring phenology at a regional, national or at a global scale is recognized by the scientific community as very important for many practical applications and notably for climate change studies. Phenological observations are classically realised for specific plant species in botanical garden or in small study areas or fields all over the world and sometimes date back to the 19th century. Although these observations are very interesting for studying the trends in phenology over time and their drivers, they are punctual and provide therefore only little information on its spatial variability. In this context, remote sensing information and especially low resolution sensors through their broad spatial resolution can provide additional information on phenology and allow creating dynamic maps of vegetation development. Different remote-sensed indicators for assessing vegetation phenology, for the most part based on smoothed NDVI curves, have already been proposed in various studies. These indicators are computed on moving averages, NDVI thresholds, logistic curves or maximum rate of changes. The phenological metrics directly derived from RS information are generally the start and the end of the growing season and also the moment of maximum greenness. Other RS phenological indicators are often derived from these metrics as, for example, the length of the growing season. RS phenological metrics can also be used as input variables in dynamic simulation models. These models unfortunately failed in non-optimal conditions (e.g. in case of damaging frost, hail, drought…). Remote sensing data could possibly be used to re-calibrate and re-adjust these models.

1. INTRODUCTION

Monitoring phenology at a regional, national or at a global scale is recognized by the scientific community as very important for many practical applications and notably for climate change studies. Analysis of spatial and temporal variations in the beginning and the end of the growing season can be used for example to determine regional variations and trends of the change in temperature and precipitation regimes. In agriculture, the accurate monitoring of crop development patterns represents an important component of farm management since it allows assessing if the most critical stages of growth occur during periods of favourable weather conditions.

Phenological observations are classically realised for specific plant species in botanical garden, in small study areas or fields all over the world and sometimes date back to the 19th century. Although these observations are very interesting for studying the trends in phenology over time and their driving factors, they are punctual and provide therefore only little information on the spatial variability.

In this context, remote sensing information can provide valuable information on phenology and allow creating dynamic maps of vegetation development.

Monitoring phenology through remote sensing is not a novelty. The idea was already suggested more than 25 years ago by Tucker *et al.* (1979). Since that time, different techniques have been proposed in literature. These different techniques can be arbitrarily classified in different categories. A distinction can be indeed made between techniques based on thresholds (Justice *et al.*, 1985; Runtunuwu & Komdoh, 200; White *et al.*, 2002; Wang & Tenhunen, 2004), derivatives (Kaduk & Heiman, 1996; Xin *et al.*, 2002; Viña *et al.*, 2004) logistic curves (Badhwar,

1984; Zhang *et al.*, 2003), moving averages (Reed *et al.*, 1994; Brown *et al.*, 2002; Schwartz *et al.*, 2002) and empirical equations (Moulin *et al.*, 1997).

These different techniques derived from literature are based, for the most part, on NDVI time series (Swets *et al.* 1999). These NDVI time series needs to be smoothed prior to the use of these techniques in order to reduce at the most the remaining noises in remote sensing products.

The aforementioned techniques have been applied for different vegetation types as field crops (Xin *et al.*, 2002; Viña *et al.*, 2004), forests (Zhang *et al.*, 2003; Schwartz *et al.*, 2002) or as savannah, shrublands… (Runtunuwu & Komdoh, 2001; Wang & Tenhunen, 2004).

This paper will present first of all briefly the different possible techniques used to smooth vegetation index (VI) time series (mainly NDVI). The different indicators that can be derived from these time series in order to monitor will be then presented as well as the different techniques proposed in literature to derive these indicators.

2. SMOOTHING METHODS TO REDUCE NOISE IN NDVI TIME SERIES

There are many complications, limitations and causes of error associated with satellite data, including sensor resolution and calibration, digital quantization errors, ground and atmospheric conditions as well as orbital and sensor degradation. NDVI data sets are generally well-documented and quality-controlled data sources that have been pre-processed to reduce many of these problems.

However, some noise is still present in the remote sensing data sets and, therefore, NDVI time-series need to be smoothed

before being exploitable. Such noise is mainly due to remnant cloud cover, water, snow, or shadow. These sources of errors tend to decrease the NDVI values. False highs, although much less frequent, can also occur at high solar or scan angles (in which case the numerator and denominator in the NDVI ratio are both near zero) or because of transmission errors, such as line drop-out. To minimize the problem of false highs, the remote-sensed products are generally based on low-angle observations wherever possible.

Most errors thus tend to decrease NDVI values. This unusual error structure, with high NDVI values being more trustworthy than low ones, breaks the assumptions of many standard statistical approaches. Further complications can arise because the error structure can vary in time and space (Pettorelli *et al.*, 2005).

Different smoothing methods exist to reduce noise in NDVI data. Some of these techniques are presented below.

Maximum value compositing (MVC) method

The maximum value compositing method (Holben, 1986) is certainly the easiest one. NDVI value for a compositing period is the highest NDVI value observed during this period (generally 1 decade or 1 month). The time period is a trade-off: a longer period decreases the amount of cloud interference, but it means missing short-term variations.

This method minimises data gaps in any particular composite image due to cloud interference or missing data and overcomes some of the systematic errors that reduce the index value. However, the procedure would be biased by a single false high (Pettorelli *et al.*, 2005)

Curve-fitting method

The curve-fitting method, initially develop by van Dijk *et al.* (1985), aims at fitting a polynomial or Fourier function to the NDVI time-series. The shortcoming of the polynomial and Fourier smoothers is that they only determine the general shape of the curve, rather than pinpointing particular cycles. The Fourier series smoother must also be rerun over the entire time series each time a new data point is added.

Step-wise logistic regression method

This method was initially developed by Zhang *et al.* (2003). These authors pretend that the bell-shaped NDVI curves can be represented using a series of piecewise logistic functions of time.

Best Index Slope Extraction (BISE) method

Initially developed by Viovy *et al.* (1992), this method is based on the slope of increasing and decreasing data values referred to as the "best index slope extraction". The method accepts a point if it has a higher value than the previous observation. Where the NDVI value decreases, the decrease is only accepted if there is no point within the next *n* periods with a value greater than 20 percent of the difference between the first low value and the previous high value.

The method is dependent on both the 20 percent threshold and the predefined period of time (i.e. *n*). The resulting profiles tend to lose some of the nuances of the NDVI profile and, in some cases, appear to be insensitive to the timing of NDVI increases.

Weighted least-squares linear regression

This method was developed by Swets *et al.* (1999). This approach uses a moving window operating on temporal NDVI to calculate a regression line. The window is moved one period at a time, resulting in a family of regression lines associated with each point; this family of lines is then averaged at each point and interpolated between points to provide a continuous temporal NDVI signal. Also, since the factors that cause contamination usually serve to reduce NDVI values, the system applies a weighting factor that favors peak points over sloping or valley points. A final operation assures that all peak NDVI values are retained.

Savitzky-Golay smoothing method

This time-domain method of smoothing is based on least squares polynomial fitting across a moving window within the data. The method was originally designed to preserve the higher moments within time-domain spectral data.

Savitzky-Golay smoothing filters, also called least-squares or DISPO (digital smoothing polynomial) filter are particular types of low-pass filters, well-adapted for data smoothing. Rather than having their properties defined in the Fourier domain, and then translated to the time-domain, Savitzky-Golay filters derive directly from a particular formulation of the data smoothing problem in the time domain (Press *et al.*, 1992).

4253H, twice smoothing method

The 4253H, twice (or T4253H) smoothing method (Tukey, 1977; Velleman & Hoaglin, 1981) belongs to a family of smoothers based on the use of running medians to summarize overlapping segments. Indeed, as the fitted curves are intended to be robust to any outlying observations in the sequence, techniques as T4253H make use of medians rather than means.

The 4253H, twice smoothing method consists of a running median of 4, then 2, then 5, then 3. This is then followed by a method known as "Hanning". Hanning is a running weighted mean, the weights being ¼, ½ and ¼. The result of this smoothing is then 'reroughed'. This involves computing residuals from the smoothed curve, applying the same smoother to the residuals and adding the result to the smooth of the first pass (NAG, 2005).

5RX, twice and 7RY, twice smoothing methods

These two smoothing methods have been proposed by Ladiray & Roth (1987) and are in a way an adaptation of the smoothing techniques proposed by Tukey (1977) and Velleman & Hoaglin (1981) and are notably based on iterative processes. Indeed, for moving medians of odd order (only), Tukey had proposed to use a smoother as much as necessary until the moment when the smoothed series become invariant to the smoothing procedure. In many situations (Ladiray & Roth, 1987), convergence is reached quite rapidly (after 4 or 5 iterations).

Ladiray & Roth (1987) propose to run median of 5 (5RX) or 7 (7RY) using this iterative process and to use then a method similar to "Hanning" except that the weights are here (1/8,1/4,1/4,1/4,1/8) and (1/8,1/8,1/8,1/4, 1/8,1/8,1/8) respectively for 5RX and 7RY.

The result of this iterative smoothing is afterwards "reroughed" (see "4253H, twice" smoothing method).

According to Ladiray & Roth (1987), these 2 smoothing methods (5RX and 7RY) are more efficient than 4253H smoothing method in many situations. However, the iterative process lead to a loss of data at the end of the series especially if the smoothing order is high and if the iterative process has difficult to convergence.

However, for many purposes, the choice of smoothing method might not be crucial. For example, in a recent ecological study, similar estimates of spring phenology were obtained using either locally weighted regressions or a simple cumulative maximum throughout the season (Loe *et al.*, 2005).

3. PHENOLOGICAL KEY INDICATORS DERIVED FROM REMOTE SENSING

Different key phenological events can be derived from NDVI or more generally from Vegetation Index (VI) time series. Whatever the technique used, three phenological key indicators called "basic" can be derived from vegetation index time series, as aforementioned most of time NDVI time series (Figure 1): the onset and the end of greenness and the maximum NDVI value. Let's note that the onset/end of greenness is not necessarily linked to the beginning/end of the growing season especially if VI time series monitor two crops during the same growing season.
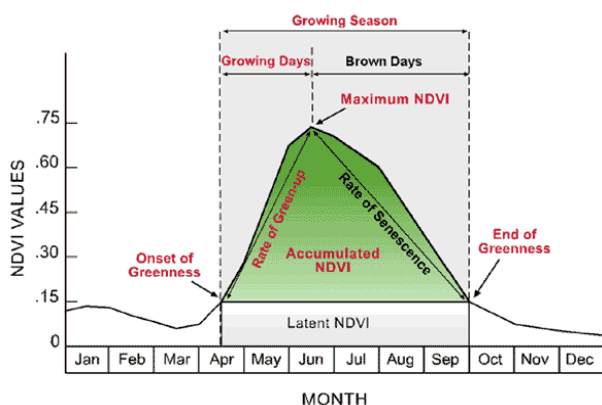

Figure 1. Phenological metrics derived from a NDVI curve (From http://www.terrametricsag.com/DataSets.html)

According to the spatial resolution and under some site-specific conditions (as the possibility to have pure pixels), phenological metrics could be associated to species-specific events or not.

For example, Xin *et al.* (2002) working in the Huang-Huai-Huai plain (China) with NOAA-AVHRR images have linked on the basis of field data the peak of greenness (maximum of NDVI value) to heading of winter wheat and tasseling of summer maize. In the same way, Thiruvengadachari and Sakthivadivel (1997) consider that the peak of greenness of a seasonal NDVI profile (for pure pixels in rice) corresponds to heading stage of rice. For Schwartz *et al.* (2002), the onset of greenness can be, to a certain extent, associated in deciduous American forest to bud-break.

From these basic phenological key events, other phenological indicators (figure 1) can be derived as for example the length of the growing (LOG) and brown (LOB) days i.e. the time between the moment of maximum (ND)VI and respectively the onset and the end of greenness, the rates of green-up (ROG) and

senescence (ROS) i.e. the rate of VI increase during respectively the growing and the brown days or the length of the growing season (LOS) corresponding to the time between the onset and the end of greenness (LOS = LOG + LOB).

4. TECHNIQUES TO DERIVE PHENOLOGICAL KEY EVENTS FROM REMOTE SENSING

Techniques based on thresholds

These techniques are certainly the most simplistic. The philosophy of these approaches is based on the definition of a VI threshold. The onset/end of greenness is defined as the moment when the VI values become higher/lower than the defined threshold
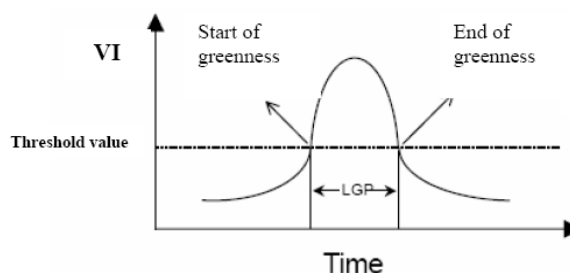
Figure 2. Determination of the start and the end of greenness based on VI threshold.

Different threshold values have been proposed in literature e.g. 0.17 (Fischer, 1994), 0.09 (Markon *et al.*, 1995) or 0.099 (Lloyd, 1990). These values are however specific to a given vegetation type and/or to a given area.

The seasonal midpoint NDVI (SMN) methodology is another method, more complex, based on threshold. This method was initially developed by White *et al.* (1997) and subsequently modified by White *et al.* (1999) and White *et al.* (2002).

In the SMN methodology, the annual cloud-screened minimum and maximum NDVI are selected and the midpoint (average) between them is computed. This operation is repeated for *X* years of the NDVI time series. The average of the *X* midpoint NDVI values (SMN value) is finally computed and used as a threshold to identify the start and the end of the growing season.

Parameters derived from this SMN method has been shown to be related to initial leaf expansion of the broad leaf forest overstory in New England (White *et al.*, 1997) and deciduous forests in France (Bondeau *et al.*, 2000).

According to Schwartz *et al.* (2002), the SMN method has the advantage to be sensitive to site-specific NDVI amplitude but, with its dependence on a time-constant NDVI threshold, an additional sensitivity to time-dependent drift in sensor calibration.

Techniques based on moving averages

This category of techniques involves applying a moving average filter to the VI time series which essentially creates a new time series with a time lag. The moving average time-series (MATS) then can serve as a predicted VI based on the *n* previous observations. When the actual (smoothed) values are greater than the value predicted by the MATS, then a trend change (onset of greenness) is occurring (Figure 3). The end of

greenness can be found similarly except that the moving average runs in the opposite direction.

The number n of previous observations to select in order to compute delayed moving averages is user-defined. For example, Brown *et al.* (2002) suggest 5 periods.
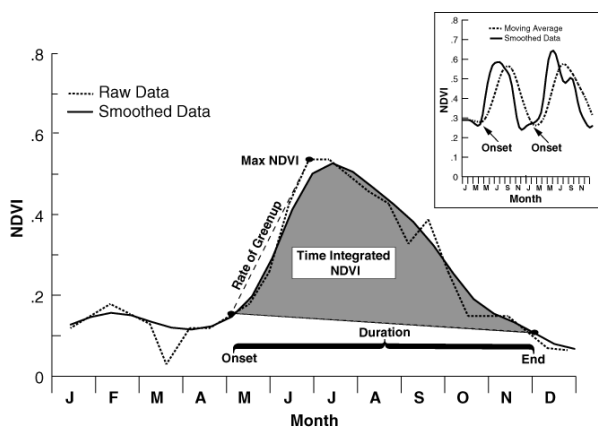
Figure 3. Illustration of a delayed moving average (DMA) approach (from Reed and Sayler, 1997)

Techniques based on first derivatives

In many situations and especially for annual species and broadleaved trees, vegetation indices as NDVI presents a bell shape as the one presented in figure 1.

With the first derivatives of the vegetation indices, it can be therefore possible to identify the onset and the end of greenness considering that these moments correspond to inflexions points. This category of techniques aims therefore to identify precisely the moment when the VI time series start increasing or stop decreasing.

In other words, according to these techniques, the onset of greenness is signalled by the x (generally 1 or 2) first positive VI increments in a given possible time window in which the event is supposed to occur. Similarly, the end of greenness is signalled by the x last consecutive decrements also in a given time window.

At the beginning of the growing season (which can be different from the onset of greenness), small increases and decreases of the signal simply due to residual noise are sometimes observed. In order to make the distinction between true onset of vegetation and these signal variations due to residual noise, a threshold of acceptable VI increase is used. As far as the end of the growing season is concerned, different studies (e.g. Xin *et al.*, 2002 ; De Wit & Su, 2004) have demonstrated that this event is generally poorly defined. In order to overcome this problem, a threshold corresponding to the VI value at the onset of greenness is used. The end of the growing season is then defined as the time step (for example the decade or the week) below or above this threshold.

Some practical applications of this category of techniques can be found for example in Xin *et al.* (2002) or Viña *et al.* (2004).

Variants in these techniques exist. For example, Zhang *et al.* (2003) have represented their NDVI time series by a series of piecewise logistic functions of time (figure 4). Periods of sustained VI increase or decrease are identified through the use

of a moving window by a change from positive to negative slope and vice-versa.
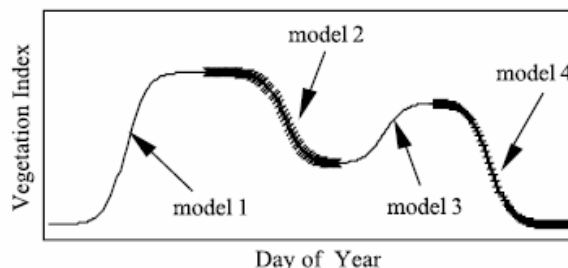
Figure 4. An idealized trajectory of vegetation index values with multiple growth periods described using several logistic models (from Zhang *et al.*, 2003)

Zhang *et al.* (2003) have afterwards identified what they have called transitions dates on the basis of the rate of change in the curvature of the fitted logistic models. Transition dates corresponds to the onset/end of greenness but also here the onset/end of the maximum of NDVI value (linked in their study to the maximum of leaf area index).

These transition dates correspond to the times at which the rate of change in the curvature presents local minima and maxima (black dots in figure 5).
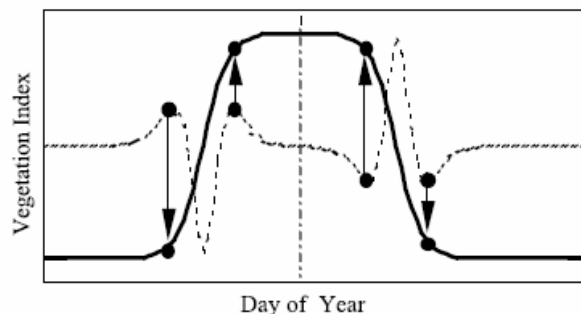
Figure 5. Schematic representation of how transition dates are estimated using time series of VI data (the solid line is an time series of vegetation index data and the dash line is the rate of change in curvature from the VI data).

Techniques based on empirical equations

Approaches based on empirical equations are certainly the most complex ones. An example of algorithm is for example provided in Moulin *et al.* (1997). In this study, the authors have used an algorithm in order to detect three transition dates (beginning, maximum and end of the vegetation cycle) through the analysis of NDVI temporal series.

With this algorithm, Moulin *et al.* (1997) does not determine an instantaneous phenological stage of the vegetation but rather the timing of the change from one state to the other that they call transition dates.

Determination of the start and end dates is done by finding the minimum of two criteria b and e computed for every week (Figure 6). The determination of the maximum of the vegetation cycle corresponds, once again, to the date of maximum value of NDVI time series.

The criterion b_i used to determine the beginning of the cycle (b_date) is based on the following considerations: (i) NDVI

value is close to a value of bare soil; (ii) the time derivative before b_date (left derivative) should be zero or close to zero, NDVI being almost constant; and (iii) on the opposite, the time derivative after b_date should be positive as the signal increases when the vegetation appears. For smoothing purposes, left and right time derivatives were computed with x_{i+2}, x_{i-2} and not x_{i+1}, x_{i-1}, such that

$$b_i = |x_i - x_0| - \lambda[(x_{i+2} - x_i) - |x_{i-2} - x_i|] \quad \text{(Eq. 1)}$$

where b_i is b_date criterion for week i (from week 5 to week 50), x_i is radiometric signal value for the date i, and x_0 and λ are empirical parameters. As the beginning of the time series cannot be filtered (boundary effect), the first two values are not significant, so the detection begins on week 5 instead of week 3.
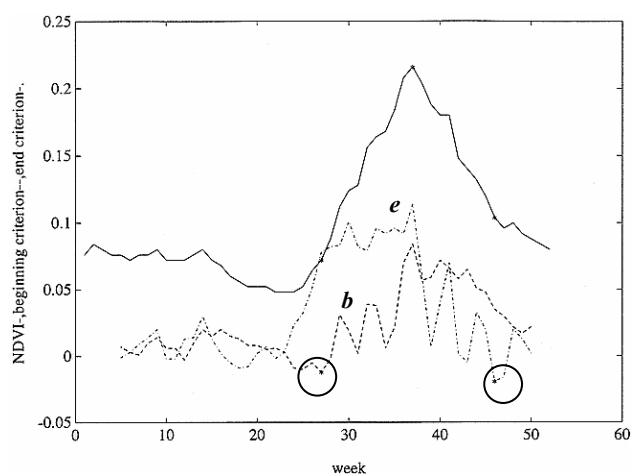
Figure 6. Detection algorithm of transition dates: NDVI time profile (solid), time profiles of criteria b and e allowing respectively the detection of start (dash-dash) and end (dash-dot) dates. Start and end dates (* circled in black) where obtained when criteria time profiles are minima (from Moulin et al., 1997)

The date at which vegetation cycle ends is calculated similarly to the beginning date. The NDVI value must be close to the soil threshold, and the left derivative is negative as the signal decreases during the senescence phase and equals zero on right, such that

$$e_i = |x_i - x_0| + \gamma[|x_{i+2} - x_i| - (x_{i-2} - x_i)] \quad \text{(Eq. 2)}$$

where e_i is e_date criterion for week i.

Each equation includes a term accounting for the mean level of the signal ("mean term") and a term accounting for the shape of the signal ("derivative term"). A soil threshold (x_0) is used in the mean term of the equation, whereas a slope coefficient (λ or γ) is used in the derivative term. Thresholds and coefficients used in the algorithm were empirically set.

With the mean term, variations of soil color and texture can induce variations of NDVI even if there is no vegetation. Among two dates leading to the same derivative term, the mean term helps the algorithm to select the one that has the lowest value (i.e., which is the closest to the soil or constant green background). For pixels covered with bare soil during a part of the year, the mean term in Eq. 1 allows to detect the beginning date of the cycle when the NDVI is close to bare soil threshold. For pixels with a constant background vegetation (and then a constant level of NDVI always above the soil threshold), the

algorithm also detects the beginning of the cycle (when the NDVI level is close to, but larger than, the background level). In Moulin et al. (1997), x_0 corresponds to NDVI values observed for the Matthews (1983) desert class.

For the derivative term, the factors λ and γ weight the derivative term of Eqs. 1 and 2. Hence, if λ and γ are too large, the algorithm may fail for pixels with a large part of the year with no vegetation (i.e., arid or cold regions). Indeed, in that case, the detection may be confused by short-term signal variations due to residual noise (e.g., soil color, directional effects). On the other hand, if the values are small, the algorithm may fail for pixels, which remain partly green during the year. According to this, λ and γ were empirically set to 3 and 5 in Moulin et al. (1997), respectively, in order to obtain a compromise between the two terms (mean and derivative). Due to the shape of seasonal profiles, the factor γ is larger than λ in Moulin et al. (1997). In fact, for a large number of grid cells, the decrease of the radiometric signal is slower than the increase. So, the weight of the derivative term must be amplified to detect the ending date.

An other example of algorithm can be found in Kaduk & Heiman, (1996).

5. CONCLUSIONS AND DISCUSSIONS

Different techniques aiming to derive agrophenology indicators from remote sensing information have been presented in this paper.

It would be unwise however to pretend that one method is better than the other. None of them are really ideal.

Indeed some of them, as the ones based simply on thresholds, are clearly specific to certain area and/or to certain species or vegetation types. In the same way, in techniques based empirical equations, proposed coefficients are always specific to the study conditions.

These methods, based mainly on NDVI time series, present also some restrictions. For example in boreal regions, it is well known that snow melting tend to increase NDVI values. Considering that in these regions the onset of vegetation and snow melting occurs globally at the same period, there is therefore a risk of confusion between an increase of NDVI due to snow melting and an increase of NDVI due the onset of vegetation, which is the event that must be detected. In other words, It is difficult in these conditions to distinguish, especially with the methods based on first derivatives or delayed moving average, the part of the NDVI increase due to snow melting from the NDVI increase due to the vegetation greening-up. Same kind of problems occurs of course also at the end of the growing season when snow reappears. Detection of the different key phenological indicators is however improved by using other VI as the Normalized Difference Water Index NDWI instead of NDVI (Delbart et al., 2005).

These techniques are not also very efficient in situations as equatorial evergreen forests. Indeed the small magnitude of the vegetation cycles compared to the effects of the important cloud contamination over these regions make the interpretation of the NDVI time profile very difficult (Moulin et al., 1997).

It seems also that the end of growing season is often poorly defined.

An other important point to consider is that these techniques and methodologies proposed in literature are not always validated with ground control observations. Questions also remain on some parameters used as for example the ideal size of the moving window used in techniques as the delayed moving average techniques.

There is therefore a need for compromise and it seems obvious that these different techniques should be adapted according to the context/situation.

Concerning the final uses of these phenological key indicators derived from remote sensing imagery, they are numerous.

First of all, considering that these phenological indicators are derived from RS information, it allows a global coverage of the different phenological events and provide more information on the spatial variability of the phenological events. It will be therefore possible to map and monitor phenology on a large area as Europe for example with a view to detect possible trends in phenology that can be linked to climate changes. This kind of study is underway in the frame of COST action 725 (www.cost725.org). In this kind of study, long time series are needed. Moreover, trends in phenology are generally not monitored for a particular species (which should be ubiquist in order to be monitored on a large area) but for global vegetation or a vegetation class according to the size of the area monitored. Therefore in this kind study, low resolution images are generally preferred.

Phenological information derived from satellite could be also very useful to recalibrate / readjust crop growth models (as CGMS or B-CGMS) which tend to fail in non optimal conditions (low models sensitivity to LAI evolution…). Remote sensing information could be therefore used to recalibrate/readjust some of the parameters of these models. As these models are crop specific, extraction of phenological parameters should be done on pure pixels and therefore in this case (very-) high resolution images are needed.

The choice of the images spatial resolution is therefore linked to the targeted objectives.

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RESPECTIVE CONTRIBUTION OF YIELD AND AREA ESTIMATES TO THE ERROR IN CROP PRODUCTION FORECASTING

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KEY WORDS: agriculture production forecasting, error, trends analysis, acreage estimate, yield estimate

ABSTRACT:

Improvement of crop production forecasting is a major research subject since many years. A systematic analysis of long time series made available through 2 extended databases for 4 crops and 15 European countries allowed investigating the basic question of the main sources of the year-to-year production variability. This statistical study could not conclude by a simple answer to this simple question. It was shown that most of the inter-annual production variability is actually due to the main producer countries. The year-to-year production variability was mainly related to the yield variation for wheat, potato and sunflower, but to the cultivated area variation for maize. Forecasting the production based on exponential smoothing technique highlighted that, in some countries, it is better to forecast the crop production knowing the cultivated surface while deriving the yield from the previous years' trend. However, the contrary was also found according to the crops and the country. Finally, the accuracy required to improve a forecasting system only based on statistical trends analysis was computed in order to define the performance target for any alternative source of information such satellite remote sensing.

1. INTRODUCTION

Forecasting agriculture production is of critical importance for the policy makers as for the market stakeholders. In a context of globalization, it is indeed very valuable to get as soon as possible accurate overall estimates of crop production at international scale. Since early days of satellite remote sensing till now, optical imagery has been experimented either to better estimate the crop acreage or to assess the canopy development as a proxy variables of the expected yield. However, a very simple but critical question remained apparently quite open: should we focus first on the crop acreage or on the yield estimation to improve the production forecasting? Even in a context of intensive cropping systems like the European Union, such basic question has been hardly addressed. Therefore, the overall objective of this study was to investigate the various sources of errors in the production estimation and to compare the respective relative errors associated to yield or acreage estimates when derived from trend analysis.

2. METHODS AND DATA SET

2.1 Overall approach

The research questions were designed from a user perspective addressing the most relevant issues to set a research agenda for the remote sensing community. The first questions concerned the inter-annual variability of productions, yields and cultivated areas for different levels of aggregation as this variability is the main justification of any forecasting system. These questions were twofold:

1. How large is the inter-annual variability of production for a given crop? How it is spatially distributed?

2. What are the respective contributions of the area and the yield variability on the total production fluctuation for a given crop?

In a second step, a forecasting perspective relying only on the existing statistics was adopted to formulate the following questions:

3. What is better to know - yield or area – to estimate the crop production for the current year?

Based on the previous results, a quite relevant question was expressed to support the remote sensing research agenda definition:

4. What is the required accuracy of any alternative source of information, e.g. optical imagery, to be able to improve a forecasting system based only on trend analysis?

2.2 Available time series of agriculture statistics

This research was carried out for 15 countries of the European Union (EU) because of the availability of long time series. The study actually relied on 2 existing data bases: the national statistics from 1950 to 2003 for 15 European countries (DB Cronos) and time series detailed by region, i.e. at NUTS 2 level in the EU administrative typology, from 1975 to 2002 (DB Regio). Both include the yields and surfaces statistics for 4 crops: wheat, maize, potato and sunflower. They were made

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available for the study by the AGRIFISH unit of the Joint Research Center (Ispra, Italy).

These statistics are routinely collected by various national statistical services and conveyed to the statistical office of the European Commission, EUROSTAT. The surface per crop is currently estimated from various sources, including field survey and remote sensing interpretation. In the EU the farmers' declarations and the related control with remote sensing of area based subsidies is a main source of information provided by each country.

3. RESULTS

3.1 Overall trends and inter-annual variability

The overall temporal evolution of the production was observed using the DB Cronos and plotted here for the 3 main producers' country of two crops (figure 1). To estimate the temporal trend, statistical test (f tests) were successively performed to select the best polynomial regression order. The polynomial of degree i (starting with i=0) was compared to the polynomial of degree i+1 thanks to the root mean square error (RMSE) between polynomial trend and real data. The selected polynomial regression order corresponded to the lowest RMSE value.

From these curves, we can not conclude to a single overall trend of the production evolution. The trends vary a lot from crop to crop: wheat and maize show a high production increase but potato shows rather stable production levels. The sunflower production has increased before the 90's and decreased during the last decade. However, some countries show different trends. For example, the production's level of wheat in Italy is stable whereas the three main producers increase their production with different rates.
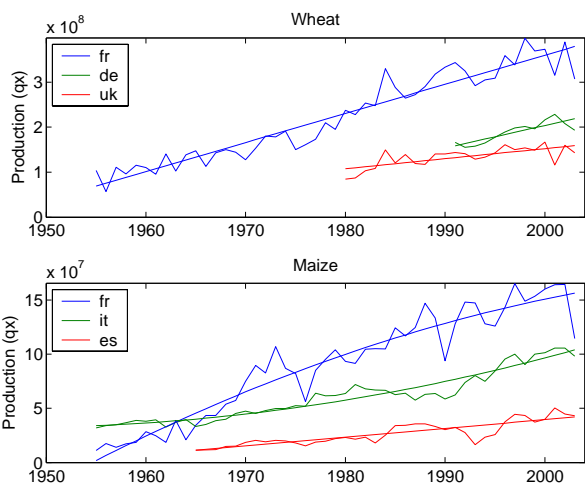
Figure 1: Evolution of the production level in the 3 main producers' country in Europe for wheat and maize.

In order assess the inter-annual variability of each producers' country, the deviation between the recorded production and the production estimated by the trend (root mean square distance) was computed for each crop. These deviations were then plotted as a function of the production averaged over the same period of time (figure 2). Most of the inter-annual variability of the productions in EU comes from the main producers' countries for all 4 crops, i.e. higher the productions level higher the

variability. At country level, the inter-annual variability of the production seems to be proportional to the production volume.
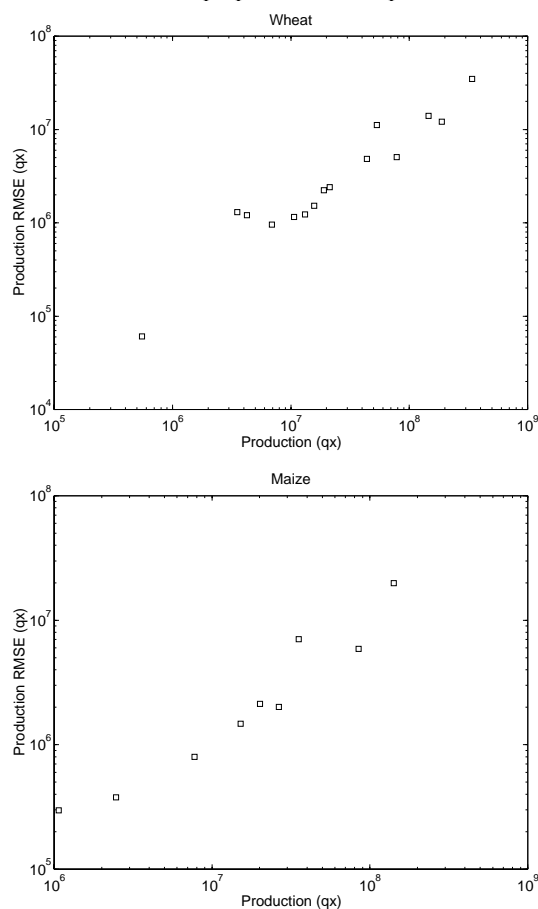
Figure 2: Relationship between the average production levels for the 15 EU member states and the respective inter-annual production variability for wheat (upper) and maize (lower).

3.2 Respective contributions to the inter-annual variability

The total crop production of a region depends on the acreage per crop and the mean yield. Year-to-year variability of the production level observed in the previous section could come from both, the yields' variability and from the areas' variability. In order to improve forecasting system, it is important to know which of these two variables was driving the production fluctuations.

The effect on the production estimate of the missing of either, the yield or the surface information, was assessed for each crop type. The error of the respective production estimate was then compared.

As a preliminary step, the yield and the surface trends of long statistical series (DB Cronos) were respectively modelled for each crop and each country using polynomial functions as described above.

In a second step, the production of each year was estimated for each crop along 2 ways: on one hand by multiplying the observed yield by the surface estimated from the trend and, on the other hand, by multiplying the observed surface by the yield estimated from the trend. The comparison of both production

estimates to the observed production was summarized by the RMSEa and RMSEy for the temporal series (table 1).

These gave an indication of the respective contribution of yields and surfaces variability on the total production for each year.

Member state	Production (T)	RMSEa (qx)	RMSEy (qx)	Main var.
Wheat				
France	3.4E+08	1.5E+07	1.9E+07	Y
Germany	1.9E+08	6.8E+06	1.3E+07	Y
West Germ.	*7.4E+07*	*2.5E+06*	*4.6E+06*	Y
U. Kingdom	1.5E+08	1.2E+07	8.2E+06	A
Italy	7.8E+07	4.4E+06	7.2E+06	Y
Spain	5.3E+07	3.1E+06	8.1E+06	Y
Denmark	4.4E+07	2.1E+06	1.7E+06	A
Greece	2.1E+07	1.4E+06	3.7E+06	Y
Sweden	1.9E+07	3.1E+06	1.5E+06	A
Belgium	1.6E+07	7.3E+05	1.0E+06	Y
Austria	1.3E+07	1.1E+06	1.0E+06	A
Netherlands	1.1E+07	8.8E+05	7.1E+05	A
Ireland	6.9E+06	6.9E+05	5.4E+05	A
Finland	4.3E+06	1.2E+06	5.9E+05	A
Portugal	3.5E+06	6.1E+05	1.0E+06	Y
Luxembourg	5.5E+05	3.3E+04	5.4E+04	Y
EU15	**9.4E+08**	**3.7E+07**	**4.9E+07**	**Y**
Maize				
France	1.4E+08	9.6E+06	9.3E+06	A
Italy	8.5E+07	4.0E+06	4.1E+06	Y
Spain	3.5E+07	3.9E+06	2.0E+06	A
Germany	2.7E+07	2.0E+06	2.5E+06	Y
West Germ.	*7.1E+06*	*9.5E+05*	*7.0E+05*	*A*
Greece	2.0E+07	2.3E+06	1.3E+06	A
Austria	1.5E+07	1.2E+06	1.0E+06	A
Portugal	7.7E+06	5.5E+05	4.3E+05	A
Belgium	2.5E+06	1.7E+05	2.2E+05	Y
EU15	**3.4E+08**	**1.9E+07**	**2.1E+07**	**Y**
Potato				
Germany	1.2E+08	1.0E+07	1.2E+07	Y
West Germ.	*1.4E+08*	*5.5E+06*	*1.2E+07*	Y
Netherlands	7.3E+07	4.3E+06	4.1E+06	A
France	5.9E+07	1.1E+07	8.8E+06	A
Spain	4.0E+07	2.2E+06	2.2E+06	A
Belgium	2.3E+07	1.2E+06	2.0E+06	Y
Italy	2.2E+07	3.1E+06	1.8E+06	A
Denmark	1.5E+07	1.5E+06	1.4E+06	A
Portugal	1.2E+07	8.3E+05	1.5E+06	Y
Sweden	1.1E+07	4.1E+05	1.4E+06	Y
Finland	7.7E+06	4.4E+05	9.6E+05	Y
Austria	7.5E+06	5.3E+05	7.8E+05	Y
Ireland	5.7E+06	8.7E+05	1.6E+06	Y
Luxembourg	2.3E+05	3.0E+04	1.1E+05	Y
EU15	**4.4E+08**	**1.9E+07**	**2.2E+07**	**Y**
Sunflower				
France	1.9E+07	4.7E+06	1.1E+06	A
Spain	9.6E+06	1.3E+06	1.8E+06	Y
Italy	4.8E+06	3.8E+05	2.4E+05	A
Germany	1.1E+06	8.8E+05	3.6E+05	A
Austria	5.7E+05	1.8E+05	4.8E+04	A
Greece	3.1E+05	3.6E+05	1.1E+05	A
Portugal	3.0E+05	7.3E+04	1.2E+05	Y
EU15	**3.6E+07**	**1.7E+06**	**3.9E+06**	**Y**

Table 1: Root mean square error of the production estimated without knowing the cultivated area (RMSEa) and without knowing yield (RMSEy). Series of West Germany stop in 1994.

Furthermore, for each country and each crop type, the comparison between both estimated production curves with

regards to the real production highlighted which one of the yield or area, is more important to know in a crop production estimation perspective (figure 3).
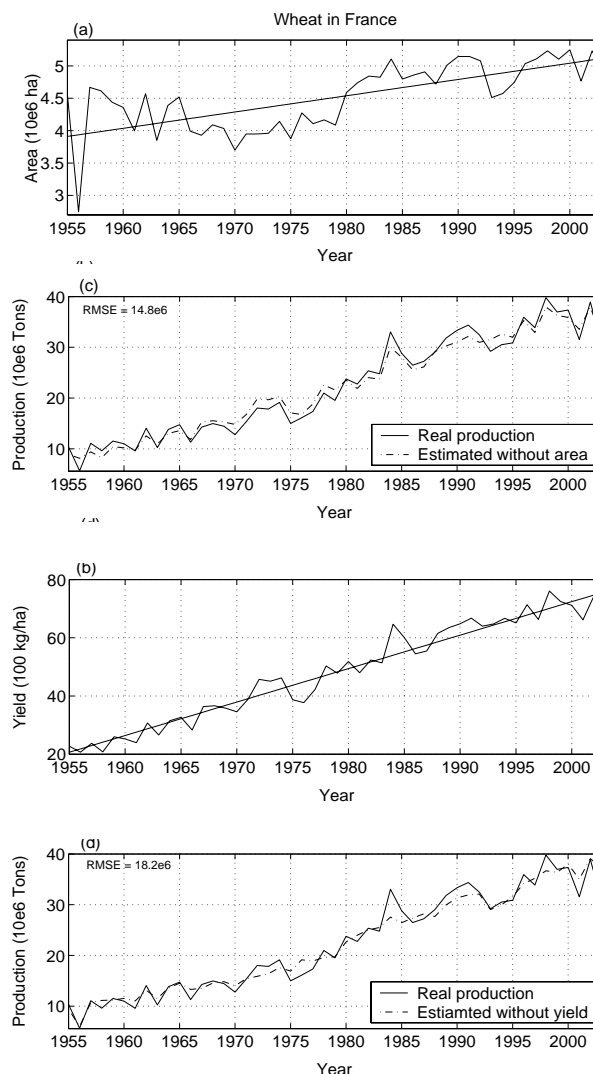
Figure 3: Temporal evolution of the wheat areas (a) and yield (b) in France with their respective trend. Temporal production and production estimated without area (c) and without yield information (d).

The trends of areas and yields were best estimated with long series. When the series length was shorter than 20 years, the temporal evolution was generally considered as constant but it would have been different if a longer series would have been available. Only the estimation made using long series are discussed. Moreover, as some countries have almost the same RMSEa and RMSEy, only some of the most contrasted situations are discussed here below.

For the wheat, 72% of the European production comes from France, Germany and United Kingdoms (91 % when adding Italy, Spain and Denmark) and the main source of variability in the production at European level is the yield variability.

Six countries are responsible of 96% of the European maize production. While the difference between RMSEa and RMSEy is rather small, the variability of the production at country level is mainly driven by the area variability. The opposite was

found at European level but from a short time series (1988-2003).

In general the potato's yields are highly variable in time whereas the surfaces cultivated in potato show a progressive decrease in time (except in the Netherlands). Whereas the contrary is observed in France and Italy, the main source of variability in production is the yields variability.

The variability of sunflower production is apparently related to the surface variability in most of the countries. However, a detailed analysis of the trends allowed adjusting more appropriate models leading to the opposite conclusion. The yield variability was finally found higher than the area variability.

Figure 4: Deviation from the temporal evolution (from 1975 to 2002) of the yield (upper) and the cultivated area (lower) for the wheat in each region.

The crop productions are also quite variable across regions and other scales of variability should be considered, in particular those related to agricultural regions or at NUTS 2 level. For instance, the RMSE of the surface allocated to wheat was calculated for NUTS 2 regions over the period (figure 3).

Regional differences may be of great importance. For instance, the France shows that the inter-regional variability of yield (6-19 qx/ha) is of the same order of magnitude than the inter-annual variability (4-7 qx/ha) observed in the French regions.

3.3 Forecasting production using time series

A crop production is calculated by multiplying the yield by the area. While observed production information is only available after harvest, production forecast is very valuable information during the growing season. Time series of cultivated areas and yields recorded in the previous years can serve to predict areas and yields of the next year. Of course, the year-to-year variability of both, areas and yields, makes inaccurate the prediction based only on the past years and additional information about the current year is very much needed. Remote sensing timely delivers information over large areas and this study could indicate on what variable the satellite observation should focus on. In other words, is the production better forecasted knowing the surface or the yield for the year of estimation?

In order to answer this forecasting question, the total production of the year n was predicted at country level in 2 alternative ways using the Cronos DB. First, the production forecasting was obtained by multiplying the area observed for the year n by the yield predicted for this year n using the yields recorded in the previous years. Alternatively, the production forecasting was obtained by multiplying the area predicted from the areas recorded in the previous years by the yield measured for the year n.

To do so, the area and yield estimate were first predicted using an exponential smoothing (Chatfield, 2003) to weight more the recent past observations, once the overall trends was removed by a linear model. The set of weights decreases by a constant ratio in such a way that the weights lie on an exponential curve defined by the α coefficient value. The α values minimising the RMSE between the predicted values and the recorded ones was selected for each time series. Then productions were computed for each year of the time series and their deviation (RMSE) with regard to the observed production was computed.

	Pred. years	Prod. RMSE (qx) forecast without:		Best to know
		Area	Yield	
Wheat				
France	39	1.4E+07	2.1E+07	Y
Germany	3	4.4E+06	2.8E+07	Y
W. Germ.	*30*	*3.1E+06*	*5.9E+06*	*Y*
UK	14	1.4E+07	7.4E+06	A
Italy	39	4.7E+06	7.0E+06	Y
Spain	29	4.7E+06	9.8E+06	Y
Denmark	39	3.1E+06	2.0E+06	A
Greece	25	1.2E+06	3.9E+06	Y
Sweden	8	4.1E+06	1.2E+06	A
Belgium	39	7.8E+05	1.2E+06	Y
Austria	27	6.9E+05	1.3E+06	Y
Netherlands	39	9.6E+05	7.3E+05	A
Ireland	39	8.0E+05	5.3E+05	A

Finland	4	9.2E+05	4.7E+05	A
Portugal	19	6.1E+05	9.4E+05	Y
Lux.	39	5.9E+04	5.2E+04	A
Maize				
France	39	1.0E+07	1.1E+07	Y
Italy	39	3.9E+06	3.7E+06	A
Spain	29	4.1E+06	2.0E+06	A
Germany	6	3.0E+06	4.6E+06	Y
W. Germ.	*30*	*7.6E+05*	*8.9E+05*	*Y*
Greece	25	2.2E+06	1.6E+06	A
Austria	34	8.8E+05	1.2E+06	Y
Portugal	19	6.0E+05	4.9E+05	A
Belgium	39	2.8E+05	2.5E+05	A
Potato				
Germany	6	1.3E+07	1.2E+07	A
W. Germ.	*30*	*1.0E+07*	*1.1E+07*	*Y*
Netherlands	38	5.2E+06	4.7E+06	A
France	38	9.1E+06	7.2E+06	A
Spain	29	3.0E+06	2.9E+06	A
Belgium	39	1.9E+06	2.1E+06	Y
Italy	39	2.1E+06	1.4E+06	A
Denmark	38	1.5E+06	1.2E+06	A
Portugal	19	1.3E+06	1.1E+06	A
Sweden	11	5.1E+05	8.9E+05	Y
Finland	10	1.8E+05	7.1E+05	Y
Austria	21	6.5E+05	8.8E+05	Y
Ireland	38	1.1E+06	9.6E+05	A
Lux.	39	5.8E+04	7.8E+04	Y
Sunflower				
France	39	2.2E+06	1.3E+06	A
Spain	29	1.7E+06	2.4E+06	Y
Italy	39	5.3E+05	2.5E+05	A
Austria	21	1.4E+05	6.9E+04	A
Greece	25	2.9E+05	1.3E+05	A
Portugal	22	1.1E+05	1.2E+05	Y

Table 2: RMSE of productions forecasting using exponential smoothing and missing one of the two variables for the current year. Column 1 gives the number of predicted years, column 2 and 3 the RMSE of the production forecasted using either the predicted areas or the predicted yields.

As shown at table 2, it is sometimes better to predict the production knowing the surface and predicting the yield for the year of estimation, but the contrary sometimes has to be preferred, i.e. better to know the yield and estimate the surface for the year of interest. In most of the countries, the wheat production is better forecasted when areas are estimated. For the other crop types, it seems to be the contrary. For the maize cultivated in the south of Europe (Italy, Spain, Greece and Portugal), it is better to forecast the production estimating the yields. Potato and sunflower productions are also, in most of the countries, better forecasted when yields are estimated.

3.4 Required accuracy for the variables

Other sources of information, such as remote sensing, can be used to support the production forecasting. To improve the performance of a forecast system based only on trends analysis, the accuracy of the area or yield estimated from any other sources of information must be higher than the deviations obtained from trends analysis only.

For wheat, maize and potato, some countries show significant errors (figure 5). The worst seems to be the estimation of wheat yield in Portugal, with an error of 25%. Such an error could probably be improved using remote sensing information for

instance. Other high errors on wheat yield predictions are also observed for Spain and Greece. Sweden and Finland show high errors on the area prediction but short series were used for these countries. The low errors (<+/-10%) obtained for the other countries using the exponential smoothing of statistical series can hardly be improved by alternative source of information.
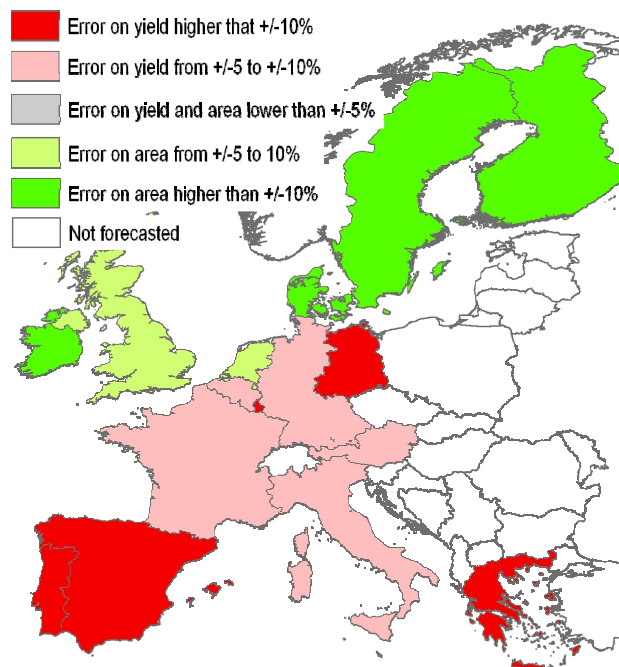
Figure 5: Map representing the maximum error on Area or Yield forecasted for wheat using the exponential smoothing.

4. CONCLUSIONS

This time series analysis demonstrated that a forecasting system for crop production in the EU can not only be based on statistical trends. Furthermore, the use of production trend is generally less efficient than area or yield trend, one of them being known. Research agenda for the improvement of a forecasting system could be defined according to 2 criteria:

- the focus on the main error source (area or yield) to improve the estimate from the alternative source to trend analysis,
- the feasibility to reach the required accuracy to reduce the prediction error obtained for the trend analysis.

The overall study approach successfully analysed the existing time series in order to document in an objective and quantitative way the need and the feasibility to improve current forecasting system simply based on trends analysis. Such an approach could be repeated at various scales and in various part of the world to define the research priorities.

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OPERATIONAL PREDICTION OF CROP YIELDS
USING MODIS DATA AND PRODUCTS

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ABSTRACT:

Official crop progress, condition and production estimates for the United States are responsibilities of the U.S. Department of Agriculture's, National Agricultural Statistics Service (NASS). In addition to weekly and monthly survey-based data, biweekly composite maps of the normalized difference vegetation index (NDVI) from the NOAA AVHRR sensor (1 km resolution) are produced by NASS's Research and Development Division (RDD) for monitoring vegetative change. This provides a qualitative assessment of differences in crop condition that may be an indication of potential yields. There is need for a more quantitative assessment of crop yields and spatial variability. Currently, NASS acquires crop yield indications via ground-based sample surveys (objective plant and fruit counts, fruit weights and farmer reports) which are collectively used to develop tools for its decision support system to assess weekly crop progress, monthly crop yield estimates for each state and the U.S, and annual county yield estimates. This paper describes the joint research between RDD and the Agricultural Research Service (ARS) of USDA for the development of simplified process models and algorithms to supplement the NASS field data collection. Potential advantages to using remote sensing include integration of spatial variability into county yields, enhanced timeliness, and efficient use of resources.

In the preliminary phase, MODIS data and products for the states of Iowa and Illinois were used to develop an operational assessment of crop yield forecasts for corn and soybeans. Spatial estimates of crop yields at county and sub-county levels offer a major improvement of current capabilities. The timeliness in producing these estimates is a vast improvement over the present assessment capability at the county level. Potential use of the estimates will supplement current tools and improve NASS' crop condition and yield decisions. Results of the pre-harvest forecasts developed for the 2005 and 2006 crop seasons are presented.

1. INTRODUCTION

Accurate and timely monitoring of agricultural crop conditions and estimating potential crop yields are essential processes for operational programs. Assessment of particularly decreased production caused by a natural disaster, such as drought or pest infestation, can be critical for countries or locales where the economy is dependent on the crop harvest. Early assessment of yield reductions could avert a disastrous situation and help in strategic planning to meet demands. The National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA) monitors crop conditions and makes the Official USDA production assessments in the U.S., providing monthly production forecasts and end-of-year estimates of crop yield and production. NASS has developed methods to assess crop growth and development from several sources of information, including several types of surveys of farm operators and field-level measurements. Field offices in each state are responsible for monitoring the progress and health of the crop and integrating crop condition with local weather information. Information on crop condition and progress is also distributed in a biweekly report on regional weather conditions. NASS offices provide monthly information to the Agriculture Statistics Board, which assesses the potential yields of all commodities based on crop condition information acquired from different sources. This research complements efforts to

independently assess crop condition at the county and state levels. The timely

evaluation of potential yields is increasingly important because of the huge economic impact of agricultural products on world markets and strategic planning.

County statistics are noted as a driving force for rural economic development, and are essential to proper management of USDA's many farm, education, and natural resources management programs. Many allocations of federal resources to states and counties are determined by their production of farm commodities. Demand for accurate commodity estimates at the lowest level of aggregation, and at the earliest possible time, has and continues to increase substantially. Literally millions of business decisions rely on this basic production data produced by USDA/NASS.

In the early 1960s, NASS initiated "objective yield" surveys for crops such as corn, soybeans, wheat, and cotton in States with the greatest acreages (Allen et al., 1994). These surveys establish small sample units in randomly selected fields which are visited monthly to determine maturity, numbers of plants, numbers of fruits (wheat heads, corn ears, soybean pods, etc.), and weight per fruit. Yield forecasting models are based on relationships of samples of the same maturity stage in comparable months during the past four years in each State.

These indications are then compared to farmer-based survey results to produce monthly yield forecasts. Additionally, the Agency implemented a midyear Area Frame Survey that enabled creation of probabilistic based acreage estimates. For major crops, sampling errors are as low as 1 percent at the U.S. level and 2 to 3 percent in the largest producing States. Accurate crop production forecasts require accurate estimates of acreage at harvest, its geographic distribution, and the associated crop yield determined by local growing conditions. There can be significant year-to-year variability which requires a systematic monitoring capability. To quantify the complex effects of environment, soils, and management practices, both yield and acreage must be assessed. A yield forecast within homogeneous soil type, land use, crop variety, and climate preclude the necessity for use of a complex forecast model.

Doraiswamy, et al. (1979), provided an inventory of various crop yield models, including statistical and deterministic models. The performance of deterministic models for large area forecasts depended on the availability of local climatic data with adequate spatial resolution. Use of remotely sensed data was limited to studying the temporal changes in vegetation condition such as crop growth and development.

Integration of remotely sensed data in crop yield models evolved during the next decade of research based on field experiments and advances in biophysical modeling. The need for linking real-time remotely sensed data initiated research on retrieval of biophysical parameters from satellite imagery.

The potential application of remote sensing technology for monitoring crop condition and predicting crop yields at regional scales have been studied extensively during the past several decades. Traditionally, the empirical approach based on statistical regression models was used with lower resolution data such as that from NOAA AVHRR. Studies have shown that the cumulative seasonal normalized difference vegetation index (NDVI) values were significantly correlated with reported crop yields (Groten, 1993). Doraiswamy and Cook (1995) demonstrated that cumulative NDVI values for spring wheat during the grainfill period improved estimates of crop yields in North Dakota. Combining a growth model with input parameters derived from remotely sensed data provides spatial integrity as well as a real-time ''calibration'' of model parameters. Moulin, et al., (1995) successfully used this approach using SPOT/HRV data in a radiative transfer model SAIL (Scattering by Arbitrary Inclined Leaves, Verhoef,1984) to map crop leaf area index (LAI) and also inversion models to that simulated canopy reflectance that were comparable with SPOT/HRS reflectance. These methods enabled constraining the model parameters with satellite observations to retrieve key parameters of soil moisture and above ground plant biomass. Doraiswamy et al. (2003, 2004, 2005) simulated LAI from NOAA AVHRR (1 km) two-band reflectance as well as MODIS (250 m) 2-band reflectance products, and used them in crop yield simulation models over small areas. The MODIS derived LAI seasonal profile was developed in the above studies using the SAIL model, and the crop yield model parameters were initialized. The MODIS 8-day composite reflectance product was acquired through the NASA–DAAC EROS Data Center, Sioux Falls, SD. The MODIS data has already been corrected for atmospheric effects and cloud cover.

The limitation in using satellite-based LAI methods with high (Landsat) and moderate (MODIS) spatial resolution data in crop yield simulation models at regional scales is that the canopy architectural parameters in the SAIL or other radiative transfer model for crop-specific LAI should be accurate. These parameters also change during the growing season. The reflectance data are used to derive LAI seasonal profile, which is used in initializing or constraining parameters in the crop yield simulation model. The temporal and spatial inconsistencies of the MODIS 8-day reflectance product data (Doraiswamy, 2006) limits its application in crop yield models at regional scales.

In this research we evaluated the use of the MODIS NDVI and surface temperature products to develop a multi-dimensional regression algorithm to predict the state and county level yields. The NDVI seasonal dynamics is representative of crop growth and biomass changes and thermal data is representative of the crop moisture stress condition.

The objectives of this research are to: a) develop a MODIS-based algorithm for operational classifications of corn and soybean crops in the U.S. Corn Belt; b) develop a multi-dimensional regression method to provide a consistent, timely and accurate yield prediction for potential use in NASS's operational program.

2. METHODOLOGY

Study Region.

The study areas presented in this paper are the states of Iowa and Illinois, which cover a major part of the U.S. Corn Belt. The two States are intensively cultivated, with approximately 75% of the land in corn and soybean crops. Crops are grown under rain fed conditions where soil moisture is normally adequate in the growing season; however, moisture stress conditions can occur in the early stages of crop development and more often during the latter part of the season. Seasonal rainfall ranged between 800 mm in the north to 450 mm in the southern part of the region. Soil moisture is generally at field capacity at the start of the season. However, because of spatial variability in the spring rainfall, planting dates across the region were variable. Crop planting in the region was completed by mid-May, with corn generally planted about 2 weeks earlier than soybeans. Crop maturity occurred by late September.

Data and Re-processing

The MODIS 8-day composite surface reflectance product (MOD09Q1 collection 4) at 250 m resolution and land surface temperature product (MOD11A2) at 1 km resolution was acquired through the NASA-DAAC EROS Data Center, Sioux Fall, SD. Imagery data for the available 5-year period (2002-2006) was acquired for day of year (DOY) from 121 to 305. The images were re-projected from ISIN projection to the standard UTM projection for zone 15 (Iowa) and 16 (Illinois) using the MODIS re-projection tool. The data was imported to ERDAS Imagine format, and NDVI time series for the crop season were calculated.

The cloud free MODIS data product has potentially three sources of errors − georeference, atmospheric influence and BRDF. The 8-day composite images always have patches even on homogeneous areas which are caused by difference in single day images used in the composites. Besides cloud cover, errors in reflectance caused by atmospheric condition always reduced the NDVI value. To eliminate these errors we used multiple-step processing of the composite data using the Savitzky-Golay

filtering technique adapted for tracking the upper envelope of the NDVI time series profile (Jonsson and Eklundh, 2004; Doraiswamy et al. 2006). The Savitzky-Golay filter uses moving 5-point window for each pixel time series profile and in each window, noisy values is approximated by polynomial to smooth NDVI values in the window. The thermal data is screened using the quality assurance data provided along with the thermal imagery, taking data with errors <= 2 degrees Kelvin.

Crop Classification

Landcover classification is an important step to assure accurate retrieval of crop specific data to monitor crop condition and predict yields. Classification has traditionally been completed at 30-m resolution using Landsat ETM+ images. In the past decade, USDA-NASS used Landsat data to develop crop classification for crop acreage estimation over selected states including Iowa and Illinois. However, the classification is usually not available until about 4-5 months after the crops are harvested. In an operational program where remote sensing data is used to predict crop yields, it is critical to have timely crop classification for assessing crop specific yields at specific time periods. Additionally, the uncertainties in the availability of Landsat data required the development of crop classification using the MODIS 8-day composite time-series data. A decision tree algorithm was developed (Doraiswamy et al, 2007) to map corn and soybean fields. In a two step process the crop area in the state is first selected using a threshold of NDVI values based on the combined crop phenology of corn and soybean crops. The next step of the decision tree algorithm separates the corn and soybean crops within the crop area. Figure 1 is the general NDVI time-series profile showing differences between corn and soybeans. The soybean crop is planted several weeks after corn and the maturity follows that of corn. The clear distinction between the corn and soybean NDVI profile occurs around day of year (DOY) 177 in Iowa and Illinois. These features are used to separate the corn and soybean crops, the predominant crops in these two states. The Landsat classification for Iowa and Illinois developed by the NASS Research and Development Division was used as the template for evaluating the accuracy of the MODIS-based classification.
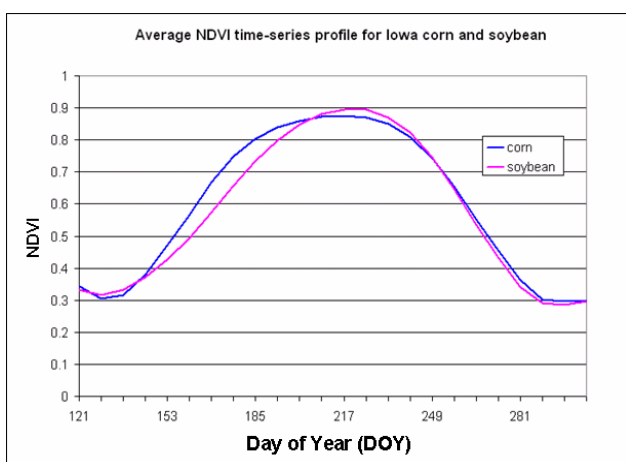

Figure 1. Example of the normalized difference vegetative index (NDVI) for corn and soybean crops using MODIS 8-day composite data (250 m) for the 2005 crop season after the data was processed with the filtering algorithm.

Crop Yield Algorithm

The NDVI and surface temperature (Ts) from MODIS imagery are parameters that are correlated with crop yields. Initial investigations suggest that these two parameters can provide spatial variability of crop growth conditions during the growing season. MODIS data shows better correlation with crop yields compared to similar analyses using data from NOAA AVHRR. The better results may be due to better spatial resolution and to the specific narrow bands in VIS and NIR of the MODIS sensors. The seasonal NDVI profile describes the crop growth and development, surface temperature provides additional information regarding potential crop stress conditions. Stress conditions may include crop water stress as well as disease and infestation. An algorithm that combines NDVI and Ts was developed that correlates with yield in a two dimensional regression equation:

$$Yield = a + b*NDVI + c*Ts \dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

Currently, one set of equations are developed for corn and soybeans for each state. The NDVI and Ts parameters are summed for a period between the mid-vegetative to mid-senescence period. The state yield estimate is obtained by averaging the parameters for all corn or soybean pixels in the state. The NDVI and Ts parameters extracted for each crop for the 2002-2005 crop season are then used in equation (1) with the NASS estimated yields. The coefficients **a**, **b** and **c** are derived and the regression equation is then used as a predictor for 2006 state crop yields.

The spatial variability of crop yields are assessed at the county level by extracting the mean NDVI and Ts parameters from corn and soybean pixels for each county. Equation (1) is used to determine the a, b and c coefficients using data from the 2002 crop season. Then equation (1) was applied to predict county level yields for successive years. The 2002 crop season data was selected to develop the regression algorithm because the MODIS data quality was better than other years and crop yields for corn and soybeans were spread over a wider range. County yields for the 2005 and 2006 crop seasons were predicted using the regression algorithm developed from the 2002 data sets. The initial predictions for state and county level yields are made in early September prior to crop harvest and updated after the senescence is completed in October.

3. RESULTS and DISCUSSIONS

The MODIS data acquired for this research covered five crop seasons when complete seasonal data was available (2002 - 2006). The results from this research are compared with USDA official estimates from NASS. Final state yield estimates are published in January of the following year. These estimates are based on objective yield and farmer-based survey data collected from well planned sampling strategies and considered to be accurate. The NASS county level estimates are generally published in March of the following year and the data used are from similar farmer-based surveys and from observed local weather and crop conditions. These estimates may not be systematic from county-to-county within the state. This research seeks to provide additional information derived from remote sensing data to supplement spatial information that would strengthen the county level estimates., at a much earlier time period.

Crop Classification

The MODIS-based classification of corn and soybean crops was developed using the NDVI time series profile, first separating the crop area from other classes by selecting pixels with an NDVI threshold of 0.4 at the beginning and end of the crop season with a value of 0.8 at mid-season. In a narrow window around DOY 177, the magnitude of NDVI for corn is greater than soybeans as shown in an example in Figure 1. The MODIS classification was compared with a NASS classification developed from Landsat ETM images for the 2005 crop season. Landsat 30 m pixels were aggregated to 250 m MODIS pixels by picking up only those pixels that contained 90% of specific (corn or soybean) crop. In Iowa 357,795 MODIS pixels had 90% of corn or soybean fields (Figure 2). These pixels were used to test the corn and soybean discrimination algorithm. The results were then compared with the Landsat classification aggregated to 250m pixel resolution. The overall accuracy was 81.7% with a kappa coefficient of 0.63. In Illinois the number of MODIS pixels with 90% crop was found to be 409,108 pixels. The comparison with Landsat classification showed that the overall classification accuracy was 75.1% with a kappa coefficient of 0.50. The accuracy for Iowa was better than Illinois perhaps because of the large variation in corn and soybean phenological stages in Illinois between the northern and southern areas of the state.
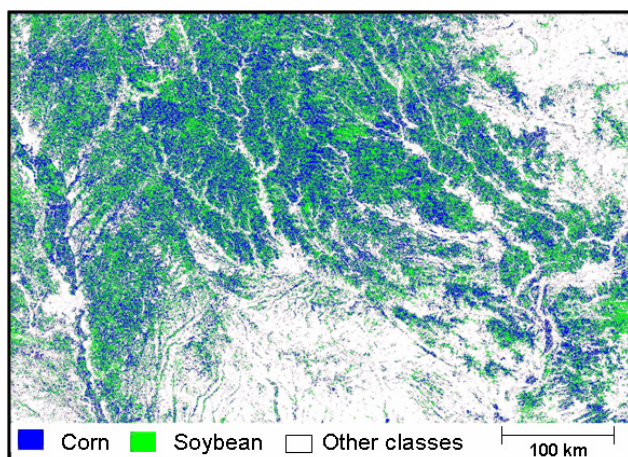

Figure 2.   The 2005 classification for Iowa using the 8-day MODIS 250 m composite imagery.

Crop Yield
Using the USDA/NASS state yield estimates for the 2002-2005 crop seasons, the multi-dimensional regression equations were developed for corn and soybean yields for Iowa and Illinois. Based on the regression algorithm, the coefficients of determination for Iowa at the state level were 0.98 and 0.88 respectively for corn and soybean crops. These equations were used to predict the Iowa state yield estimates for 2006 corn and soybeans. The regression algorithm yield predictions for the 2006 season for corn was 170 bushels per acre (b/ac) and 52.2 b/ac for soybeans versus NASS's estimates of 166 b/ac and 50.5 b/ac respectively.   In Illinois, the regression algorithm was developed for the same period (2002-2005), and showed coefficients of determination of 0.98 and 0.36 respectively for corn and soybeans. The low coefficient of determination for soybeans is due to disease outbreak in parts of Illinois during the latter part of the crop season in 2003 (Malvick, 2003). This occurred during the latter part of the season and the yellowing of the foliage due to disease was not observed from imagery. Nevertheless the yield predictions from the regression algorithm

for 2006 were 165.2 b/ac and 47.8 b/ac versus NASS's estimate of 163 b/ac and 48 b/ac respectively for corn and soybeans.

The state level predictions for the 2007 crop season will be based on a 5-year multi-regression algorithm developed from 2002-2006 state estimates.   The coefficients of determination for Iowa corn and soybeans were 0.96 and 0.88, and for Illinois they were 0.98 and 0.438, respectively. Eliminating the 2003 year from the regression algorithm for soybeans in Illinois increases the coefficient of determination to 0.97.
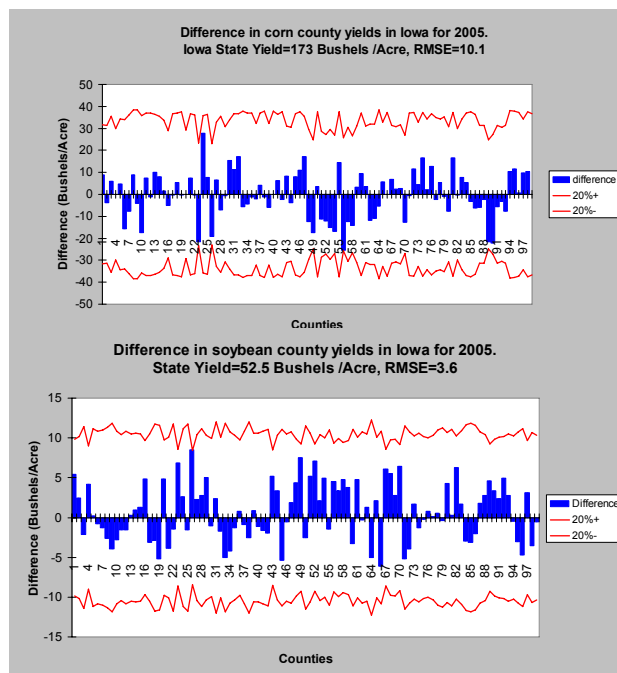
Figure 3.   Difference in county yields between the regression algorithm predictions and NASS estimated yields for the 99 counties in Iowa for the 2005 crop season.

The county level yield predictions were completed at the same time as the state predictions. The regression algorithm developed from the 2002 data provided the coefficients for the multidimensional regression algorithm. The multidimensional coefficients of determination for Iowa were 0.86 and 0.71 and for Illinois they were 0.82 and 0.86 respectively for corn and soybeans. These relatively high values indicate that the MODIS data for 2002 were good and the predictions fit well with the NASS crop yield estimates. For the other crop seasons the coefficient of determination was lower.   County level predictions are more sensitive to the quality of the remote sensing data, combined with the accuracy and consistency of the estimation of NASS county yields.

Using the regression model developed from 2002 crop season, the corn and soybean crop yields for 2005 were predicted and results compared with the NASS estimates. The coefficient of determination for corn is 0.73 and for soybeans is 0.59, and for Illinois these coefficients are 0.60 and 0.52 respectively. The regression coefficients are strongly dependent on the quality of satellite imagery and NASS county yield estimates for that particular year. Figure 3 shows the difference in county yields between the NASS estimate and the regression algorithm predicted yields for Iowa 2005 crop season. The red lines are the +/- 20% standard deviation from the NASS estimated yields. The regression algorithm predicted yields are all within

20% of the NASS estimates, and the great majority are within 10percent. RMSE for predicted yield for corn and soybeans in Iowa are 10.1b/ac and 3.6 b/ac and in Illinois are 19.3 b/ac and 5.6 b/ac respectively.

4. CONCLUSION

Timely and accurate prediction of crop yields is critical for agricultural markets, planning and development. Daily frequency of MODIS data acquisition at 250 m pixel resolution offers a great potential for use of the data and products in operational yield prediction programs. In this study, a simple algorithm that uses near-real time MODIS imagery and products was developed to predict crop yields at county and state levels. The algorithm includes crop-specific classification and yield prediction prior to crop harvest. The crop classification was developed using a decision tree algorithm that relied on the characteristics of crop growth phenology without the need for ground-based data. The classification accuracies were compared with the USDA NASS Landsat-based classification data and found to be acceptable for yield predictions. The correlation between NDVI and crop yields and between surface temperature and crop yields are integrated in a multidimensional regression model for predicting yields at the county and state levels. Differences between the NASS state level yield estimates and the regression algorithm predictions for both Iowa and Illinois for the 2006 season was less than 4 b/ac for corn and less than 2 b/ac for soybeans.

The quality of MODIS data is very critical for crop yield predictions and this paper describes some of the steps that we achieved to enhance the quality of data for cloud cover and atmospheric effects. The computational scale appeared to make a difference in the tolerance on the imagery data quality. Although the same algorithm was used for both state and county level yield predictions, the county yield predictions appeared to be more sensitive to quality of the images and the yield predictions were not as well correlated with the NASS estimated yields. Another important factor in this lower coefficient of determinations at the county level was that the NASS estimates have an error that is not reported. However, assuming an error in the NASS county yield estimates, the predictions are well within a 20% standard deviation of the estimates.

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USE OF REMOTE SENSING IN SUPPORT OF
CROP AREA ESTIMATES IN SOUTH AFRICA

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KEY WORDS: Satellite Imagery, Crop Area Estimates, Aerial Survey, Point Frame, Crop Type Classification & Spatial Analysis

EXTENDED ABSTRACT:

In South Africa the National Department of Agriculture (DoA) is the custodian of the Crop Estimates Committee (CEC) that is responsible for the grain crop production estimates, published monthly. The CEC meets monthly to review and debate the current status of cropped area and conditions, to determine crop production estimates for grain crops. Grain crops in South Africa consist of two groups of which crops such as maize, sunflower, Soya beans, and sorghum, are cultivated during summer. The second group of crops are grown during the winter and include wheat, barley, oats and canola. Information about crops was previously only supplied by provincial and industry representatives along with qualitative reports on weather patterns and crop conditions that resulted in subjective calculations.

In 1994 South Africa entered a new political dispensation, which also saw the abandonment of governmental control and subsidies for agricultural crops. This left the South African grain farmers exposed to the free market and global supply and demand trends, which necessitated the requirement for objective and statistically reliable crop production information. The DoA realised the importance of conducting independent scientific production estimates in 2001 and awarded a tender to the National Crop Statistics Consortium (NCSC). The mandate of the NCSC was to develop and implement a system to estimate planted areas and forecast yields based on a geographic point sampling frame that is stratified according to cultivation density, while also continuously improving the system.

A system was designed and implemented whereby satellite imagery was used as a first step to stratify the country by separating all non-agricultural areas from agricultural areas. The agricultural areas were stratified for rangeland and cultivation areas, and subsequently the cultivation areas were further classified into three cultivation intensity classes: high (>65%), med (30%-65%) and low (<30%). A point grid with 225m intervals was generated across the cultivation intensity areas, which was used for a geographic systematic random selection of points, with an increased sampling rate in higher density cultivation areas. These selected points are surveyed by field staff (predominantly farmers) that conducts an interview

with the farmer to complete a questionnaire to gather information on crop types, area planted and expected yields. Information is captured into a digital questionnaire with checks and balances to reduce errors, and downloaded daily through internet connections to a central database, where statistical processing takes place to calculate a crop area estimate for each crop type per province. As this system is dependant on information gathered directly from the farmer, it is essential to have the co-operation of farmers. Over the last three seasons the response rate to interviews has decreased to such an extent that it has prompted the NCSC to look for alternatives, while at the same time retaining the confidence of a Coefficient of Variation of below 5% at national level.

In combining and integrating satellite imagery, remote sensing, point frame statistical platforms, GIS and aerial observations, a Producer Independent Crop Estimate System (PICES) was developed in a pilot project over the Gauteng province to demonstrate the feasibility of such a method. As a first step satellite imagery (Landsat 5) over three seasons was used to capture field boundaries for all cultivated fields in the province. The field boundaries that were mapped, replaced the cultivation density stratum, and were used as a frame for a random geographic systematic selection of sample points across each province. These selected points were sampled to determine the crop type for each field/point by aerial observations using an Very Light Aircraft (VLA). For the aerial survey trained observers (predominantly farmers), that could identify different crop types, were employed to record crop information for selected points on a digital tablet PC with a touch screen in combination with a GPS navigation instrument. The observers also recorded additional information while in transit between selected points, for fields clearly visible with identifiable crops, from the aircraft.

Information gathered during the aerial survey was firstly used to calculate a statistical area for each crop type per province. Secondly it was used as training sets for satellite imagery during classification procedures to generate a crop type for each individual field. During the growing season both Landsat 5 and Spot 2 and 4 images were recorded and used to perform a crop type classification. From the classified satellite imagery, the

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crop type was assigned to individual field boundary polygons to provide a complete set of classified fields for each province.

Subsequently the methodology has been expanded and implemented in the four major summer grain producing provinces on an operational level that is functional in providing reliable crop area estimates. These provinces are Northwest, Mpumalanga, Freestate and Gauteng where the grain crops are predominantly cultivated under rain fed conditions, relying on summer rainfall. The same procedure as explained above was followed to digitise field boundaries for 280 000 fields, covering 6,5 million hectares across all four provinces. These provinces represent approximately 90% of the total area in South Africa under summer grain production. For the satellite image classification, images were recorded within the growing season, by Landsat 5 as well as Spot 2 and 4, but due to rainfall and associated clouds many images recorded were not suitable because of high cloud cover. Suitable images with the least cloud cover were selected for the months of February and March, which coincide with maximum vegetative development of the summer grain crops. All clouds were mapped for each individual image in a shape file, and the fields intersecting with cloud polygons were removed before further processing. Field boundaries were used as masks, in order to retain only the spectral information with in the fields, thereby enhancing the image histogram for crop type discrimination.

Information on crop types captured during the aerial survey was used as input to the image training procedure. The additional information on crop type captured in between selected points was used as training for the signature files, while the selected points with crop type information was retained for accuracy assessment. Fields in all four provinces planted with maize covered 80% of the summer grain fields, while sunflower covered only 10% and Soya beans 5% with other crops less than 2%, according to the ratio of crop types generated from the aerial field surveys. This ratio of very few points for crops with a low representation had the effect that there were no field verification samples available on certain images. To overcome this problem, satellite images recorded on the same day were all mosaiced together, which resulted in long strips of imagery to allow field verification across a larger area that had a better chance of all the crops being represented. This approach improved the possibility to generate signature classes for all crops on all images, although on certain individual scenes it was still not always possible.

Signature files were generated for each field masked image, considering the crop phenology stages for each crop type. Crop types such as sunflower and maize had substantial overlap in the signature files, and maize was split into six classes of more specific spectral types. Another factor contributing to overlap between classes is the less than 100% canopy cover that causes a high proportion of soil reflectance to be included in each of the crop type signature classes. This is due to the arid conditions with high summer temperatures and average rainfall of only 700 mm per season. Crops are therefore planted at a low density, which results in a less than 100% canopy cover. With crops not growing at optimal conditions, the heterogeneity within crops fields are emphasized and subsequently limit the possibility of having pure signatures for specific crop types.

Signature sets were evaluated for separability for each image using the Jefferson-Matusita analysis and each signature class in a set was refined to reduce overlap between classes. Before classification, the different bands in each image were also evaluated to determine the best combination to discriminate between different crop types, and it was found that generally the red band along with the infrared bands provided the best separation. Images were classified using the Erdas supervised classification approach and selecting the maximum likelihood combined with the parallel-piped functions. Crops such as Soya beans and sunflower have typically shorter crop phenology cycles, compared to that of maize. It should therefore have been potentially possible to discriminate on this basis. This did not realise in practice. Farmers generally stagger planting dates for all crops from October until December to spread the risk of erratic rainfall across the season, which makes it impossible to fix the crop calendar for specific crops according to planting dates or times of harvest.

After the supervised classification procedure, a zonal majority function was used to assign a crop type to each field boundary polygon based on the raster classification. This step generated an ArcView shape file with a crop type for each field during a specific season for an entire province, providing a basis for various queries and analysis.

Through integrating and combining technology it was possible to calculate statistical area estimates for each province through aerial surveys, while also generating a map showing the spatial distribution of crop type patterns. It is now possible to extract information on sub provincial level such as agro-climatic zones or district level, or any polygon boundary of importance. This provides decision makers with spatial analysis possibilities not previously available.

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USE OF REMOTE SENSING FOR CROP YIELD
AND AREA ESTIMATES IN THE SOUTHERN OF BRAZIL

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KEY WORDS: Agriculture, developing countries, mapping, modelling, satellite

ABSTRACT:

The purpose of this paper is to describe the main actions undertaken by the Federal University of Rio Grande do Sul (UFRGS-Universidade Federal do Rio Grande do Sul) in activities related to crop monitoring and forecasting in Rio Grande do Sul State, the most southern state in Brazil. First the importance of agricultural activity is placed in the context of the state, showing grain production data. A short description of UFRGS and the group of researchers is also presented. Then several actions developed by the University to monitor crops and forecast harvests are presented, by discussing the methodology and main results of project GeoSafras (GeoHarvests). This is a multi-institutional nationwide project coordinated by the National Supply Company (CONAB-Companhia Nacional de Abastecimento). From the methodological standpoint, the project uses a set of techniques and methods, some already tested and others under development, in the fields of remote sensing, geoprocessing and agrometeorology. In this paper as an illustration, some results are presented using soybean crop. Finally, a report is made on actions in cooperation with Joint Research Centre (JRC), the results of which were presented at a JRC workshop in Montevideo, comparing ECMWF (European Center for Medium range Weather Forecasting) simulated data to observed data at several surface meteorological stations, as well as, evaluating the use of simulated data in the soybean yield model in Rio Grande do Sul State.

1. BRAZILIAN AGRICULTURAL CONTEXT

Brazil is one of the main grain producers and exporters in the world, and agribusiness is crucially important for the economy of the country. Regionally, Rio Grande do Sul, the most southern state of the country, is the third largest grain produces among the Brazilian states. In the last 5 years the average contribution of Rio Grande do Sul has been about 17% of the national harvest. The largest volumes of grain in the state are soybean (6025579.8 t), rice (5576242.6 t), maize (4064680.8 t) and wheat (1609823.8 t) (IBGE, 2006).

Since the agricultural industry has produced the main trade balance surplus in Brazil, in the last few years, government actions are required for effective control of imports and exports of agricultural products, both as regards the trade balance and adequate supply for the domestic market.

Surveys of Brazilian harvests have traditionally been performed using shire information obtained in a subjective survey system, based on the opinion of technical and economic agents involved in the sector.

Recently, the National Company for Supply (CONAB – Companhia Nacional de Abastecimento – http://www.conab.gov.br), the institution responsible for generating national agricultural estimates, proposed a project to revitalize the institution by improving the system of estimating areas and agricultural yields in Brazil. The work have been developed using a multi-institutional network to developing objective methods that can be absorbed by the institution and implemented operationally. This project is called GeoSafras (Geoharvests).

2. MAIN CROP MONITORING AND FORECASTING ACTIONS AT UFRGS

2.1 Background

The research group on harvest monitoring and forecasting at Federal University of Rio Grande do Sul State (UFRGS – Universidade Federal do Rio Grande do Sul http://www.ufrgs.br) is currently participating in the GeoSafras project, proposing methodological developments and tests that can be passed on to CONAB and incorporated to the crop monitoring and forecasting program in Brazil.

UFRGS, located in Porto Alegre, capital of the state of Rio Grande do Sul, is a century-old institution. Courses of study in all fields of knowledge at all levels, from Basic Education to Post-Graduate studies are taught at the University. Currently, the University has 355 research groups. One of the outstanding groups researches crop monitoring and forecasting. These researchers are located at the Faculty of Agronomy (http://www.ufrgs.br./agronomia) and at the State Center of Research on Remote Sensing and Meteorology (CEPSRM-Centro Estadual de Pesquisas em Sensoriamento Remoto e Meteorologia – http://www.ufrgs.br/srm).

Nowadays, the team working on this line of research includes permanent UFRGS staff (Denise Cybis Fontana, Jorge Ducati, Mônica Kreling, Moacir A Berlato, Homero Bergamaschi and Laurindo Guasselli), and FEPAGRO staff (Ronaldo Matzenauer and Jaime Maluf), masters scholarship students (Eliana V. Klering and Amanda H. Junges), scientific initiation students

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(Ana Paula A. Cordeiro, Fernando T. Machado, Laurie F. Cunha, Lucas S. Borne and Márcia dos Santos), technical development people (Ricardo W. Melo, Anibal Gusso and Gilca M. Alves) and consultants (Ana Paula L. Wagner and Eliseu Weber).

Joint CONAB-UFRGS activities began during the 1998/99 crop yield, in a pilot experiment in the state of Rio Grande do Sul, using only a Landsat scene covering part of the northwest of the state. In 1999/2000 the work were repeated but the coverage area was greatly increased, now to approximately 50% of the soybean-cultivated area in Brazil (Fontana et al., 2000). Despite promising results, work was interrupted, and it was only from the 2003/2004 crop onwards that the partnership was established again. During the period of the interruption, three workshops were held, which made it possible to prepare a new institutional arrangement for cooperation, in which a group of research institutions from several Brazilian states participated, working in an integrated manner. Among the participating institutions were UNICAMP, INPE, INMET, EMBRAPA, IBGE, and others.

At UFRGS GeoSafras-related work is oriented towards the three segments that constitute a crop forecasting program: estimates of cultivated area, estimates of yield and monitoring during the crop development period. A few of the experiments developed with soybean crops in the state of Rio Grande do Sul will be described in this document.

2.2 Methodology

Methodologically, the actions present a set of techniques and methods, some of them already tested and others still under development, in remote sensing, geoprocessing and agrometeorology.

With remote sensing, the land surface characteristics can be measured based on high-altitude sensing devices, on board airplanes or satellite. Satellite images, in particular, have allowed increasingly detailed studies on a regional scale, due to the possibility of viewing the same territory at regular time intervals. This characteristic shows its potential to follow the changes that occur on the earth surface over time. Furthermore, the images allow measuring the characteristics of the surface in different bands, both in the visible and in the infra-red region. Analysis of these bands allows mapping the different types of land cover, including agricultural crops. Using geoprocessing, it is possible to locate geographically and quantify the cultivated areas, integrating regional or national information. In agrometeorology models are already available to quantify the plant-climate relationship by using data from surface meteorological stations together with satellite images to forecast yield.

2.3 Main results of project GeoSafras-UFRGS

A methodological possibility that has been tested at GeoSafras is the combined use of medium and low spatial resolution sensors. The sensors with medium spatial resolution can contribute detailed information in certain areas, while the lower spatial resolution sensors can help generalize information. We have worked with the three main crops in the Rio Grande do Sul State, that are: soybean, rice and wheat. As an illustration, some results are presented in this paper using soybean.

2.3.1   Landsat/TM – for crop area mapping: Most of the work done with medium resolution sensors in Brazil has used Landsat/TM satellite images. The results accumulated by the group at UFRGS using these images to estimate the area

planted with soybean during several crops years have proved promising, revealing high accuracy when evaluated based on field data (Motta, 2002; Weber et al., 2005). However, despite the high concordance between the results of image classification and ground control, in many cases considerable discrepancies were found between area estimates obtained at a municipal level from images and estimates supplied by CONAB and also by Brazilian Institute of Geography and Statistics (Instituto Nacional de Geografia e Estatística – IBGE). For all the years studied, despite the good results obtained with several classification methodologies, the greatest challenge was to render actions that could supply the information needed for large regions operational, in a timely manner compatible with the schedule of official surveys. One of the greatest obstacles in this sense is always how long it takes to obtain the Landsat/TM images, which has delayed the beginning of their processing and, consequently, obtaining results. The mapping of the 2005/06 crop is shown in Figure 1, making it clear that most of the soybean cultivated in Rio Grande do Sul is concentrated in the center-north region of the state.
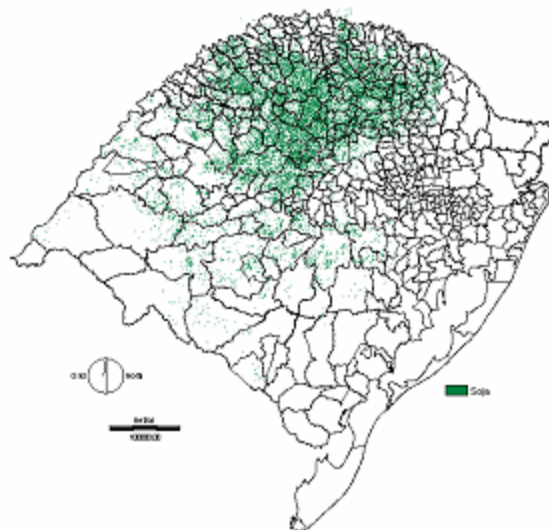
Figure 1. Soybean cultivated area in Rio Grande do Sul State, mapped using 11 Landsat-TM images, during 2005/06 crop year.

2.3.2   Terra/MODIS – for crop area mapping: As to the low resolution sensors, the initial attempts to estimate the crop area with low spatial resolution images were performed using AVHRR/NOAA images. Despite the feasibility of using these images in monitoring programs, the study performed by Motta et al. (2003) showed that the potential of using these images to make inferences about the cultivated areas had to be further evaluated because of the 1 km spatial resolution at the nadir. Later, MODIS/TERRA images began to be used. These images have a spatial resolution of 250m and a temporal resolution of 16 days, adequate for this type of study. In this case, the studies to determine the crop area were performed by analyzing the time variations of the vegetation index. Throughout the growing season, the crops present a time variation different from the other types of ground cover. At the beginning of the cycle, during the crop implantation phase, the vegetation index values are low, increasing as crop growth and development occurs, and diminishing again at the end of the cycle as the plants become senescent. During the 2004/05 and 2005/06 harvests, tests of the

use of MODIS/TERRA images were made to map soybean in Rio Grande do Sulk State. At both harvests, two methods were tested, based on the use of the Normalized Difference Vegetation Index (NDVI): one tries to individualize the soybean areas using an image of difference and another uses reclassification through an NDVI threshold in two periods and then cross-matches binary images. In both techniques, images of contrasting periods are used in terms of NDVI, one for the phase during which the crop is planted, and the other when the crop is fully developed. In these two methodologies, the analyses were also based on field data recorded by GPS in several crops. The results obtained have been very promising and the data obtained for the 2005/06 harvest are shown in Figure 2. A more detailed analysis of the results obtained is ongoing with a view to applying it to other crops and in other regions, especially concerning the practicality, low cost and easy data generation.
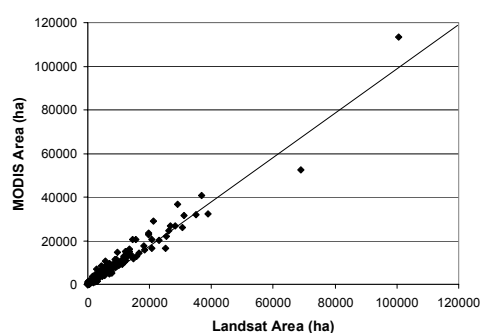

Figure 2. Comparison between soybean area from Landsat and MODIS images, using just counties 100% covered by images without clouds, in Rio Grande do Sul State during 2006/06 crop year.

2.3.3 NOAA/AVHRR – for monitoring and yield estimates: Another low spatial resolution sensor used lately by the UFRGS group is the AVHRR/NOAA images, now for monitoring and yield estimates. Yield, defined as grain production per unit of area, is a result of the complex interaction between soil conditions (physical and chemical conditions), management (cultivar, spacing,...), and the meteorological conditions (water, thermal,…). On the other hand, modelling the environment may be conceived as the simplified representation of the relationship between the crop and the environment. Agrometeorological model characteristics are accuracy, objectivity, easy implementation and low costs. They can be used to predict plant behaviour, if a given condition exists in crop forecasting programs. This type of modeling is based on establishing growth and development relations for the vegetation, with variables describing the meteorological conditions during the cycle. The functions consider the differences in crop sensitivity to stresses throughout the cycle, the so-called "critical periods". In Rio Grande do Sul a few previous studies, such as those performed by Berlato (1987) and Fontana et al. (2001), proposed the use of soybean yield prediction models (similar to others non-irrigated spring-summer crops), and the independent variable to be used was some expression of water availability. In these models different weights are assigned to the different stages of crop development, according to the relative sensitivity of the plant to the water deficit. Later, Melo et al. (2003) added a spectral term

to the agrometeorological model. The hypothesis to introduce remote sensing techniques is based on the fact that plant growth and development may be monitored by orbital remote sensors, that the remote measurement of the biomass may be a complementary estimator of grain yield, and, finally, that measurement from satellites allows improved detailing of spatial variations of yield. The spectral term is given by the Maximum Value Composites (MVC) of the Normalized Difference Vegetation Index (NDVI), obtained from satellite images with low spatial resolution but high temporal resolution, as in AVHRR/NOAA. In the case of these types of models, the agrometeorological term covers the thermal and water conditions, while the spectral term introduces into the model other factors that determine growth and are not taken into account in the agrometeorological term, such as differences in management practices, cultivars and other stresses. The results of applying this model for the last 4 crops is shown in Figure 3. It is found that the estimates accompany the tendencies of the official statistics (IBGE), although with less sensitivity, ie, the estimated yields are below those observed in the high yield years and above those of low yield. It is thus found that the model proposed can potentially be used at a regional level, fulfilling the demand of agencies in charge of official crop surveys in Brazil. For monitoring activities, AVHRR/NOAA images have been tested with success for Rio Grande do Sul conditions (Fontana et al., 2002) These images are available at CEPSRM web site (www.ufrgs.br/srm).
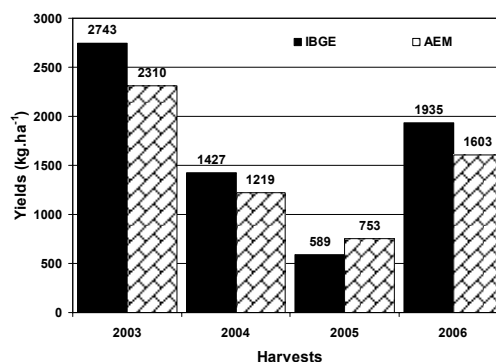
Figure 3. Soybean yield by IBGE and estimated by the agrometeorological-spectral model (ASM) for the last four harvests in Rio Grande do Sul State.

3. ACTIONS IN COLLABORATION WITH THE JRC

During the International Workshop of Crop Monitoring and Forecast, held in Montevideo, October 9-11, 2006, a few results of work done in cooperation between AGRIFSH/MARS-FOOD and UFRGS were presented (Melo e Fontana, 2006). In this study, meteorological data simulated by the JRC and measured at meteorological stations during the January 2003-December 2005 period were used.

The data simulated, all of them for 10 days, were obtained from the website of JRC (JRC, 2006) in the form of GeoTIFF images of maximum, minimum and mean temperature, rainfall and evapotranspiration. The meteorological data from 17 surface stations located in the state of Rio Grande do Sul were obtained from the observation networks of the 8th District of the National Institute of Meteorology - 8º DISME/INMET – 8º Distrito do Instituto Nacional de Meteorologia) and from the State Foundation of Agricultural and Livestock Research of the

Department of Science and Technology (FEPAGRO/SCT - Fundação Estadual de Pesquisa Agropecuária da Secretaria de Ciência e Tecnologia).

The results showed that the maximum temperature data simulated overestimated by 5.2ºC, on average, the data observed at the meteorological stations, while the minimum temperature data presented a mean underestimate of 4.9ºC. The mean temperature data simulated presented a slight tendency to underestimate, and were very close to the 1:1 line, with a standard deviation of 1.1ºC (Figure 4).
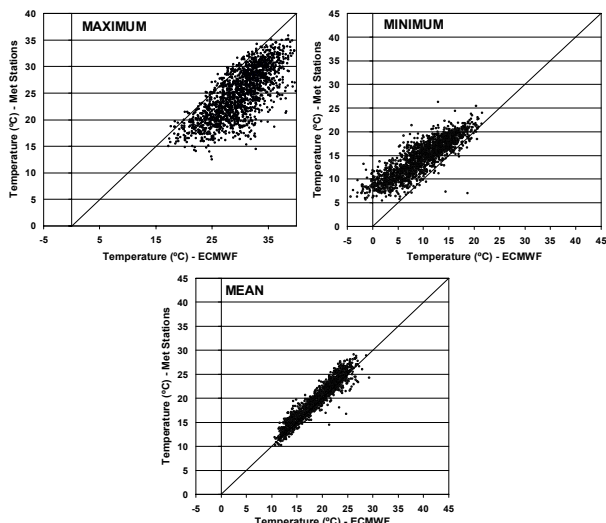
Figure. 4. Maximum, minimum and Mean Temperature measured (Met Stations) and estimated by ECMWF in the Rio Grande do Sul state.

On the other hand, the rainfall data presented a wide dispersion compared with the data observed at the surface meteorological stations (Figure 5). Part of the dispersion may be due to the fact that analysis was performed comparing data collected at an observation point (meteorological station) and mean data from a grid generated by the JRC model. Analyzing the evapotranspiration data simulated by JRC, a slight tendency to underestimate small values and overestimate values with a greater magnitude, compared with the values calculated based on the meteorological data was observed at the surface stations (Figure 5).

Figure 5. Ranfall and Evapotranspiration (ET) measured (Met Stations) and estimated by ECMWF.

In the follow up of this paper, the performance of the agrometeorological-spectral model to estimate soybean yield was evaluated, for the region with the highest soybean production in the state of Rio Grande do Sul, using data from surface meteorological stations and data simulated by ECMWF.

The study showed that the meteorological simulated data may be used as an alternative source of data to calculate the estimated soybean yields in the region with the highest production in the Rio Grande do Sul State (Figure 6).
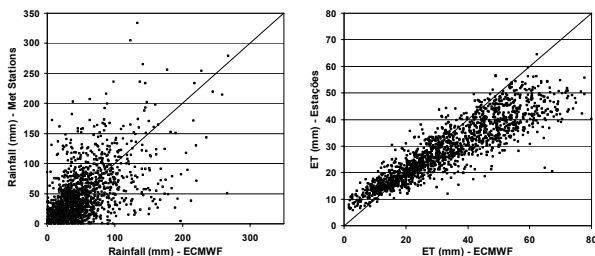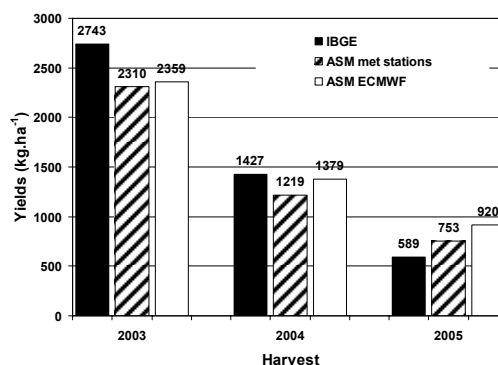

Figure 6. Soybean yield by IBGE and estimated by the agrometeorological-spectral model (ASM) using data from meteorological stations and by ECMWF simulations.

4. FINAL CONSIDERATIONS.

The partnership between UFRGS and CONAB, established through the GeoSafras project, has provided an excellent environment to exchange experiences between the two institutions, as well as with the other partner institutions. Besides testing and developing techniques and methods, the vocation of the University is to train human resources, providing trained professionals who may be taken on by the institutions responsible for obtaining information on agricultural crops. On the other hand, in this partnership, CONAB and UFRGS has an opportunity to perform research on an applied topic, which has led to establishing and maintaining this research group.

The methods developed at GeoSafras project fulfilling the demands by objectivity, accuracy, low costs and practicity of the estimations. Of course, the methods need of continued improvement especially for crop area and yield forecasting, what justifies founding allocation. Finally, according to the UFRGS researchers, the experience exchanges are welcome.

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THE USE OF MODIS DATA IN SOUTHERN RUSSIA FOR CROP ACREAGE ESTIMATIONS AND INTER-COMPARISON OF RESULTS FROM VARIOUS CROP ACREAGE ESTIMATION METHODS

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KEYWORDS: Crop Area Estimations, Methods Comparison, South-East Russia, Remote Sensing

ABSTRACT:

The first part of this paper presents a methodology on crop acreage estimations using the MODIS 16-day composite NDVI product. Particular emphasis is placed on a good quality crop mask and a good quality validation dataset. A novel approach which is based on the sampling of pure fields has been developed. The novel approach has been tested in previous work using a traditional maximum likelihood classification for 5 different crops. This novel approach has been further developed in this paper by applying a rule based approach which allows the estimation of winter wheat acreage in the study region. The advantage of such an approach is its simplicity, reasonable dataset input requirements and its potentially good forecasting capabilities. Training and rules are based on the year 2002. Results from this approach are shown together with an inter-comparison study which covers the second part of this paper.

An inter-comparison study as part of the GEOLAND project in the Observatory for Food Monitoring (OFM) was carried out. In order to study the capabilities of the different methods to estimate crop acreage 2 study areas were chosen, Belgium and the South-West of Russia. 3 crop types namely winter crops, maize and sugarbeet /potatoes were compared for Belgium for the year 2003 from the partners Infoterra France (ITF) and Vito. For the Russian test site, a common study area was defined for all 3 partners (Vito, ITF and JRC) which includes 6 Sub-Oblast administrative regions (districts) and winter crops were chosen as the common crop type. An extended area (22 districts) was defined for the 2 partners Vito and JRC. For the common test sites differences of the acreage estimates are highlighted, absolute errors and root mean square errors are examined and the significant differences of the datasets are explored.

1. INTRODUCTION

Recent developments in remote sensing technology, in particular improved spatial and temporal resolution, open new possibilities for estimating crop acreage over larger areas. Remotely sensed data allow the estimation of crop acreage statistics independently of sub-national survey statistics. This work focuses on the use of MODIS data acquired in 2001/2002 and 2004/2005 over the Rostov Oblast in Russia, by the Azov Sea. The region is characterized by large agricultural fields of around 75 hectares in average. The pure pixel sampling approach is a novel approach and uses segments derived from high resolution images in combination with coarser resolution MODIS data. This method takes on the one hand advantage of the high spatial resolution of high resolution data (e.g. Landsat) and of the high temporal profile of Medium resolution data (e.g. MODIS). In the following sections we consecutively describe the selection of the MODIS product, its geolocation quality, the way the high quality crop mask was derived, and the pure pixel sampling approach. The following sections describe how the method was implemented using the MODIS products as input for the medium resolution data and Landsat as input for the high resolution data. In the second part of this paper an inter-comparison study of the different methods applied in the GEOLAND Observatory for Food Monitoring (OFM) is presented.

2. MATERIAL AND METHODS

2.1 The appropriate MODIS product and its geolocation

Since there are many different MODIS products, it is not easy to decide which one is best suited for crop acreage estimations. The different available products were compared and advantages and disadvantages were considered. Other studies, for example a study which focused on the detecting of clear cuts in Russia, have shown that the 250 meter product is superior to the 500 meter product when smaller areas have to be monitored (Stibig and Bucha, 2005). The MOD13 product has been identified as the most useful product as NDVI are available and no pre-processing and compositing is required. Other current studies also use this product for acreage estimations (see Lobell and Asner, 2006). The 16-days product is a Maximum Value Composite (MVC), which selects the least cloud-atmosphere contaminated pixel and also tends to select the closest near-nadir view (Huete et al., 2002).

In order to use the MODIS data for acreage estimations the geolocation accuracy is an essential issue. Whereas former sensors such as AVHRR were prone to a high geolocation error, the MODIS sensor has much better geolocation accuracy. According to Stroeve et. al. (2005) the MODIS geolocation accuracy is better than 150 m at the 99% confidence interval. Nevertheless in case the product is used for acreage estimations a distance of 150 meters can matters, even though fields can be up to two square kilometres. However, it has been found on a

sample site that the intra-geolocation error between the MODIS images is quite low and therefore a systematic correction can be performed.

2.2 The crop mask based on high resolution images and a report with field data graphic files ration

A general problem for acreage estimations in different places of the world is the lack of data to separate the natural vegetation from the agricultural areas. Due to the fact that for example grassland can show a similar profile as certain crop types, a good quality crop mask is essential to avoid classifying the natural vegetation as a crop or vice versa. Therefore, in case a crop mask is available for the region under analysis it is of advantage. Even if data on crop distribution is published in reports and only available as graphic files a crop mask can be derived by geo-referencing the graphics file to the Landsat data. For example vector segments can be derived (e.g. from the e-cognition software, Baatz and Schäpe, 2000) and all those segments can be removed which do not coincide with fields on the geo-referenced graphic files.

2.3 Landsat Segmentation and pure pixel sampling approach (PPS)

The method of segmentation was applied as to obtain an image which could be used to remove unwanted mixed pixels between fields. The full segmentation algorithm is described in Baatz and Schäpe (2000) and implemented in the e-cognition commercial software. The segmentation was applied to a selection of bands (band 3,4,5) for 4 images of the ETM time series. The software allows the user to choose the segmentation size and specify whether more compact features should be preferred. After trying different settings, a relatively small segmentation size was selected to ensure that all fields were segmented. The disadvantage was that some of the larger fields were divided into up to 3 segments.

We applied a method which removed all those pixels which were located on the border of a segment (the delineating vector of the segment). This reduced the overall number of pixels by more than 80%. Since by the removal of those potentially mixed pixels we reduced the overall area, we needed an estimator to calculate the overall area of a certain crop. We used a simple proportional estimator (see equation 1) and derived the estimated overall winter crop area for each district. We refer to this method as pure pixel sampling approach.

$$NS_W = \frac{S_W}{S_A} * NS_A \qquad (1)$$

Where :
S_W = the number of pixels classified as the crop of interest
S_A = the number of all pixels which were sampled (pure pixels)
NS_A = all pixels found in the crop mask

In order to test the approach described above be applied it to the South-Western region of Russia the Oblast Rostov. It is located at the Asov Sea. When the Landsat image is segmented the borders between fields can be quite well captured. In a previous study we compared the pure pixel sampling approach with a hard classification. We applied a simple Maximum likelihood classification (Fritz et al, submitted). When undertaking the pure pixel sampling approach, the overall number of used pixels was reduced to around 16% of the total, but this still allowed to produce the confusion matrix. Whereas similar pattern as found

in the other matrices evolve, the overall kappa coefficient is significantly better for the pure pixel sampling approach. Furthermore, the overall percentage RMSE of the official winter crop area was lower. Moreover, producers and users accuracy for winter crops improved which make this approach an attractive candidate for studies on the discrimination of different crops. It also allows to study other methods such as Neural Networks (NN) or rule based methods. We applied a rule-based method for the discrimination of winter crops from the others. These rules to discriminate winter crops from the rest is shown in Figure 1.
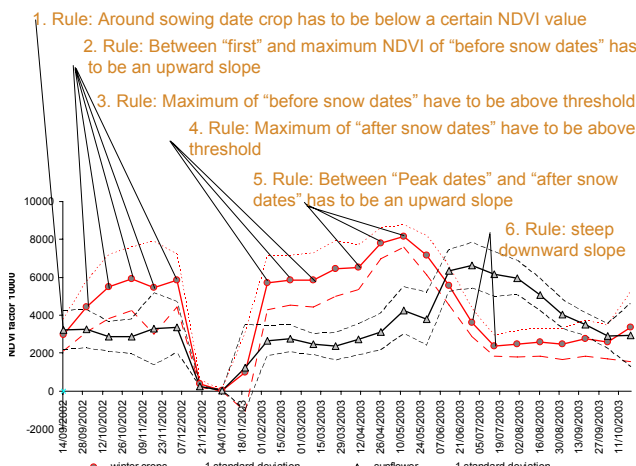
Figure 1: Six derived rules for the identification of winter crops

As it can be seen by applying the 6 rules, the different profiles of sunflower and winter crops can easily be distinguished. The profile of sunflower is used here as an example since it is the second cash crop in this area. The question remains where to define the thresholds which define the rules.

2.4 Standard approach

The crucial question for the rule based approach is how to define these rules. One objective way is to use a value which can be derived from a statistical analysis. Therefore we used 1 standard deviation of the different crops as a criteria to define our rules. For example in our example we see that winter crops in the sawing period have a low NDVI and define it for the first rule to be below 0.4 (with factor 10000 below 4000) and for the third rule that the maximum of the 16-day composites between the 28th of September and the 7th of December is higher than 0.4 (is higher than 4000). If all the 6 rules are fulfilled the crop qualifies for a winter crop. These rules are defined with the use of one standard deviation in the JRC standard approach. This approach of the use of one standard deviation is quite conservative and the maximum of a number of dates in a 16-day composite is expected to be quite stable over the years. However, the downside of this approach is that certain climate variations over years are not taken into account. Current research therefore focuses on a better way of defining these rules for example by using a field homogeneity index. This index is based on the homogeneity of crop pixels within the Landsat TM segments.

2.5 Approach which uses statistics from the same year for calibration

Instead of deriving the thresholds for the 6 rules from one standard deviation, the rules can be derived directly from statistical information which can be collected with the use of in-situ measurements and/or high resolution data. This means that for example in one area farm data could be collected earlier in the year or even a satellite image covering that area such as Landsat or Aster image of that year can be used to derived information on acreage in one sub-administrative unit. The rules are for this method defined by an exhaustive search where those 6 rules are used which minimise the RMSE for one sub-administrative unit. The exhaustive search is based on small incremental thresholds for each of the 6 rules. An optimal combination of the 6 rules is found based on information of one sub-administrative area. In our case study this means that the surrounding 5 sub-administrative regions could be estimated and the rules are derived from the smallest one. The method proved to be very accurate and is therefore presented in this study. It has to be however pointed out here that this method is using data which has not been available to the other partners (from the year 2005). It is therefore strictly speaking not part of the inter-comparison, which is based on data for the year 2005.

2.6 Discussion and conclusions on the pure pixel sampling approach

The described approach has shown that additional input data from high resolution Landsat data (freely available though: http://glcfapp.umiacs.umd.edu:8080/esdi/index.jsp) can be combined with information from the freely available MODIS dataset with a very good temporal coverage. The advantage is that the fields do hardly change over time and the segments can be used over a period of several years. Nevertheless, it has to be outlined here that the basic assumption was made that the proportion of pixels laying inside a segment is the same as the proportion of pixels laying on the border (segment vector) of two segments. This assumption can be made if there is no tendency to give preference to have certain crop types on smaller fields since only the pixels within bigger segments (fields) are considered. In areas with big fields and high proportions of cash crops these assumptions are valid. **Results of the pure sampling approach are presented in the next section which shows results of the acreage inter-comparison study for which this approach was used.**

3. RESULTS FROM VARIOUS CROP ACREAGE ESTIMATION METHODS

The three methods compared in this study use MR-LR data which have a high temporal resolution: SPOT-VEGETATION (VGT), MODIS and MERIS. VGT and MODIS have a near global coverage every day and MERIS every 2 days. The VGT sensor has a spatial resolution of 1 km in five channels, MODIS 250 meters in two channels and MERIS 300 meters in 16 channels. Pixels of MR-LR data are usually of a mixed nature and thus encompass several Land covers. A hard classification method assigns the pixel to the dominant class and therefore often under- or overestimates certain classes. All three partners use more advanced approaches with respect to the hard classification which can deal with mixed pixels. However, the methods have differences with respect to the used sensor, input data and approach. VITO uses a neural network (NN), ITF uses an inversion model and JRC a pure pixel sampling (PPS)

approach to estimate class proportions. In this report, a comparison of the three methods is performed.

Acreage estimations were compared for two sites: Belgium and South-West Rostov (Russia). The inter-comparison is based on qualitative and quantitative measures. The qualitative assessment compares the methods with respect to a number of criteria (e.g. amount and cost of input data). The quantitative assessment is based on a number of criteria such as the root mean square error, mean absolute error, a significance test and the coefficient of determination.

In Belgium three crop groups were investigated for the year 2003: winter crops, maize and sugar beet/ potatoes. However, in this paper only 2 crops groups (maize and sugarbeets +potatoes) are presented since they represent the spectrum of differences between the 2 methods. Whereas for the sugarbeets/potatoes the 2 methods show no significant difference, a significant difference in accuracy ? and a high difference in performance of the 2 methods can be found for maize. For Belgium VITO and ITF provided area estimations for the three crop groups in 26 agro-statistical districts (= administrative unit).

In the second area of interest, the Rostov Oblast, winter crops were chosen as the crop of interest. The three partners provided area estimates for this region. Crop acreages were evaluated with respect to statistics available for six districts in the SW of the Oblast. Calibration of the methods was done for 2002 on the SW Rostov and acreage estimates were calculated for 2005 for the whole or SW part of the region.

3.1 Sugar beets / Potatoes in Belgium

Figure 2 illustrate that the inversion model (ITF) seems to overestimate in nearly all cases whereas this is not the case for the NN (VITO). However, in the districts Tournai, Hasselt and Diskmuide, a relatively high error can be noted for the NN, for MODIS as well as VGT. Even though overall the NN applied on VGT data performs best in terms of RMSE and MAE (see Table 2) there is no significant difference between the three methods (see results of T-test, Table 1).

Figure 2: Difference for sugarbeets/potatoes acreage estimations compared with IACS database (Reference)

Table 1: Results of the T-test and rejection or approval of the null hypothesis (p-value = significance probability) for sugar beets/potatoes

	Students T-Value	p-value < 0.1	p-value <0.05
VGT - MERIS	0.218	No	No
MODIS – VGT	0.479	No	No
MODIS - MERIS	0.593	No	No

Table 2: RMSE (Root Mean Square Error) and Mean Absolute Error (MAE) for estimated sugar beet/potatoes acreages in Belgium for 2003 (in km²)

	ITF (MERIS)	VITO (VGT)	VITO (MODIS)
MAE	24.52	18.15	21.73
RMSE	31.15	25.48	28.57

3.2 Maize in Belgium

The Estimation Error of the methods is demonstrated in Figure 3. For maize, the NN (VITO) performs significantly better than the inversion model (ITF). Moreover, the NN calibrated with VGT data outperforms significantly the NN calibrated with MODIS data (Table 4). This phenomenon is surprising as the resolution of MODIS is much higher. Table 4 shows the t-values and the significance for the three methods

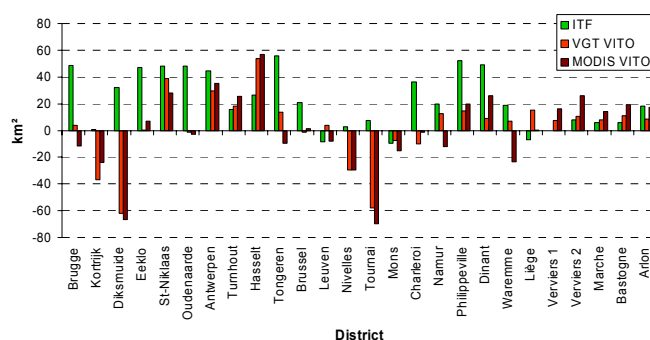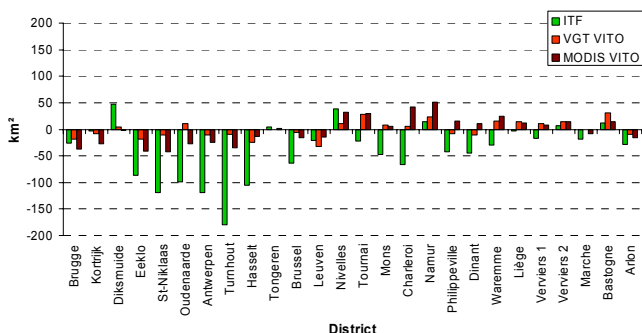Figure 3: Difference for maize acreage estimations compared with IACS database (Reference)

Table 3: Results of the T-test and rejection or approval of the null hypothesis (p-value = significance probability) for maize

	Students T-Value	p-value < 0.1	p-value <0.05
VGT – MERIS	0.000	Yes	Yes
MODIS – VGT	0.010	Yes	Yes
MODIS - MERIS	0.005	Yes	Yes

Table 4: RMSE and MAE for estimated maize acreages in Belgium for 2003 (in km²)

	ITF (MERIS)	VITO (VGT)	VITO (MODIS)
MAE	48.61	13.43	21.84
RMSE	66.26	16.08	25.95

3.3 South-West Rostov

This study area was chosen as common test site for all three methods. Comparison of the three methods was performed for six districts in South West Rostov. These administrative units were taken since ITF and JRC needed a crop mask for application of their method. This mask was, however, only available for these districts. Data from the year 2002 was provided to the partners for calibration. Comparison of estimations was performed for 2005 (see Figure 4). The main difference between Rostov and Belgium is the size of the fields: the AOI is characterized by large fields, while in Belgium small fields are usually present.
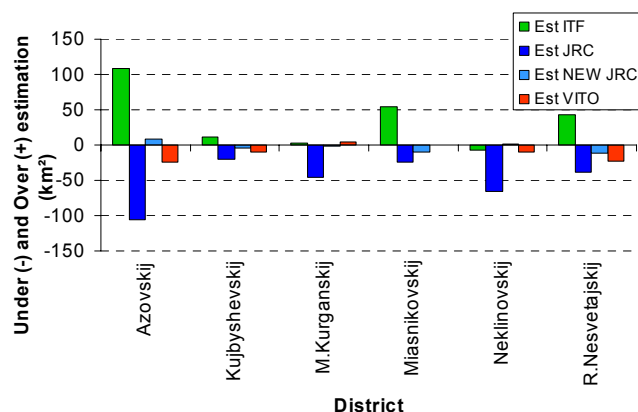

Figure 4: Acreage estimation error (km²); under (-) and overestimation (+) with statistics.

Another way of looking at the estimations is to assess the improvement of the estimations in 2005, compared with the statistical data from 2002 and to estimate the maximum detectable change in absolute terms. The maximum detectable change is simply calculated by the difference of the statistics for 2002 and 2005 in each district. The change for each RS method expressed in Figure 5 is the difference between the RS estimates for 2005 and the statistical data of 2002. Such an analysis is useful as statistical data from the year 2002 was given to the partners to train their model. VITO predicts detectable change in 4 districts well (in Azovski M. Kurganski, Miasinowskij and Neklinovski) whereas ITF predicts in 3 cases well Azovski, M.Kurganski and Neklinowski, though in the other 2 districts the prediction is worse than the statistics from the year 2002. The PPS (JRC standard method) which bases information on the year 2002 only predicts better for 2005 than the statistics in 2002 in the district Azovski (which experiences the most change). However, the PPS (JRC new statistical) method which is fed by information of one district performs very well and predicts winter crop acreage well in all 6 districts with a high accuracy. Since the analysis has been carried out in only 6 Districts none of the methods were significantly different. MAE and RMSE are given in Table 5.
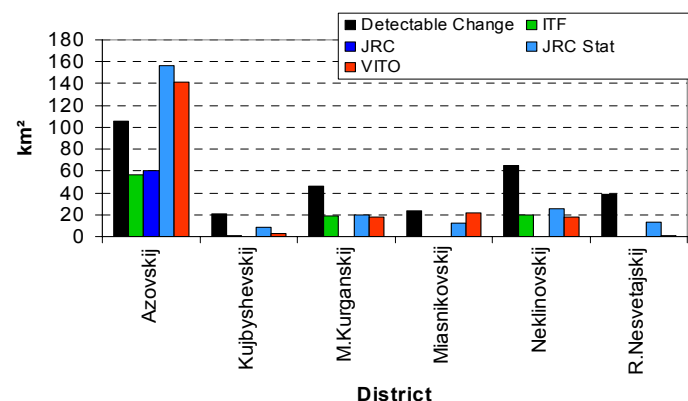
Figure 5: Districts in which the RS area estimation is better than the statistics for 2002 and area of winter crop difference between estimated figures in 2005 and statistics of 2002. If no bar is shown on the graph for a particular method the estimate is worse than the figure of the 2002 statistics

Table 5: MAE and RMSE for the 6 common districts

	JRC 2005	ITF 2005	VITO 2005	JRC new RS/stats
MAE	49.98	37.65	11.78	6.48
RMSE	57.65	52.69	14.75	7.62

4. CONCLUSIONS AND DISCUSSION

In order to undertake a quantitative comparison different error measures have been chosen. The performance was evaluated according to the Estimation Error (EE), the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE).

Following conclusions can be drawn for Belgium:
- The inversion model of Infoterra-France (ITF) did not work very well in Belgium, in particular for maize. It tends to systematically over/underestimate for maize and sugar beet/potatoes. The main reasons identified are the geolocation problem of MERIS data at the time of analysis and the complexity of the landscape, characterised by small fields.
- Most promising results are obtained by the Neural Network (VITO) in Belgium. However, better results were in general obtained when using VGT instead of MODIS data. Further investigation should be made to clarify this surprising result, and to verify the performance of NN in less favourable conditions where less exhaustive in-situ data is available.

For the six districts of South West Rostov the following can be concluded:
- All methods work reasonably well for large fields, and
- There is no significant difference between the different methods.
Taking these points into account, the methods can be further improved and applied. Clearly it has to be considered in which regions the approach performs well and for which areas there are limitations. Therefore, further investigation should envisage, besides a longer time series of estimates, a range of test sites within varying landscapes and climates. For example extension of the methods to Africa is of particular interest as on the one hand the reliability of statistics on acreage in some African countries is questionable and on the other hand there a lot of uncertainty on area and spatial distribution of agricultural land. These information are however crucial for food security early warning systems and rural development policies. For those regions the models will still need to be tested and further research is required.

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REVIEW OF THE MAIN REMOTE SENSING METHODS FOR CROP AREA ESTIMATES

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ABSTRACT:

This paper is a complement to two review papers published in the last years (Gallego, 2004, Carfagna and Gallego, 2005). In these papers an analysis is provided on the different ways satellite images can be used in for crop area estimation. We can group the methods into three categories:
- Pixel counting or similar approaches, including sub-pixel analysis : Estimates coming essentially from remote sensing. Ground data have a secondary role: training data for image classification, or sub-pixel analysis. In general this type of approaches should not be used unless there is no reasonable alternative. The statistical justification for this type of methods is very weak and there is a very high risk that the final estimates come essentially from the a priori belief of the analyst.
- Methods combining exhaustive but inaccurate information (from satellite images) with accurate information on a sample (most often ground surveys): Main types of methods in this category are regression, calibration and small area estimators. This is often the soundest way to use remote sensing for area estimation.
- Satellite images are used as support to build area frame surveys: to define sampling units, for stratification; as graphic documents for the ground survey, or for quality control.
Cost-efficiency is discussed: Operational use of remote sensing had reached the cost-efficiency threshold in some types of landscapes (large fields and few crop types) with Landsat TM images. New assessments are needed now for other image types. Some comments are made on the reason why many administrations are reluctant to integrate remote sensing in the production of area statistics.
The specific experience of the MARS Project on area estimation is reported here with more detail on three activities:
- Regional crop inventories (1988-1993), that combined ground surveys and satellite images with a statistically consistent regression estimator. The remote sensing part that did not reach the cost-efficiency threshold at that time.
- Rapid Crop Area Change Estimates (Action 4 or Activity B). This was an attempt to provide area estimates without ground surveys. The reasons for the failure of this activity are briefly analysed.
- Eurostat's LUCAS 2006 survey: the main contribution of remote sensing was a stratification of a large pre-sample of points by photo-interpretation on aerial orthophotos.

1. INTRODUCTION

Land cover area estimation is one of the most obvious applications of remote sensing. However the use of satellite earth observation tools for the production of official statistics has remained modest. In the field of agricultural statistics very few operational activities remain. One of the reasons of such a low level of development is the lack of continuity of the Landsat program. Alternative images of similar type are now available but little enthusiasm is shown to assess their use. Part of the problem may be the over-marketing in the past of methods that were not sufficiently solid from the statistical point of view. This paper gives an overview of different ways to use satellite images for land cover area estimation. It provides a complement to two previous papers (Gallego, 2004, Carfagna and Gallego, 2005). Approaches are grouped into three categories:

1.1 Pixel counting and sub-pixel analysis.

Using remote sensing as the primary information source. Ground data, are used as auxiliary tool, mainly as training data for image classification, or sub-pixel analysis. Area estimates from pixel counting are sometimes used without a solid statistical justification. The main limitation of this approach is that there is little guarantee of unbiasedness: image classification can be tuned to get the number of pixels we wish in a given category. The bias of area estimation can be potentially nearly of the same order of the commission or the omission errors. An image classification error of 20-30% can be considered a good result, but a bias of that order is generally not acceptable for land cover area estimation. These limitations and risks apply both to pixel counting approach and to polygon measurement in a land cover map, such as CORINE Land Cover. Additional problems appear if land cover maps are used for direct area estimation: bias coming from scale and incompatibility of statistical land cover maps nomenclature with statistical needs.

1.2 Regression, calibration and small area estimates.

Methods, such as regression, calibration and small area estimators, combining exhaustive but inaccurate information (from satellite images) with accurate information on a sample (most often ground surveys). The statistical basis of this category of methods is generally solid, but they require a know-

how that is generally not available in official institutions. Combining a sample of high or medium resolution images with a blanket coverage of coarse resolution images provides a solution to area estimation problems when ground surveys are not feasible because of difficult access or high cost. The need of qualified staff to carry out this type of methods is a limitation for official organisations, but this approach should be re-assessed with new image types (DMCII for example).

1.3 Supporting area frame surveys.

Satellite images can support area frame surveys in several ways: to define sampling units, for stratification; as graphic documents for the ground survey, or for quality control. We give an estimation of the relative efficiency of the point sampling plan of the Eurostat LUCAS survey (Land Use/Cover Area-frame Survey). The sampling plan of LUCAS (Delincé, 2001) is based on unclustered points that are sampled with a two-phase scheme: A systematic sample in the first phase is stratified by photo-interpretation. The second phase subsampling concentrates the sample on the most agricultural strata. The efficiency of different point sampling approaches comes from three sources: systematic approach in the first phase, separating strata (post-stratification) and applying unequal probability to subsample in each stratum. The efficiency due to each of the three reasons is estimated separately.

2. THE EXPERIENCE OF THE MARS PROJECT IN THE 90'S

2.1 : Area Sampling Frames in the Regional Crop Inventories.

The method was applied to a number of selected regions in different EU countries. It was based on two elements: a ground survey on a sample of pieces of land (segments), and an optional improvement of the results with high resolution satellite images (Gallego, 2000, Taylor et al, 1997). The size of the segments usually varied from 25 ha to 200 ha depending on the agricultural landscape, especially on the size of fields. For the area survey, surveyors located the segments, delineated fields on a transparent sheet placed over an aerial photograph, and wrote down their land use. About 5% to 10% of the segments were visited again by supervisors to assess the quality of the ground work. Area estimates and their standard error were computed with usual formulas for stratified sampling. A major component was the assessment of area frames in the EU, in which geographic elements are sampled instead of farms (FAO 1996, FAO 1998); satellite images are a major tool to define such frames.

Comparisons were made between different types of area sampling frames:
- Frames based on the so-called segments with physical boundaries (Cotter and Tomczac, 1994) as used in the June Enumerative Survey (JES) by USDA.
- Geometrical, usually square, segments (Gallego, 1995).
- Point frames, as used for example in the French TER-UTI survey.

Square segments and segments with physical boundaries gave similar results (González et al, 1991); square segments were preferred because there were cheaper. Point surveys turned out to be less appropriate for geographical co-registration with satellite images, but had in general better cost-efficiency for a ground survey, needed less infrastructure for data management and avoided the bias due to the elimination of thin "linear elements".

A method was developed to sample farms through a sample of points (Gallego et al, 1994), that avoided some complications of traditional approaches to sample farms from area segments (Hendricks et al, 1965), known as open segment, closed segment and weighted segment. The main limitation was that a bias can appear if the concept of Utilised Agricultural Area (UAA) used at the sampling stage does not coincide with the concept of farm area used by surveyors when they interview the farmer.

Stratification based on a coarse photo-interpretation of satellite images was cheap and proved to be cost-efficient, in spite of moderate values for the relative efficiency. A further analysis suggested that better efficiencies can be obtained with CORINE Land Cover as a basis for the stratification (Gallego et al, 1999).

2.2 Remote Sensing Correction.

A careful image classification Landsat-TM or SPOT-XS images in the EU can give an accuracy of 70-80% when the region is not too complex and the classification nomenclature is not too detailed, for example 4 to 6 main crops and another 6 to 8 land cover categories. However the MARS project confirmed that image classification often becomes poorer in an operational context with large, heterogeneous regions and operators working under time pressure to obtain results within a narrow deadline. Table 1 gives a summary of average user and producer accuracy for main crops in pilot regions for regional inventories between 1988 and 1993. We can check that the accuracy is not always satisfactory.

Crop	producer accuracy	user accuracy
All Wheat	66%	61%
All Barley	45%	51%
Maize	42%	54%
Rice	56%	89%
Dried pulses	50%	57%
Oil seed rape	56%	65%
Sunflower	41%	49%
Sugar beet	46%	57%
Wood	79%	82%

Table 1. Average classification accuracy for crops in pilot regions for regional inventories (1988-93)

Regression estimators were used to integrate classified images as auxiliary information to improve the accuracy of the estimates from ground surveys. An alternative procedure based on confusion matrices (Czaplewski and Catts, 1992) has been tested with results that are very close to those of the regression estimator (Gallego, 1994).

The regression estimator is not very exigent in terms of pixel-by-pixel accuracy; in the Regional Inventories the relative efficiency of regression has been often of the order of 2 with classification accuracy values around 50%. This surprising result is partly due to collocation inaccuracy between the ground survey drawings and satellite images when no ortho-

photos were available and common aerial photographs were used as ground survey documents. Collocation inaccuracy can make that correctly classified pixels appear as errors, but has little impact on the regression estimator, that only uses the global number of pixels per class in the segment. The regression estimator is unbiased if ground observations are unbiased even if the image classification is biased.

The economic assessment of remote sensing can be made through the relative efficiency (table 2), a concept based on the ratio of estimator's variances. The efficiency of remote sensing is better if the landscape has large fields with few dominant crops. For example the USDA reached the cost-efficiency threshold of remote sensing with the regression estimator on Landsat-TM images in the mid-late 90's (Hanuschak et al 2001).

	EC 1988-92
Wheat	2.11
Barley	2.04
Maize	1.68
Oil seeds	1.80
Dried pulses	1.77

Table 2 : Median values of the relative efficiency of remote sensing in the European Union from 1988 to 1992

An efficiency of 2 means that the accuracy obtained with a sample of 1000 segments and remote sensing is the same as the accuracy with a sample of 2000 segments without remote sensing. The cost efficiency threshold can be different with two different points of view: In this simple example, with an efficiency value of 2 for remote sensing and a sample of 1000 segments, we can look at it in two different ways:

- If we introduce remote sensing we can reduce the sample to 500 segments instead of 1000. Therefore remote sensing will be cost-efficient if its cost is less than the cost of surveying 500 segments.
- If we introduce remote sensing the variance will be divided by a factor 2. To obtain the same result enhancing the ground survey, we should increase the sample size from 1000 to 2000 segments. Therefore remote sensing will be cost efficient if its cost is less than the cost of 1000 segments in ground survey.

This simple example illustrates also that the value of remote sensing in the context of a regression or calibration estimator is proportional to the effort made in the ground survey, since the efficiency is approximately independent of the sample size.

The MARS Project concluded in the late 90's that remote sensing could become cost-efficient in Europe with Landsat-TM images, but this option is not any more applicable. New assessments are necessary with new sensors of comparable resolution and possibly wider swath.

2.3 Rapid Estimates of Crop Area Changes in the EU.

The objective of the "rapid estimates of crop area changes in the EU" also called "Activity B" or "Action 4" of the MARS Project was to provide early information on changes in crop acreage each year compared with the previous year, as well as qualitative indicators of potential yields. We make here some comments about the area change estimation. Area estimates for year t were obtained by applying the estimated area change rate to official statistics for year $t-1$. The targeted crops were: common wheat, durum wheat, barley, grain maize, field peas,

rapeseed, sunflower, rice, potatoes and sugar beet. A long term objective of the activity was to develop a method that could be applied outside the EU as an alternative to the approach of the USDA Foreign Agricultural Service (Taylor, 1996), that combines reports from the agricultural attachés in the embassies around the world with satellite image analysis to identify or quantify major anomalies.

The size of the study area (the whole European Union) did not allow to regularly acquire an exhaustive coverage of high resolution images. Hence a set of 60 sites of 40 km × 40 km was selected. The activity made frequent use of the SPOT satellite's technical capacity for off-nadir pointing (taking an image out of the vertical). The size of the site was determined to ensure that the area could be included in a SPOT image, whatever the viewing angle. The size of the area represented in a SPOT image with a vertical view is approximately 60 km × 60 km. Some Landsat-TM and IRS-1C images were analysed as well. Since these images covered a much larger area, only pieces of a suitable size were delivered. For most sites the target is acquiring four high-resolution satellite images during the main season of crop activity. For some sites with less intensive agricultural activity, one image in the agricultural season is considered enough.

Images were analysed with a method that involved multi-step computer assisted photo-interpretation and pixel clustering (unsupervised classification) leading to an image classification. Until 1995, most pixels were labelled as belonging to a land cover class, such as "winter cereals", "summer crops" or "grassland". About 8% of pixels received multiple or generic labels, such as "sunflower or fallow", or " light reddish turning to light greenish". In 1996, the labelling system changed and become something similar to a fuzzy classification. Each cluster of pixels was linked to one or several land cover classes through a correspondence table used later to compute estimates. The operator could tune the cluster labels. to modify the number of pixels for each class to a certain extent (±10% to ±30%). This gave a flexibility to combine image classification with general information, such as knowledge of the Common Agricultural Policy for the current year or information provided by national publications. In other words the result could be adjusted to match the a priori information of the analysis team and it is not clear that remote sensing had an influence on the final estimates of area change.

In Activity B it was improper to speak of standard error of the estimates, because the panel of sites was not a sample in the strict sense and the degree of mutual dependence of the estimates per site is difficult to assess because the labelling system in the basis is not formula-driven. However it is easy to compare the estimates every month with the official Eurostat figures known at the end of the year. Table 3 gives the mean square accuracy provided by these comparisons. In April the system had very few or no images. We can interpret the accuracy in April as the accuracy that can be obtained from simple expert knowledge. The improvement along the year can be interpreted as the contribution of remote sensing. In 3 cases (common wheat, durum wheat, rapeseed) the accuracy becomes worse; for maize it remains more or less constant. This means that the contribution of remote sensing to the quality of the results is very debatable.

A comparison was made in 1996 of the area change estimated in each of the 40 km × 40 km sites from image analysis and

from ground surveys. The values of r^2 were lower than 0.1 for most crops. This means that the change estimated in each site by remote sensing was essentially independent of what was observed on the ground for that site. This confirms that the estimates were more driven by external information (a priori belief) than by image analysis.

	April	May	June	July	Aug.	Sept.	Oct.
Common wheat	1	1.2	1.9	1.6	1.5	1.4	1.4
Durum wheat	2.1	3	2.8	2.6	2.7	2.7	2.6
Barley	4	4	3.2	2.5	2.7	2.4	2.4
Rice	7.7	9.9	9.6	6.1	5.7	5	5
Maize	4	2.5	2.4	2.8	4	4.3	4
Total cereals	1.4	1.3	1	0.9	0.8	0.7	0.7
Sugar beet	6.7	4.6	4.4	2.8	4.3	2.9	3
Sunflower	16.6	12	6.5	7.4	6.3	6.7	7.3
Rapeseed	6.3	9.6	9.8	11.5	11	10.4	10.3

Table 3. Average RMS errors of the rapid estimates of area changes along the year.

A general reflection on the objectivity of remote sensing can be made around the comments in the previous paragraph: satellite images are perfectly objective as radiometric measurements, but extracting information from these images involves an important human input, that becomes essential when the ground data are scarce.

For the area change estimation without ground data of the current year, as in the "rapid estimates" of the Actibity B, the number of pixels classified into each class can be adjusted by the operator to a certain extent, that depends on the classification accuracy for this class. For classes such as winter cereals the flexibility margin may be around 10% to 20%, so that general knowledge may be included to adjust the classification. For example if the compulsory set aside rate (% of arable land that farmers have to leave uncultivated to be eligible for subsidies) goes from 5% in year t to 10% in year $t+1$, the area of cereals may be expected to slightly decrease. A priori information can be often found in national publications, such as provisional estimates published by ministries of agriculture. The amount and quality of this type of external information integrated in the procedure determines to a great extent the quality of results.

3. POINT PHOTO-INTERPRETATION FOR STRATIFICATION: THE CASE OF LUCAS 2006.

LUCAS (Land Use/Cover Area-Frame survey) is a point survey run by Eurostat. It was carried out in 2001 and 2003 with a two-stage systematic design in EU15, i.e. the 15 countries that were member states in 2001 (Delincé, 2001). Primary Sampling units (PSU) were selected with a grid of 18 km without stratification. Each PSU is a cluster of 10 points following a 5x2 rectangular pattern with a 300 m step. The "point" is conceived as a circle of 3 m diameter. LUCAS has a double nomenclature: each point has a land cover code (57 classes) and a land use code (14 classes).

A test was made in the whole territory of Greece in 2004 with a different sampling scheme, inspired on the Italian AGRIT survey (Martino, 2003). The test in Greece clearly proved that a stratified sampling scheme of unclustered points is more efficient than the previous system and was applied for the new LUCAS 2006 survey (Jacques and Gallego, 2005). The new sampling scheme is based on a single 2 km grid that covers EU25 with about 990,000 points that have been photo-interpreted for stratification with a simple nomenclature of 7 categories.
1. Arable land
2. Permanent Crops
3. Permanent Grassland
4. Wooded areas, shrubland
5. Low or rare vegetation
6. Artificial land
7. Water, wetland

In most cases the photo-interpretation has been made on aerial orthophotos, but Image2000 (JRC-EEA, 2005) has been used in some areas, mainly due to the high cost of the copyright of orthophotos Each class or stratum is subsampled with a different rate for the ground survey: in most cases 50% for agricultural strata (1 to 3) and 10% for the rest. In 2006 the ground survey has been carried out in 11 countries, that represent the 73% of the agricultural land of EU25 and the 75% of the arable land. The final sample for ground survey in these 11 countries has 169,000 points. For points of very difficult access, the ground observation is substituted by photo-interpretation.

Ground obs strata	Arable	Perm. Crops	Perm. Grass	Wood, shrub	Bare	Artificial	Water	Total
Arable land	**61165**	1894	18728	2139	5846	1611	255	*91638*
Permanent Crops	410	**9536**	601	630	217	172	6	*11572*
Permanent Grassland	4210	682	**29068**	4340	1187	1425	421	*41333*
Wooded areas, shrubland	1220	930	9725	**84715**	1245	2225	805	*100865*
Bare land or low vegetation	75	65	505	530	**725**	395	195	*2490*
Artificial land	365	170	2255	520	245	**9280**	90	*12925*
Water, wetland	15	10	100	70	45	20	**2765**	*3025*
Total	*67460*	*13287*	*60982*	*92944*	*9510*	*15128*	*4537*	*263848*

Table 4: Confusion matrix of the photo-interpretation for stratification with the ground data (weighted observations)

A confusion matrix of the photo-interpretation is reported in table 4. Observations in strata 4-7 have been weighted inversely to the sub-sampling probability, i.e. if points in the stratum "forest" are sampled with a probability 5 times lower than in the agricultural strata, each point has a weight 5 times higher.

We can observe in the confusion matrices that stratum 1 (arable land) is strongly overestimated. This has an impact on the efficiency of the stratification (that remains still at a good level), but does not introduce any bias in the estimates, as long as it is used for the stratification and not to substitute ground observations. Photo-interpreted observations to substitute ground survey can be used nevertheless without generating any bias on the agricultural estimates when the absence of agriculture is guaranteed (mountains, for example). If the total area of arable land had been estimated by photo-interpretation the bias would have been around 35%.

3.1 Efficiency of the LUCAS 2006 stratification.

We study here the efficiency of the point sampling scheme used in LUCAS 2006 compared with other possible single-stage sampling schemes. The variance comparisons have been made using always LUCAS ground observations on different subsamples and involve some approximation. The subsamples used have different sizes. The relative efficiency of the sampling approach A compared with the sampling approach B has been always computed as:

$$Eff(A/B) = \frac{Var(B) \times n_B}{Var(A) \times n_A} \qquad (1)$$

Where *Var(A)* is the estimated variance for a given land cover type with the approach A and n_A the sample size. The approaches considered are:

1. Simple random sampling (srs). We cannot make an exact estimation of the variance of area estimators for srs because we do not have an srs. We make an approximation applying the srs variance estimation formulas to the LUCAS systematic sample. This corresponds to the variance of random subsamples of the available systematic sample.
2. The second alternative considered is a pure systematic sample. LUCAS 2006 does not fully fall on this type, but pure systematic subsamples with an 18 km step can be extracted. We have selected in the LUCAS 2006 sampling plan the first 8 replicates, that were chosen in all strata. Thus we have a systematic sample that repeats a pattern of 8 points every 18x18 km. There is no unbiased estimator for the variance under systematic sampling. We have used an estimator based on the comparison of each point with the observations in its neighbourhood.
3. A third alternative is defined with the same systematic samples exploiting the information provided by the photo-interpretation of the 2-km grid (post-stratification).
4. The fourth alternative is the actual LUCAS 2006 sampling: systematic sampling, i.e, two-phase systematic sampling with subsampling mainly concentrated on agricultural strata.

There are several implicit assumptions in this comparison:

- That the cost of the survey per point is the same in any of the sampling schemes.
- That the bias of the variance estimator used is of the same order in all cases. In fact this assumption is reasonable for the different systematic sampling options

Efficiency	Systematic (2/1)	Post-stratification (3/2)	Unequal probability (4/3)	Total (4/1)
Cereals	1.11	1.40	1.26	1.95
Common wheat	1.11	1.16	1.42	1.83
Durum wheat	1.43	1.29	1.41	2.60
Barley	1.15	1.17	1.40	1.88
Maize	1.21	1.19	1.43	2.06
Potatoes	1.09	1.06	1.36	1.57
Sugar beet	1.05	1.01	1.59	1.69
Sunflower	1.09	1.07	1.88	2.19
Rapeseed	1.07	1.10	1.50	1.77
Temp. Grass	1.20	1.21	1.28	1.85
Olive groves	1.63	1.82	0.89	2.63
Vineyards	1.43	1.55	1.44	3.19
Forest	1.00	1.74	0.38	0.66
Perm. Grass	1.12	1.38	0.64	1.00

Table 5: Relative efficiency between different point sampling approaches

The efficiency of remote sensing with the LUCAS 2006 stratification approach is estimated multiplying the second and third column of table 4 and is in general satisfactory.

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A COMPARISON AND EVALUATION OF PERFORMANCES AMONG CROP YIELD FORECASTING MODELS BASED ON REMOTE SENSING: RESULTS FROM THE GEOLAND OBSERVATORY OF FOOD MONITORING

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ABSTRACT:

In the context of the GEOLAND EC FP6 project the comparison of different remote sensing based approaches for yield forecasting over large areas in Europe are tested and results inter-compared. In particular the methods tested include the ones in use within the MARS-Crop Yield Forecasting System as the results from the Crop Growth Monitoring System model and vegetation indicators derived from Low Resolution SPOT-VGT and NOAA Images, METEOSAT based yield forecasting and ERS-Scatterometer Crop Performance Index. Performances of the different models were tested in Spain, Belgium and Poland.

The inter-comparisons of the crop yield forecasts were mainly based on the forecasting error obtained from the different approaches based on the Root Mean Square Forecast Error (RMSFE). This error was derived by comparing the predicted yields of the different models with the official yield as from official statistics (EUROSTAT). The comparison of the RMSFE was used to verify the convergence of results from the different models, the reliability of the information, i.e. precision and bias, and its precocity compared to the crop cycle. The results showed that the indicators are able to give reliable information with some differences: remote sensing indicators are more precise and accurate in southern areas (less cloud cover) while in northern areas good results are obtained under the use of better local calibrations of traditional crop yield forecasting systems and/or the use of additional information for instance remote sensing data as inputs into advanced crop modelling systems. Furthermore, in order to take care of the different time series length available, a qualitative indicator called Performance Score (Ps) was introduced. The analysis of the Ps showed that when a long time series of observation is available greater advantages are obtained from RS rather than from more advanced crop models.

1. INTRODUCTION

GEOLAND is an Integrated European Research Project (FP6) of the EC (http://www.gmes-geoland.info/), carried out in the context of GMES to build up a European capacity for Global Monitoring of Environment and Security. Within this project the use of remote sensing is being researched within a semi-operational context for different targets, including studies on agriculture grouped under the Observatory of Food Security and Yield Monitoring (OFM). More specifically, the OFM focuses on developing a global crop yield and crop area forecasting service for food security purposes.

In this context, the analysis described hereafter is an evaluation of the final crop yield forecasts generated during the season by different model-based approaches. These reference models generate indicators using either direct remote sensing observations, mixing them with exogenous data such as meteorological observations, or building more sophisticated crop growth models. The indicators generated in such a way describe different part of the plant biomass or of its cycle during the year, and are then used as predictors in the regression models that produce as outcome the yield forecasts.

The forecasts to be compared were chosen by the GEOLAND partners as the ones generated for the countries of Belgium, Poland and Spain with reference to wheat yield. Wheat has been chosen as the crop of interest. The analysis window for Belgium and Poland was April to August and for Spain March to July; this choice reflects the crop cycle in the mentioned countries and the fact that within the period of the plant cycle the forecasts have a greater value than after the plants have been harvested.

Five project partners provided the wheat yield forecasts (hind cast) heterogeneously in a period ranging from 1998 to 2004;

forecasts were produced in a standard approach in which each of them is based on a regression model where the regressors are the indicator/predictors generated by the different models and the true observations are the official EU statistics available for each country (EUROSTAT CRONOS and REGIO DB sources). The evaluation reported in this paper takes care of different aspects that are expected to be fulfilled by a forecasting approach or system: the global error/uncertainty of the forecasts (precision and accuracy), their precocity coupled with their goodness, the forecasting performance of the systems in extreme years (including bias) and their capacity to keep performances in different areas and provide enough information to feed the statistical/mathematical object used in the forecasting solution. However, the different approaches cause some bias in this evaluation. In fact the different time series of the predictors affect both precision and uncertainty of the prediction. A qualitative approach was then introduced in order to weight for the structural differences of the error indicators: a synthetic Performance Indicator (Ps) was defined weighting the errors indicators according to the "importance", as given by the forecast customers, of the different aspects they refer to. The results are presented and discussed.

2. DATA and METHODOLOGY

The data and models which have been used within the Geoland OFM can be grouped into 4 categories.

- 1st Category: are the forecasts which are not based on remote sensing, they are the benchmark forecasts produced automatically from a Crop Growth Monitoring System

(CGMS). CGMS is a crop growth simulation model based on the WOFOST model (Boogart et *al.*, 1998) and in use operationally in the MARS (Monitoring Agriculture with Remote Sensing) System (Lazar et *al.*, 2004). The forecasts obtained basing on crop indicators/predictors produced by CGMS were delivered by the project partner Alterra (NL). The CGMS based forecasts can also be simple extrapolation of trend time series according to the an error evaluation based on jack-knife statistical method comparing trend based forecast with crop simulated parameters based forecasts. The approach is described in De Koning et *al.* (1993).

- 2nd Category: includes those forecasts which are derived from indicators/predictors obtained from a modification of the CGMS model by plugging in some way Remote Sensing (RS) data. The modifications and runs of CGMS basing on RS inputs were made by Alterra. In particular, scatterometer-radar data (soil water balance; Wagner et *al.* 1999), and METEOSAT based indicators (radiation and temperatures estimates; Rosema et *al.* 1998) were used.

- 3rd Category: are those forecasts which are based purely on RS indicators (e.g. Scatterometer-NEO; NDVI-VITO; VCI/TCI-IGIK); Dabrowska-Zielinska K et *al.*, Wagner et *al.*, Eerens et *al.*)

- 4th Category: are those forecasts derived from RS data further transformed according to crop models (assimilation models) such as DMP/fAPAR-VITO Eerens et *al.*), and the EARS-indicators (Rosema et *al.*)

For further information and a detailed description of the indicators the reader can consult the GEOLAND-OFM Methods Compendium Report (GEOLAND 2006)

The indicators/predictors produced by each approach were basically used as in-dependent variables according to a classical regression approach where:
(Observed)Yield= f (RS indicator, METEO data) where in most of the cases the relation was assumed to be linear, for instance:
(Observed)Yield= a+b RSind + error. Where the error is a white noise. A similar approach is described in Genovese et *al.* and De Koning et *al.*
Once the parameters were estimated the models were used to produce the forecasts. Due to the fact that it was necessary to use the major part of the time series for calibration, in some cases the forecast could be computed only for few years. Therefore, often only a short time series of the forecast was available for testing the model in an 'operational' condition. This was taken into account in the forecast error calculation.

2.1 Category 1: Forecasts based on the Crop Growth Monitoring System:

In this paper these forecast are referred with the suffix: CGMS, or CGMS-EUR, and CGMS enhanced). The difference among the EUR and the "enhanced" versions of the model is that the latter was improved with a re-calibration using more recent observations.
The standard CGMS indicators provided by ALTERRA (NL) (see Boogart at al, 2002) where:
CGMS-WLY_STORAGE – Uses as predictors the simulations of the total weight of the storage organs (grains) for wheat under water limited conditions (rainfed);

CGMS-WLY_BIOMASS – Uses as predictors the simulations of the total weight of the above ground biomass for wheat under water limited conditions (rainfed);
CGMS-PY_STORAGE - Uses as predictors the simulations of the total weight of the storage organs (grains) for wheat under potential conditions (non-water limited);
CGMS-PY_BIOMASS - Uses as predictors the simulations of the total weight of the above ground biomass for wheat under potential conditions (non-water limited).
An enhanced CGMS was prepared using in the study areas more updated and refined data for calibration (see GISAT, 2003). The resulting forecasts were referred as:
CGMS_ENH-WLY_STORAGE
CGMS_ENH-WLY_BIOMASS
CGMS_ENH-PY_STORAGE
CGMS_ENH-PY_BIOMASS

2.2 Category 2: Forecasts provided based on Crop Growth Model modified with RS data

The related forecasts are referred here with the suffix CGMS SCAT, when scatterometer-radar data where introduced in the model, and CGMS EARS indicators, since they when based on METEOSAT indicators. The Scatterometer based water balance data were supplied by the Univ of Vienna and NEO (NL).
The water balance of the CGMS crop growth model (see Boogart et al, 2000) was substituted with an approach of estimation of water balance based on data from the **ERS-Scatterometer**). The corresponding forecasts in this contribution are:
CGMS_SCAT-WLY_STORAGE
CGMS_SCAT-WLY_BIOMASS

Meteorological variables (radiation, temperature and precipitation) derived from **METEOSAT** were used as an alternative data set into CGMS (see De Wit et al, 2004). The integration in CGMS and the calculation of the new predictors was performed by ALTERRA (NL). The corresponding forecasts are referred in this contribution as

CGMS_EARS-WLY_STORAGE
CGMS_EARS-WLY_BIOMASS
CGMS_EARS-PY_STORAGE
CGMS_EARS-PY_BIOMASS

2.3 Category 3: Forecasts based on remote sensing SPOT-VGT and NOAA-AVHRR data.

The forecasts where developed and provided by IGIK (PL). The assumption of the approach (see Dabrowska et al, 2002) is that the maximum amount of vegetation is developed in years with optimal weather conditions. Conversely, minimum vegetation amount develops in years with extremely unfavourable weather, which suppresses vegetation growth. Therefore, the absolute maximum and minimum of NDVI are calculated from several years. The different stages of crop growth are sensitive to crop development conditions, which are monitored by remote sensing. Developed indices are based on the reflection properties of vegetation in the visible and infrared spectrum and to the radiative temperature of crop. The dekad number in each year has been expressed in the value of accumulated NDVI representing each of the development stage in the given year. For these periods it is essential to deduce soil moisture using developed method of calculating evapotranspiration and

Vegetation Condition Indexes (VCI) and Temperature Condition Indexes (TCI) indices.
The corresponding forecasts are named:
PTVCI_from_SPOT (not available in for Belgium)
PTAVCI_from_SPOT (not available for Spain and Belgium)
MTCI from NOAA (not for available for Belgium and Poland)
VCIAVG_average_of_VCI_from_NOAA_model16km2 (not available for Spain and Belgium)

2.4 Category 3: Forecasts based on Remote Sensing: ERS-SCATTEROMETER.

Crop water limitation is derived from the Soil Water Index (SWI). The methodological approach to retrieve soil moisture information is based on a change detection algorithm exploiting the short revisit capabilities of the ERS scatterometer. The ERS Scatterometer is a single frequency (5.3 GHz) single polarised (VV) low resolution active band. Forecasts of this type are referred as NEO (NL) (see Wagner, 1999).

2.5 Category 4: Forecasts based or Remote Sensing models and/or coupled with RS based on Spot-VGT

The list of indicators evaluated includes: NDVI; DMP; Improved DMP (with improved fAPAR); the Vegetation productivity indicators (see Eerens et *al*, 2000). These indicators were provided by the VITO-TAP Centre (B).

Table 1: Description of Vito indicators

Code	Description
VGT_DMP_No-unmixing	Overall mean DMP of all pixels n for the region of interest
VGT_DMP_Weight-means_50%	Weighted mean DMP of all pixels m with fraction f > 0.5
VGT_DMP-improved_fAPAR_No-unmixing	Overall mean DMP (calculated with the improved fAPAR derived by means of a neural network on S10 images) of all pixels n for the region of interest
VGT_DMP-improved_fAPAR_Weight-means_50%	Weighted mean DMP (calculated with the improved fAPAR derived by means of a neural network on S10 images) of all pixels m with fraction f > 0.5
VGT_Hist_classified_DMP_No-unmixing	Overall mean of all pixels n for the region of interest. (The historical classified DMP is calculated on an analogue way as the VPI. Instead of using NDVI, DMP is used.)

2. 6 Category 4: Forecasts based on model coupled with RS data, based on METEOSAT.

The EARS (NL) Crop Yield Forecasting System (CYFS) is based on satellite derived radiation and actual evapotranspiration data from the Energy and Water Balance Monitoring System (EWBMS). These data enter into a crop growth model, which generates crop yields. Underlying theories are those of radiation and energy transfer at the surface and in the atmosphere. More details on the crop yield modelling EARS approach can be found in Rosema et al, 1998. Three indicators were used; the corresponding forecasts are named:

- EARS_actual yield: water limited, simulated with radiation and relative (actual/potential) evapotranspiration as observed;
- EARS_NON_WATER_LIMITED_YIELD: simulated with radiation as observed and relative evapotranspiration is set to 1 (so for: potential evapotranspiration);
- EARS_act_yield_rel2_non_water_limited_yield: called relative yield, is the ratio of the two previous indicators.

3. FORECAST ERRORS AND PERFORMANCE SCORES INDICATORS

The forecasting power of the OFM models was evaluated with respect to the following criteria:
A – the global error/uncertainty of the forecasts (precision and accuracy);
B – the precocity (how early in the year the forecast is made) of the forecasts coupled with its goodness;
C – the forecasting performance of the systems in extreme years including bias;
D – the capacity of the system to keep performances in different areas and provide enough information to feed the statistical/mathematical object used in the forecasting solution.
The evaluation of the listed criteria leads to a ranking of the performances of the different systems and the evaluation of the significance of the differences between one system and the other. A similar approach was undertaken in previous studies (see Genovese et al., 2004).
Assuming that the final user of the forecasts has as quadratic reference loss function (i.e. the higher the error in both directions, the higher the impact on his decision) the error indicator selected was the root mean square forecast error (RMSFE). Defining the forecast error as the difference between the forecast and the true value of the variable of interest:

$$e_t = \hat{Y}_t - Y_t,$$

where Y_t is the true value of the variable at time point t and $\hat{Y}_t$ is its forecast, the RMSFE is an aggregation over a given period of time consisting of T points according to the following formula:

$$\sqrt{\frac{\sum_{t=1}^{T} e_t^2}{T}}.$$

The RMSFE takes only positive values, and gives an average size of forecast error over the given period.

Three types of comparison have been performed based on on the RMSFE:

- Comparison of overall error, computed by averaging over all months and all years of the interested period separately for each forecasting system;
- Comparison of error across month, averaging for each forecasting system over the figures for the same months in all the years of the interested period. This analysis has been carried out in order to assess the performance of each forecasting system across the whole crop growing season, quantifying for each of them its risk of mistakes and reliability along the forecasting year;

- Comparison of error across years, averaging for each forecasting system over the figures for all months of each year. The purpose of this comparison is to determine whether there are years in which one system performs significantly better than the others, and to test their improvement and refinement in the last years.

Furthermore, the forecast performances have been evaluated by comparing the same error indicators with forecasts obtained with simple linear trends.

Finally, a synthetic Performance score (Ps) has been calculated. The final purpose of this synthetic Performance indicator is to score the results obtained taking into account "uncertainty" given by the heterogeneity of the initial data. A similar approach has been used in soil science to evaluate pedo-tranfer rules models (Donatelli *et al*., 2004). The advantage of such a synthetic performance indicator is to be able to summarize aspects related to forecasting (precision, accuracy, timeliness, consistency and cost) into one single information, taking into account the final user view. This last point is also a drawback as weights are given to the different component of the synthetic indicator subjectively. In this context the weight are calculated according to the number of sub-components indicated by the users as important for the evaluation.

The Ps is a qualitative indicator defined as the count of the results of the following criteria:

- *Criteria 1*: Length of time series: N° of available years >5. Is equal to 1 if the time series of forecasts available includes at least five years, 0 otherwise;
- *Criteria 2*: Overall RMSFE≤0,2 (i.e. less than 2 quintals/ha). Is equal to 1 if the overall (averaged over years and dekades) RMSFE is ≤0,2, 0 otherwise. The same criterion was repeated to analyse forecasts results at the beginning of the forecasting season and at the end (*Criteria 3*);
- *Criteria 4*: Stability of the forecast: April forecast > July forecast. Is equal to one if the RMSFE is higher in April than in July, 0 otherwise. The same criterion was also analysed taking into account inter-forecast variability;
- *Criteria 5*: RMSFE ≤0,2 in the extremes bad years. Is equal to 1 if the RMSFE averaged over dekades of the extreme year, 0 otherwise;
- *Criteria 6*: At least in one year in the period analyzed 50% dekades are better than trend; is equal to 1 if there is at least one year in the period under study in which the forecast are at least 50% of times better than a simple trend extrapolation, 0 otherwise. This criterion was evaluated also at sub-regional level.

The number of criteria to evaluate was discussed and decided together with final customers, which are the operational users of the forecasts. The number of subcriteria associated to the criteria class determined the importance (weight) in the final calculation.

Only exception concerned the length of the time series that counts for nearly 30% in the computation of the final score, being this requirement a fundamental in order to draw conclusion about the performance of each indicator. The weight of each criterion in the calculation of the Ps is reported in the following table:

Table 2: Description of Criteria used for the Ps

CRITERIA	Final weight %
1- Lenght of time series	28%
2 – Overall RMSFE<=0.2	8%
3- Timeliness and accuracy of forecast	17%
4- Stability of forecasts	17%
5- Extreme years	14%
6- Vs trend	17%

Calculation of scores per indicator/predictor

The scores were summed up for each indicator, giving a sum (Sc) ranging from 0 to a maximum of 36 (27 criteria counting one each except for the criterion measuring the length of the time series, counting 10).

Calculation of penalties

A decision had to be taken in case the Criteria were not applicable to a predictor or the subcriteria summed 0. For instance a method gave predictors only for few years and only on one test area. In such cases the method had to be evaluated as operationally limited. Penalties were attributed in the following way:

Pe = Sc * Mc/6

Pe: penalty

Sc: sum of scores compliant with criteria

Mc: number of missing criteria or number of criteria giving 0 (max possible 6).

The Mc ranges from 0, when all of the criteria scores 1, to the maximum of 6 when no criteria are compliant (missing or 0).

Calculation of the final score x indicator/predictor

A final score was then obtained for each predictor according to the following:

Ps = (Sc-Pe)/Ac

Ps: Performance Score

Pe: penalty

Sc: sum of scores compliant with criteria

Mc: number of missing criteria

Ac: Total number of accounted sub criteria (i.e. where either 0 or 1 was available)

The Ps ranges between 0 and 1. The higher the Ps the higher the overall performance of the predictor. In the extreme situation that a predictor has an Ac of 0 the Ps is undetermined. In fact this is obtained when no one of the 6 criteria was available for evaluation.

4. SOME RESULTS

Complete results are available in the GEOLAND technical report on the yield inter-comparison study (G. Genovese et.al, 2006). Before reading them it is recommended to look at them as a guide to take decisions on the approaches not for an eventual absolute conclusions. Table 3 reports the results of the overall RMSFE obtained by country for each model, and their average over countries (mean).

Table 3: RMSFE for BE, PL, ES and overall mean (error is expressed in t/ha).

	BE	PL	ES	Mean
CGMS_EARS-WLY_BIOMASS	0.3	0.3	0.3	0.3
CGMS_EARS-WLY_STORAGE	0.3	0.3	0.2	0.3
CGMS_EARS-PY_BIOMASS	0.3	0.3	0.3	0.3
CGMS_EARS-PY_STORAGE	0.3	0.3	0.3	0.3

|				
PTVCI_from_SPOT		0.4	0.3	0.4
VGT_Hist_classified_DMP_Weight-means_50%_MAvg_Sum	0.5	0.5	0.1	0.4
PTAVCI_from_SPOT		0.4		0.4
CGMS_ENH-WLY_STORAGE	0.5	0.3	0.4	0.4
CGMS_ENH-WLY_BIOMASS	0.5	0.3	0.3	0.4
VGT_NDVI_Weight-means_50%_MAvg_Sum	0.5	0.4	0.4	0.4
CGMS-WLY_STORAGE	0.5	0.3	0.4	0.4
VGT_NDVI_No-unmixing_MAvg_Max	0.47	0.74	0.1	0.4
CGMS-WLY_BIOMASS	0.56	0.37	0.4	0.4
CGMS_ENH-PY_STORAGE	0.51	0.33	0.5	0.4
CGMS_ENH-PY_BIOMASS	0.55	0.29	0.5	0.5
VGT_DMP-improved_fAPAR_No-unmixing_MAvg_Max	0.6	0.4	0.4	0.5
VGT_DMP-improved_fAPAR_Weight-means_50%_MAvg_Sum	0.5	0.5	0.3	0.5
VCIAVG_average_of_VCI_from_NOAA_model16km2				0.5
CGMS-PY_STORAGE	0.5	0.4	0.5	0.5
EARS_act_yield_rel2_non_water_limited_yield	0.5	0.4	0.5	0.5
VGT_VPI_No-unmixing_Sum	0.5	0.5	0.5	0.5
CGMS-PY_BIOMASS	0.6	0.4	0.5	0.5
VGT_DMP_Weight-means_50%_MAvg_Sum	0.5	0.5	0.4	0.5
VGT_VPI_No-unmixing_MAvg_Max	0.7	0.4	0.3	0.5
EARS_NON_WATER_LIMITED_YIELD	0.6	0.5	0.4	0.5
VGT_Hist_classified_DMP_No-unmixing_MAvg_Max	0.8	0.4	0.3	0.5
EARS_actual_yield	0.5	0.4	0.6	0.5
CGMS_SCAT-WLY_STORAGE	0.5	0.4	0.7	0.5
CGMS_SCAT-WLY_BIOMASS	0.7	0.4	0.6	0.6
VGT_DMP_No-unmixing_MAvg_Max	0.5	0.5	0.3	0.7
NEO	1.5	1.1	0.5	1.0
MTCI_from_NOAA			3.4	

Only in few cases the RMSFE was < 0,2 while in several cases it was <= 0,3. CGMS based results appeared as a whole better than the ones based on RS.

From the regional analysis conducted at NUTS2 level the following results emerged: a general trend (Fig.1) is observable at sub-regional level, i.e. an increasing error patterns (south-north) coupled with the use of the best models.

Figure 1: Spatial distribution of RMSFE of best forecasting indicator (error is expressed in t/ha) per NUTS region, and names of best systems.

A statistical test on the differences among the error distributions of the different forecast has revealed that only in few cases the methods gives significantly different forecasts. Again this analysis is affected by the different populations confronted in terms of number of cases and years covered.

An analysis on the extreme years results in the conclusion that all methods in all regions (with different error results) underestimated in good years and overestimated in bad years. In the hypothesis the reference statistics are of good quality, this should then be a matter of reflection for a choice of future crop forecasting systems.
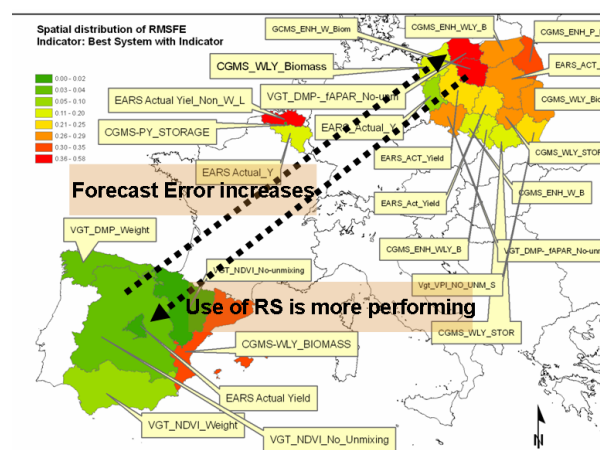
From the Ps analysis the following results emerged by category:

- 1 In the first best 10 Ps (RMSE Criteria = 0.2) 5 are within the CGMS pure model category. Within these 6 the Potential Biomass is excluded and the CGMS enhanced (re-calibrated) water limited biomass shows the best Ps. The absolute best is an indicator of the RS-pure group: VCIAVG_average_of_VCI_from_NOAA_model16km2, followed by PTVCI_from_SPOT in second position. Within the category of RS-models only the DMP (Hist Class) based on VGT seems of interest. Thus according to the requests of the user (to have a method giving an error on wheat not higher than 2 quintals) the CGMS models seems more attractive basing on the available data in the OFM
- 2 When relaxing the RMSE criteria to 0.3 (3 quintals of error) CGMS pure seems still the best strategy (7 bests in the first 10). On the remote sensing side VCIAVG_average_of_VCI_from_NOAA_model16km2 and the PTVCI-SPOT approach are still the best in absolute. This conclusion can be interesting in the areas where it is not possible to use different approaches than just remote sensing data (lack of other data) and the user can accept an error of 3 quintals per hectare fault of better information.
- 3 Conclusions would change dramatically in case longer time series of forecasts would be simulated on the available methods. All the first 10 positions would be occupied by indicators from RS: 4 of them would be on VGT data (NDVI, VPI), being the best in

absolute the one based on MAX Ndvi from VGT. In the category RS-Model we would find now 4 others best placed among which the second absolute which would be a DMP (Hist Classif.). Although these results come from a simulation we can see the advantages of having longer time series in calibrating stable models. **Continuity in the Remote sensing missions seems fundamental to consolidate the usefulness of the data.**

From this study there is an indication that for certain regions in some months early in the year a remote sensing indicator might deliver better results than the CGMS model. From our regional analysis it is evident that when RS is performing well, the absolute level of error is lower than what obtainable with crop models (CGMS) (see fig.1). Furthermore, there is an indication that Remote Sensing data can support the CGMS-system, and potentially improve the forecasts when included into the crop model (CGMS). For instance, there is an indication that by incorporating data from METEOSAT into the CGMS an improvement might be achieved. Finally, the data available so far indicates that the enhanced CGMS system with a better crop calendar and certain modifications performs better.

A number of more specific conclusions can be drawn: first of all, the incorporation of the Meteosat data delivered by EARS into CGMS, a Crop Growth Simulation Model existing (and running operationally in MARS), shows promising results and performs very well in the 2-3 year time period considered.
The analysis purely based on the EARS data undertaken for a 3 year period (2002 – 2004) does give reasonable results.
The indicators PTVCI and PTAVCI from IGIK show promising results in particular for Poland: the forecasts for these two indicators show nice convergence, the forecast later on in the year closer to the harvest tends to be better than the ones early in the year.
The forecasts based on the Vito indicators show in particular promising results for Spain, however forecasts tend to get worse over the season for Spain and for Belgium. This implies that the Vito indicators based on NDVI might give better forecasts early than later in the year.
The NUTS 1 (and NUTS 2 for Poland) analysis has revealed that there is a relatively high variation of the RMSFE over the different NUTS regions. Furthermore, the regional analysis has shown that in South-western regions (Spain) the error performance of Remotely Sensed (RS) derived indicators such as SPOT-VGT is very good, while more complex models which are not using RS at all (e.g. CGMS-ENH) or those models which incorporate information from RS (e.g. EARS models) perform better in North-eastern regions.

5. CONCLUSIONS AND RECOMMENDATIONS

- The incorporation of RS data into Crop Growth Simulation Model can be a valid and performing strategy;
- The indicators based on NDVI - PTVCI and PTAVCI (IGIK) - show promising results with forecast at the end of the crop cycle more precise than earlier in the year; in SPAIN simple NDVI based approaches (VITO) are well performing, also early in the season;
- In terms of behaviour in extreme years there is currently no clear pattern visible as data availability is scarce. Nevertheless RS based indicators did perform better in some situations (NDVI, SPAIN);

- the regional analysis has revealed that in South-western regions (Spain) the error of Remotely Sensed (RS) derived indicators such as VGT is the lowest, while more complex models which are not using RS at all (e.g. CGMS-ENH) or models which incorporate information from RS (e.g. EARS models) perform better in North-eastern regions. The complexity of the approach (so possibly the costs) increases with a northern direction .Nevertheless, moving from southern regions northwards the error of the forecast increases as well as the associated variability (uncertainty);
- Based on the Performance score (Ps) analysis and according to the user requests to have a method giving an error on wheat not higher than 2 quintals/ha, the CGMS models seem more attractive among the available data in the OFM;
- Based on the Performance score (Ps) analysis, in case the error is relaxed to 3 quintals/ha, remote sensing based results appear in many situations attractive;
- Based on the Performance score (Ps) analysis following the criteria of 2 quintals error, when long time series of data are available from RS (see indicator PTVCI - based on SPOT) the corresponding forecasts are better performing than CGMS. Therefore continuity in the Remote sensing missions is a MUST to have adequate time series to support a performing crop yield forecasting system.

As a further step a cost/benefit and a sustainability analysis of the forecasting methods should be added. The sustainability of the methods implies as well discussions on the durability of satellite platforms and missions.

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7. ACKNOWLEDGEMENT

NON-PARAMETRIC CROP YIELD FORECASTING,
A DIDACTIC CASE STUDY FOR ZIMBABWE

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KEY WORDS: Agriculture, Climate, Crop, Developing Countries, Impact Analysis, Prediction, Decision Support, Accuracy

ABSTRACT:

Operational crop yield forecasting is mostly achieved with empirical statistical regression equations relating regional yield with predictor variables, termed "factors". Regional yield (the "dependent variable") refers to average yield over districts, provinces or, more rarely, whole countries; they are provided by national statistical services. The factors can be any combination of raw environmental variables such as weather variables or indices, satellite indices such as Normalised Difference Vegetation Indices (NDVI), farm inputs (fertiliser use) or outputs from simulation models, for instance water transpired over a given phenological phase, maximum leaf area index (LAI), average soil moisture, etc. The approach above is termed "parametric" for two reasons: (1) it derives or requires a number of parameters, for instance regression coefficients and the parameters characterise crop simulation models and (2) it attempts to identify the factors that condition yields and to understand their action. The difference between "parametric" and "non-parametric" methods is not clear-cut; it is mostly operational. Parametric forecasting approaches derive a "model" (through a process known as "calibration") based on historical yield and climatic data. The model is subsequently applied to current crops and within season data to issue a forecast of yields. A number of calculations are performed; they are basically the same in the calibration and in the forecasting phases. Non-parametric crop yield forecasting techniques attempt to establish a typology (qualitative description) of the environmental conditions that occur during the growing season, assuming that similar types of seasons lead to similar yields. Similar years are grouped in classes. During the calibration phase, the types of seasons are defined in such a way as to minimize the variability of yields within classes and maximise between-classes variance. The forecast proper is done by categorizing the current year into one of the classes, and by assigning the class yield to the current forecast. Depending on the actual method, the forecast itself may require little more than comparing some variables with reference values, e.g. a threshold. This paper offers a rough comparison of simple yet classical parametric approaches with two different non-parametric methods, applied to national maize yields in Zimbabwe. The conclusion suggests that the simple non-parametric approaches are not inferior, in terms of accuracy and ease of use to the more complex parametric models

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1. INTRODUCTION

Operational crop yield forecasting is mostly done with crop simulation models and empirical statistical regression equations relating yield with predictor variables, usually termed "factors". For the purpose of this paper, crop forecasting and crop yield forecasting refer to operational within-season regional yield forecasts, i.e. forecasting of average crop yield (tons of agricultural product per ha) over large areas. The areas are administrative units, as this is the scale at which most socio-economic data and crop statistics are available to decision makers.

It is stressed that crop forecasts are eventually calibrated against crop statistics, so that, strictly speaking, crop forecasts are actually forecasts of agricultural statistics; they incorporate all the errors and biases that affect statistics.

Crop forecasts are typically issued between the time of planting and the time of harvest. They use past data (data between planting or before, and the time of the forecast) and "future" data. Future data can be implicit or explicit. In the first case, the future is assumed to be "normal" whereas the second requires that numerical values be actually specified, for instance historical data or stochastic weather generator outputs (Lawless and Semenov, 2005; Hansen et al., 2006).

There is a variety of generic forecasting methods, of which most can somehow be applied to crop forecasting as well (Petr, 1991). According to Armstrong (2001b), "judgement pervades all aspects of forecasting", which is close to a definition which the author has frequently applied to crop yield forecasting, which can be seen as "the art of identifying the factors that determine the spatial and inter-annual variability of crop yields" (Gommes, 2003). In fact, given the same set of input data, different experts frequently come up with rather different forecasts of which, however, some are demonstrably better than others, hence the use of the word "art".

There appears to be no standard classification of forecasting methods (Makridadis et al., 1998; Armstrong, 2001a). Forecasting methods can be subdivided into various categories according to the relative share of judgement, statistics, models and data used in the process. Armstrong identifies 11 types of methods that can be roughly grouped as *judgemental*, based on stakeholders' intentions or on the forecaster's or other experts' opinions or intentions, and *statistical*, including univariate (or extrapolation), multivariate (statistical "models") and theory-based methods. *Intermediate* types include expert systems, basically a variant of extrapolation with some admixture of expert opinion, and analogies, which Armstrong places between expert opinions and extrapolation models.

In this paper, we consider "parametric models" to be those that attempt to interpret and to quantify the causality links that exist between crop yields and environmental factors – mainly weather-, farm management and technology. They include essentially crop simulation models and statistical "models" which relate crop yield with assumed impacting factors. Obviously, crop-yield-weather simulation belongs to Armstrong's Theory-based Models. Non-parametric forecasting methods are those that rely more on the qualitative description of environmental conditions and do not involve any simulation as such (Armstrong's expert systems and analogies).

There are few explicit applications of non-parametric forecasting methods to agricultural yields, among others because of differing usage of the term "non-parametric (*e.g.* in Orlandini et al., 2004). Some methods are described by Gommes et al., 2007.

The paper provides a rapid comparison of four forecasting methods in the specific case of maize in Zimbabwe (Southern Africa). After a short introduction to climate and cropping in the country (2.1), two parametric methods are illustrated first (regression, in section 2.2, and model and regression based, section 2.3). The two non-parametric methods that are described next include a threshold-oriented approach (2.4) and an approach using the statistical clustering of annual rainfall profiles (2.5). The overall performance of the four methods is summarised in table 2.

2. A SIMPLE CASE STUDY FOR MAIZE IN ZIMBABWE

2.1 General setting and removal of yield trends

To illustrate and compare some non-parametric methods, a didactic example was prepared to estimate yields in Zimbabwe (Southern Africa) covering 41 years from 1960-61 to 2001-2002 (21 years from 1982-82 to 2001-02 for the simulation approach in 2.3).
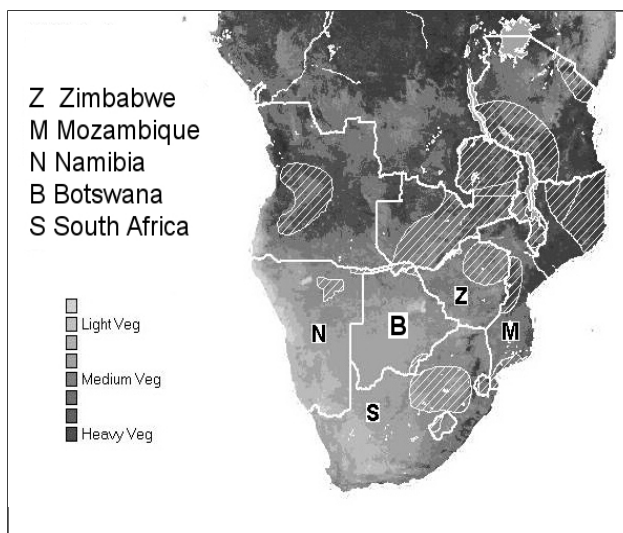
Figure 1: Map of Southern Africa. The hatched area corresponds to the main maize growing areas. The background map shows vegetation densities as estimated from satellite indices (light, medium and heavy vegetation)

Rainfall over the main maize growing area was extracted from NOAA monthly rainfall grids[*] using the WINDISP[**] software after the grids were converted to WINDISP format. All climate and crop statistics given hereafter refer to the maize growing area of NE Zimbabwe illustrated in Figure 1.
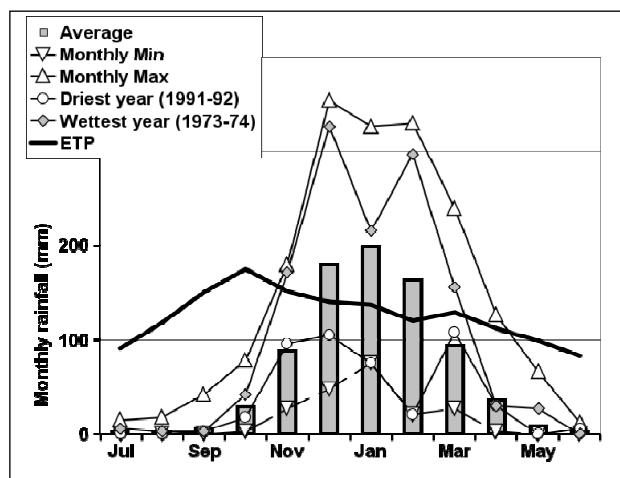

Figure 2: : Rainfall and ETP (evapotranspiration potential) patterns in Zimbabwe between 1960-61 and 2001-2002: average monthly values, maximum and minimum recorded for each month, as well as rainfall profiles of driest and wettest years.
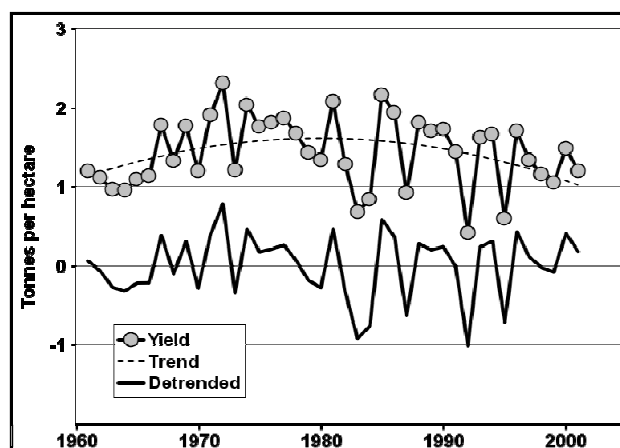

Figure 3: Maize yields in Zimbabwe, together with their trend and the and detrended value (departure of actual values from the trend).

Average rainfall amounts to 812 mm per year, but the driest year (1991-92, an El Niño year) recorded only 462 mm, while the wettest experienced 1278 mm in 1973-74. Note, incidentally, that 1973-74 corresponds to a severe drought in the West African Sahel; this "correlation" derives directly from the movements of the Inter-Tropical Convergence Zone (ITCZ). In Zimbabwe, the growing season roughly covers the period from November to March-April (Figure 2), and is also

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dependent on the different behaviours of the two main sectors of the Zimbabwean agriculture, i.e. large-scale commercial farms on the most suitable soils and subsistence farmers in so-called "communal lands". Part of the country being semi-arid with a marked dry season, water is the dominant factor driving the inter-annual variability of crop yield.

Since independence in 1980 but particularly after 1990, the country has been affected by a somewhat disorderly land reform aiming at redistributing part of the land under large-scale farms. The combination of land reform and changes that were made to the national agricultural statistical system, in particular the inclusion of "communal lands" in the statistics, results in figure 3. A curvilinear trend had to be fitted to the data. Clearly, the trend itself is due to a combination of factors where weather plays only a minor part. The trend must be removed before any agrometeorological analysis can be carried out. This was done for the lowermost curve in Figure 3, where yield is expressed as the difference between the observed values and the trend. The trend accounts for 13 % of the interannual yield variability, which is in line with the fact that parts of the country are semi-arid.

2.2 First parametric approach: yield-rainfall relations between 1961-62 and 2001-02

The simplest possible parametric method to estimate crop yields is to regress them against rainfall, particularly in areas where water is the dominant limiting factor to agricultural production (Palm, 1997). Figure 4 shows the roughly linear relation between yield and rainfall, with a coefficient of determination amounting to 0.4563, i.e. about 46% of the variability of detrended yields can be assigned to rainfall (Table 2).

2.3 Second parametric approach: simple simulation of maize yields in Zimbabwe (1981-82 to 2001-02)

The second parametric approach that is being illustrated uses the standard FAO methodology (Gommes et al., 1998; Gommes, 2003) and the AMS[*] software. A crop specific soil water balance was computed for the years 1981-82 to 2001-02 using 10-daily data from 25 meteorological stations in Zimbabwe and 245 in the surrounding countries. Actual maize crop evapotranspiration (ETA, mm) was computed for all the stations, gridded over the region and averaged for the maize growing areas.

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[*] AMS, the AgroMetShell is the standard FAO software used for crop forecasting at the national level. It can be downloaded from
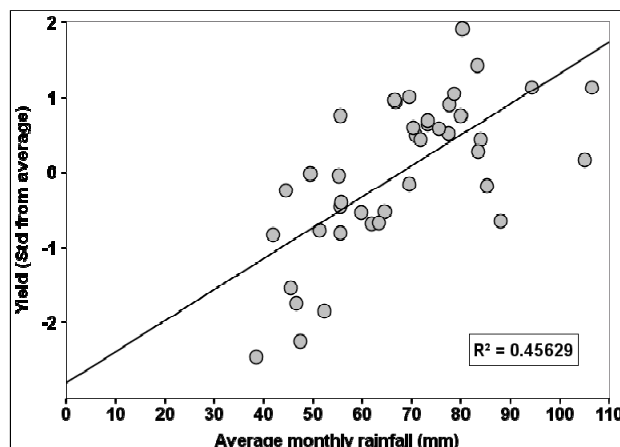ftp://ext-ftp.fao.org/sd/reserved/agromet/agrometshell

Figure 4: Relation between detrended maize yield (expressed as standard deviations from average) and average July-June rainfall in maize growing areas of Zimbabwe between the cropping seasons of 1961-62 and 2001-02.

Water balance parameters, in particular ETA, are ideal "value-added" variables to be used in crop forecasting (Gommes, 1998), and they are at the heart of the FAO crop forecasting approach. Water balance parameters include actual crop evapotranspiration, water surplus and water deficit over main crop stages (e.g. emergence, vegetative phase, flowering).
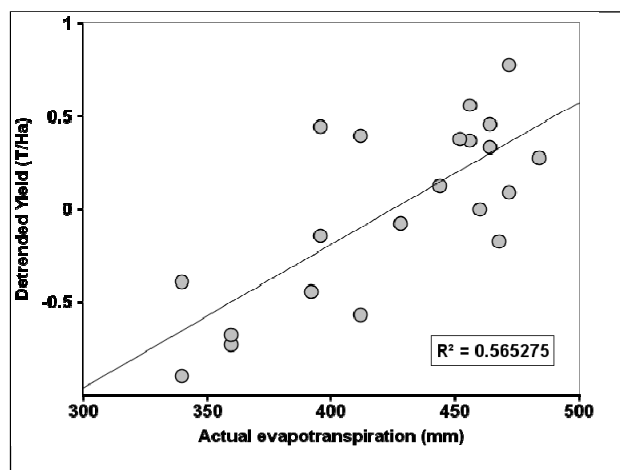

Figure 5: Relation between detrended yield and actual maize evapotranspiration in maize growing areas of Zimbabwe between 1982 and 2002.

The basic idea behind the methodology adopted by FAO is that, as de Wit was among the first to recognise in the mid fifties, there is a direct link between plant transpiration and productivity (van Keulen and van Laar, 1986). For "not too severe" water stresses, yields are rather linearly correlated with actual evapotranspiration. Interestingly, this relation holds across various spatial scales, from leave to plant to field to administrative region. The relation between ETA and maize yield is shown in Figure 5 Altogether, ETA and trend account for about 73.75 % of the interannual variability of maize yields (Table 2).

2.4 First non-parametric approach: threshold based yield forecasting (1961-62 to 2001-02)

The first non-parametric method is a simple threshold-based crop-forecasting table.

In Zimbabwe, like in most of southern-central Africa, there is a tendency for rainfall distribution to be bimodal, with a dry period in January or February, as can be seen in Figure 2. In fact, when correlating yields with monthly rainfall, the coefficient turns out to be highest in January (R=0.656) and February (0.500). The next highest value corresponds to March (R=0.367)

Criteria 1 January rainfall (mm)	Yield (average and 95% confidence interval)	Criteria 2	Threshold	
75 to 155	-1.07 -1.64 to –0.50	February rainfall	< 120 mm	>120 mm
			-1.74	-0.52
			-2.35 to -1.13	-1.16 to 0.12
156 to 249	0.25 -0.05 to 0.55	February rainfall	< 170 mm	> 170 mm
			0.07	0.57
			-0.50 to 0.35	0.25 to 0.89
250 to 327	0.78 0.35 to 1.08	December rainfall	< 190 mm	> 190 mm
			0.92	0.66
			0.23 to 1.63	0.08 to 1.25

Table 1: Example of a threshold-based crop forecasting table for maize in Zimbabwe, based on yields recorded during the period 1961-62 to 2000-2001. Yields are expressed in standard deviations about the average for the period.

It was found that a good separation of yield categories could be achieved when grouping years by January and February rainfall totals as shown in Table 1.

For instance, yields fall in the range of –0. 05 to 0.55 standard deviations from average when January rainfall is between 156 and 249 mm: they are about average (0.25 standard deviations higher than the average). When we now separately examine the group of years characterized by January rainfall from 75 to 155 mm (Group 1, Table 1), 156 to 249 mm (Group 2) and 250 to 327 (Group 3) rather contrasting correlations are found between yields and monthly rainfall.

In Groups 1 and 2, the highest correlation is between yield and February rainfall while in Group 3, we find a negative highest correlation between yield and December rainfall. This results from the fact that high January rain will not have a detrimental effect on yield only if December is relatively dry.

The described method will of course forecast only the six yield values that appear in Table 1, together with their confidence interval. Yet, the strength of the correlation remains comparable with the one obtained with the less empirical simulation approach (Figure 6).

The threshold-based approach also illustrates the fact that this non-parametric method can somehow be seen as a discrete variant of 2.2: two regression equations between yield and rainfall could be developed, one using January and February rainfall during relatively dry years, and another based on January and December precipitation during wetter years.
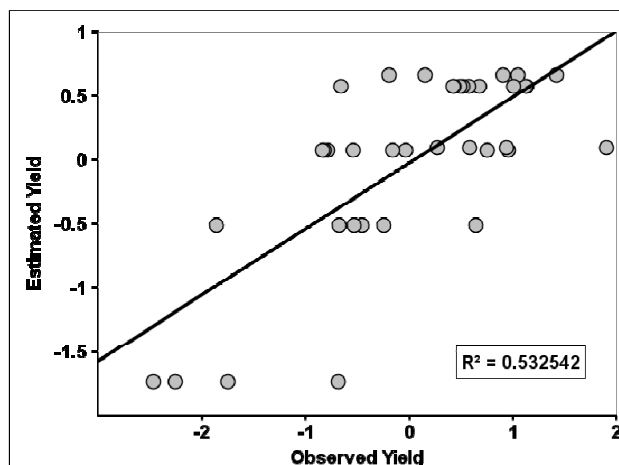

Figure 6: Comparison of estimated and observed yields in Zimbabwe between 1961-62 and 2001-02 using the threshold method described in Table 1. Yields are expressed in standard deviations from the average.

2.5 Second non-parametric method: rainfall profile clustering method (1961-62 to 2001-02)

For this second non-parametric method, the basic assumption is that similar rainfall profiles (July to June) will on average result in similar yield categories.

The profiles were obtained using the ADDATI[*] multivariate statistical package developed by Griguolo at the university of Venice. The number of classes to adopt is somewhat arbitrary. In this case, 12 were found to be a good compromise. Some typical rainfall profiles are shown in Figure 7.

They can all be described in terms of rainfall distributions and amounts. For instance class 1 stands for "low but well distributed rainfall", class 3 for "abundant and well distributed rainfall with a mid-season dry spell", etc.

Regarding the potential value of the method as a crop-forecasting tool, the coefficient of determination R^2 of 0.5692 is amazingly close to the one obtained with the crop specific soil water balance (0.5653, Figure 5).

With the classification method, the number of different yields is obviously the same as the number of classes. To use the approach for crop forecasting in operational mode, a given season is compared with the 12 classes and assigned to one of them. The yield for the year is then taken as the average yield (with confidence interval) of the class.
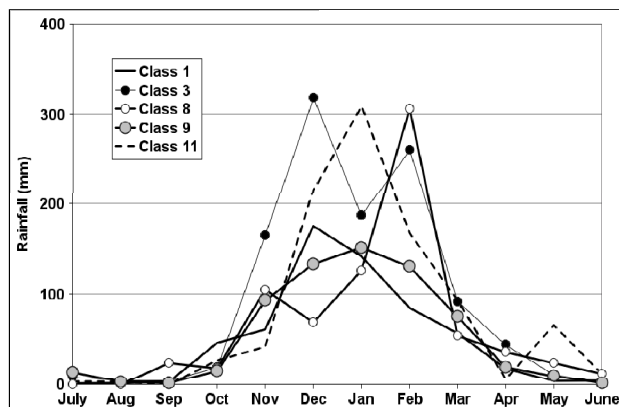

Figure 7: Some typical rainfall profiles for Zimbabwe. Each

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* The latest update can be downloaded from the website given hereafter: http://cidoc.iuav.it/~silvio/addati_en.html

profile is the average of a number of different years that have been assigned to that class by the clustering programme. Rainfall is expressed in mm.
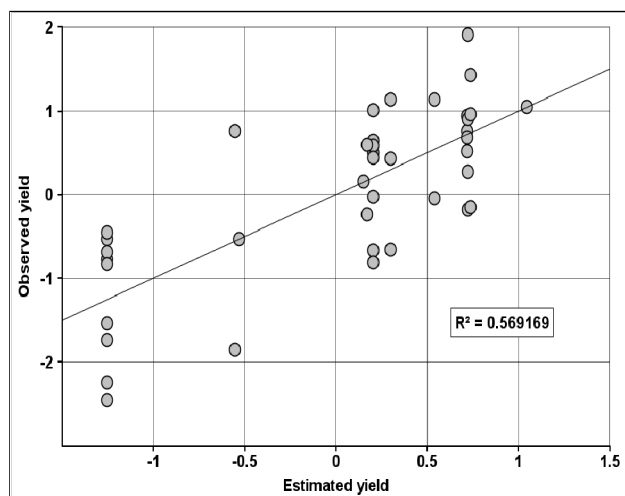

Figure 8: Comparison of estimated and observed yields in Zimbabwe between 1961-62 and 2001-02 using the rainfall profile method. Yields are expressed in standard deviations from the average.

A technique is needed to assign the current season to one of the classes. This can be done with various distance functions between the profiles, and the reference curves. It may, naturally happen that the assignment of a given year to a reference class changes as the season develops. If necessary, this can be avoided by expressing yield as a weighted average of several classes, where the weight is given by the above-mentioned distance function.

Method	R^2		
	Trend	**Method**	**Total**
Average Rainfall	0.1702 +	0.4563	0.6265
Water Balance		0.5653	0.7355
Threshold		0.5311	0.7013
Clustering		0.5692	0.7394

Table 2: comparison of several maize yield forecasting approaches in Zimbabwe (fraction of variance accounted for by the different methods).

3.   CONCLUSIONS

The inter-comparison of the four illustrated crop-forecasting approaches is given in table 2. Remember that the number of years and the source of the weather data is different for the water balance approach compared with the other methods: the length of the time series is shorter (21 years instead of 41), but the quality of the data is better given that actual station information was used rather than grids.
It appears that, with the exception of the simple use of seasonal rainfall totals, the methods tested yield similar results.

The reason why, in spite of their conceptual simplicity, non-parametric approaches yield good results lies in the fact that weather variables are correlated, and the fact that they do not vary randomly over space and time. Therefore, one variable, especially a seasonal time-profile, can indirectly capture a number of environmental factors. It is certainly worth remembering the classical work of Cane et al (1994) on the relations between El Niño-Southern Oscillation (ENSO) indices and maize yields in southern Africa: better correlations are obtained between ENSO indices and yields than between rainfall and yield. ENSO is a more comprehensive variable that describes, albeit indirectly, the overall behaviour of weather conditions during the growing season better than a single variable.
Timeliness, cost and spatial scale are some of the criteria that are adopted when selecting crop-forecasting methods. In view of the ease of implementation of the non-parametric methods, it is certainly worth exploring their potential further.
It appears further that non-parametric methods are as accurate as the deterministic ones, and that they are comparable in terms of timeliness. Non-parametric approaches, however, are much less demanding in terms of inputs and "technology" (processing power), so that some of them can even be applied at village level (the "threshold-based" approach).

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WHEAT PRODUCTION ESTIMATION USING REMOTE SENSING DATA:
AN INDIAN EXPERIENCE

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ABSTRACT:
The present paper highlights the experience of development of satellite-based methodology, results and achievements of wheat production forecasting in Haryana state of India under the project since 1989-90. Haryana with a geographical area of 44,212 km2 is the major agricultural state of the country. At the beginning of the project the area estimates were provided at the state level and then at district-level. Subsequently, the work on production estimation was also started in the year 1990 at the district level.

Single date in-season digital satellite data coinciding with peak vegetative stage of wheat crop was analyzed for wheat acreage estimation using Maximum Likelihood (MXL) supervised classification. Ground truth is collected near synchronous to satellite pass from large contiguous and homogeneous sites of wheat grown under different physiographic conditions. To save the computer timings and to complete the estimates in the large areas of the state well in time, stratified random sample segment approach has been adopted for analysis. The segment size was initially kept at 10*10 km which was reduced to 7.5*7.5 km and finally to 5*5 km. The sampling fraction was also increased from 10 to 20 percent. However, complete enumeration approach was followed subsequently, that involved analysis of the satellite data for the complete district, as the computer speed and capacity increased and the size of the districts decreased with creation of new districts in the state. Yield of wheat was estimated using multiple regression models developed using satellite based spectral vegetation indices along with meteorological and historical yield data. Zonal Spectro-trend, Trend-agromet and Spectro-trend-agromet models for wheat production forecasting were developed for different regions of the state of which the last one gave the best results. The performance of wheat acreage and yield estimates was evaluated by computing Relative Deviations (RD%) with Department of Agriculture (DOA) estimates.

It was observed that the area and production estimates improved with decrease in the segment size and increase in the sample segment as the size of various district decreased gradually. During the last 15 years of estimation the spatial resolution of the satellite data has gradually improved from 80 meter of MSS to IRS-IA/ IB/ lC/ ID (LISS-I/ II) and finally 23.5m LISS-III of Resourcesat which is being currently used for this purpose. Besides the spatial resolution, the spectral and temporal resolution of the satellite data has also improved which drastically improved the crop discrimination. Both accuracy as well as precision of the estimates improved over the years, as reflected by the relative deviation and CV values respectively, for various districts. However, the northern districts having large contiguous areas of the crop showed better accuracy and precision as compared to southern districts having a mix of various crops. Presently remote sensing technology is able to provide district level acreage and production estimates with 95 % accuracy.

1 INTRODUCTION

The use of Remotely Sensed (RS) data is being investigated all over the world crop production forecasting. Crop production consists of two components, i) area under the crop, and ii) yield per unit area. Acreage estimation using RS data has been demonstrated in various parts of the world. Dadhwal and Parihar (1985) made first attempt in India towards the use of satellite digital data for wheat acreage estimation in Karnal district of Haryana State. A project on Crop Acreage and Production Estimation (CAPE) under the Remote Sensing Applications Mission (RSAM) with enlarged scope and objectives was formulated in 1986. A concentrated effort has been made under this programme to develop methodology applicable over large areas (Sahai and Dadhwal, 1990).
However, yield prediction is a subject of intensive research and is still at a developmental stage. Remote Sensing (RS) can provide information on important crop growth variables on a regional scale. Vegetation Indices (VIs) derived from RS data acquired at maximum vegetative growth stage are indicative of

crop growth, vigour and potential grain yield. Numerous factors including weather parameters and agronomic practices, which vary from area to area affect crop yield in a given region. Over the past decade, a number of crop yield forecasting models using RS data have been developed (ldso et. al., 1980; Dubey et al., 1994; Datta et. al. 1995.; Kalubarme et. al., 1998 and Urmil Verma et. al. 2003).
The work on production forecasting using satellite data for major crops of Haryana state is being carried out under CAPE project for the last about 16 years. The present paper deliberates on the development of satellite-based methodology for wheat yield forecasting, improvements in accuracy and timeliness and experience gained in the field over the years using mostly the data from a series of Indian Remote Sensing (IRS) series of satellites.

2 STUDY AREA

All the districts of the state were covered for wheat estimation. Initially the state had 12 district which subsequently increased

to 20 with the creation of 8 new districts in different years. Haryana state lying between latitude 270 39' 00'' to 300 55' 05'' N and longitude 740 27' 08'' to 770 36' 05'' E covers the total geographical area of 44212 sq. km. Wheat crop is grown in all the 20 districts of the state with varying density. The density of crop increases from northern to central districts. The districts of Kurukshetra, Kaithal, Karnal, Panipat, Jind, Rohtak, Sonipat and Jhajjar have the maximum density of the crop. The crop density again decreases in the south-western district which have sandy areas and limited irrigation facilities. Almost 99 percent of wheat crop in the state is grown under assured irrigation. The annual rainfall in the state range from 400 mm in the south-western part to 1400 mm in the northern Shiwalik hill areas. The crop is grown during the winter season known as Rabi season in the state. Sowing is generally done in the month of November and December and crop is harvest in the middle of April. Location of the study area is provided in figure 1.

LOCATION MAP
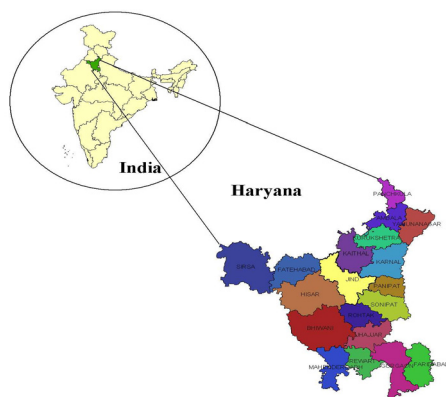
Important information about Haryana state is provided below:

	Area (sq km)
Geog. Area	44212
Net sown area	34580 (78.2%)
Double crop area	25770 (58.3%)
Gross crop area	60350 (136.5%)
Cropping intensity	175 %
Wheat area	22670 (51.3%)
Forest area	1558 (3.5%)

(figures in parenthesis indicate % of total geographical area)

No. of Villages	6955
No. of Towns	84
No. of Districts	20

Population (2001 Census)
Total	21.15 million
Rural	71%
Urban	29%
Density	478 per sq km

3   DATA USED

Data from a variety of satellites were used depending upon the availability since the beginning of the project. Initially data only from American Landsat Satellite was available. Subsequently,

with the launch of a series of Indian Remote Sensing Satellites

Fig. 2. Wheat Area Estimates in Haryana
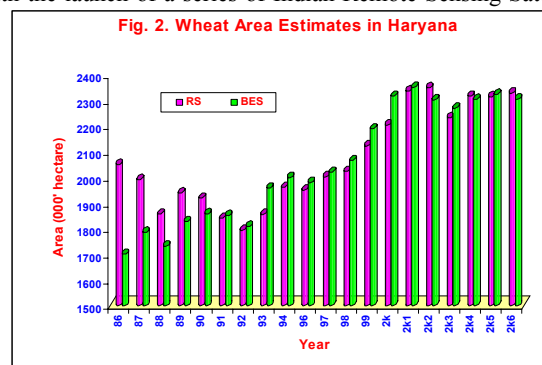
(IRS), their data was opted for use due to easy availability and

less cost. The spatial resolution of the satellite data continued to increase with the advancement in the sensors from new generation satellites. The list of satellites/ sensors whose data was used is provided in table 1 below.

Satellite	Sensor	Spatial Resolution (m)
LANDSAT	MSS	80
LANDSAT	TM	32
IRS1A/1B	LISS-I	72
IRS1A/1B	LISS-II	36
IRS1C/1D	LISS-III	24
Resourcesat-P6	LISS-III	24

Table 1. List of satellites/ sensors and their spatial resolution

Single date satellite data acquired around the peak vegetative stage of wheat crop i.e. around third week of February was used for analysis. Satellite data date normalization was done by generating a profile curve of the crop to overcome the variation in the date of data acquired.

4   METHODOLOGY

4.1   Stratified Random Sampling / Complete Enumeration Approach

Initially looking into the limitations of digital computer processing speed and reducing the time of analysis stratified random sampling approach was used. The stratification was done by overlaying a 10*10 km grid over the previous year satellite data and visually categorizing each segment into A, B, C, D or Non-agricultural (NA) type based upon the spread of agriculture in each segment as under:

A > 75%   B = 50-75%   C =25-50%   D = 5-25%   NA < 5%

Subsequently, Digital Stratification based upon thresholding of Vegetation Index was attempted and found to be more accurate and easy to use. With the changes in the land use new stratification was done with fresh satellite data after every 3-5 years. Segment size which was 10*10 m initially was subsequently reduced to 7.5*7.5 m and finally to 5*5 m to improve the accuracy of the estimates. Similarly the sampling fraction was slowly increased from 10 % to 15 % and finally to 20 % with the reduction in size of the districts.

After 1999-2000, when the size of some of the district became very small and the processing speed increased many times, we switched over to complete enumeration approach. In this approach the satellite data for each district was extracted by

overlaying the administrative district boundary and analysis of the data for the entire district was done.

4.2 Digital analysis

In season ground truth was collected by approaching each selected segment of the district. Satellite data was acquired at the peak vegetative stage of the crop. Satellite data was rectified and registered with respect to Survey of India topo-sheets.

Digital analysis was carried out using Supervised Classification and Maximum Likelihood (MXL) algorithm. In this approach the training statistics was generated after feeding the ground truth collected. Based upon the training statistics the wheat pixels were classified for each district which were converted to area. Wheat area in the district was computed by applying the area correction factor for the district.

4.3 Yield Modelling

Initially the yield estimates for each district were provided based upon trend analysis of the historical yield data collected from Department of Agriculture. Subsequently, when database on the Vegetation Index of each district for 5-6 years was generated, multiple regression models including trend predicted yield and VI were developed, which increased the accuracy of estimates for most of the districts. Finally Zonal-spectral-trend yield models were developed using agro-meteorological indices like accumulated rainfall, minimum temperature, maximum temperature and growing degree days (GDD) etc. The meteorological data was available only for the four different regions of the state. These models further improved the accuracy of the estimates.

5 RESULTS AND DISCUSSION

5.1 Acreage Estimation

The area estimates of wheat were provided in the beginning of the project at the state level using

Landsat MSS data. Subsequently, area estimation at district level was initiated.

Figure 2 provides the wheat area in the state estimated using Remote Sensing (RS) data in comparison with Bureau of Economics and Statistics (BES) estimates since the beginning of the project.

Fig. 3. Districtwise wheat acreage for the year 2004
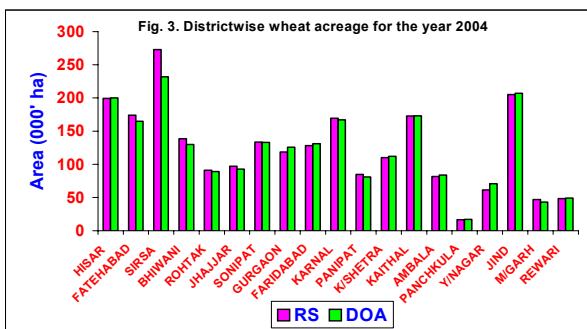
It is clearly visible from the figure that their exited wide gaps between RS and BES estimates at the start of the project. However, with the improvement in methodology the difference in the two estimates narrowed down and currently we have a difference of 2-3 % at the state level. District-wise estimates for the year 2004 are provided in Figure 3. At district level the

difference in the RS and field based Department of Agriculture (DOA) estimates range from 3-5 % except

for Sirsa district where it is about 10 %. The difference is more in the south-western districts of Sirsa, Fatehabad and Bhiwani where the mixing of crop is more compared to central and northern districts. It is clear from the results that wheat acreage at state and district level can be estimated using satellite data with fairly good accuracy.

Fig. 4. Wheat Production Estimates of Haryana

Fig. 5. Districtwise Wheat Production for the year 2004
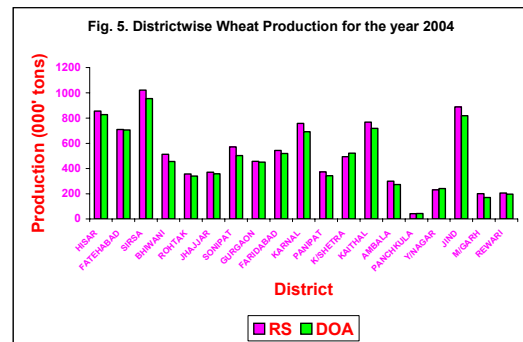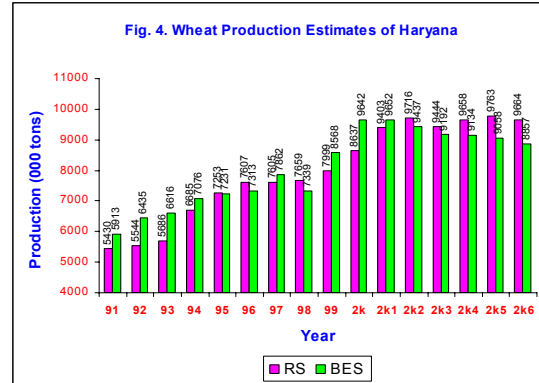
5.2 Production

Production estimation was initiated in the year 1990-91 using trend predicted yield. Subsequently, yield was estimated using multiple regression models developed using spectral vegetation indices from satellite data along with meteorological and historical yield data as described in the methodology. Zonal Spectro-trend, Trend-agromet and Spectro-trend-agromet models for wheat production forecasting were developed for different regions of the state of which the last one gave the best results.

Zonal spectro-trend-agromet yield models developed for the year 2004 are as under:

Zone 1: Ambala Panchkula, Y/Nagar and Kurukshetra
$$Y = -39.96 + 0.932 GDD_1 - 0.567 ARF_6 + 0.801 Y_t - 1.662 VI$$
$R^2 = 0.89$

Zone 2: Karnal, Kaithal, Jind, Panipat, Sonepat, Rohtak
$$Y = -10.46 + 0.146 TD_1 + 0.148 TD_3 + 0.175 GDD_3 + 1.079 Y_t - 0.585 VI$$
$R^2 = 0.92$

Zone 3: M/garh, Rewari, Jhajjar, Gurgaon, Faridabad
$$Y = -11.46 + 0.045 TD_6 + 0.28 ARF_4 + 1.04 Y_t - 3.391 VI$$
$R^2 = 0.91$

Zone 4: Sirsa, Hisar, Fatehabad and Bhiwani
$$Y = 13.768 - 0.217 GDD_4 + 0.138 GDD_7 + 0.16 ARF_1 + 0.855 Y_t - 3.101 VI$$
$R^2 = 0.91$

Where:	
VI = Vegetation Index	1. Crown root initiation stage
Yt = Trend predicted yield	2. Tillering stage
TD – Temperature Difference	3. Jointing stage
GDD – Growing Degree Days	4. Flowering stage
ARF – Accumulated Rainfall	5. Milking stage
VI = Vegetation Index	6. Dough stage
Yt = Trend predicted yield	7. Maturity stage

State level production estimates since the beginning of the project are provided in figure 4 and district level production estimates for the year 2004 are provided in figure 5. Results indicated that the difference in the RS and BES estimates have narrowed down over the years since the beginning of the project but not to the extent as in case of acreage estimation. This indicates that we still need to improve upon our yield models to make them more robust to predict the yield more accurately. Similarly, variation in the production at the district level are still more pronounced. This indicated that we need to have districtwise yield models in place of Zonal models to improve the accuracy of the estimates. Availability of the meteorological data at the district level is the main hurdle in developing such models.

5.3 Accuracy

The accuracy of the satellite-based estimates depends on the methodology adopted for interpreting and analyzing the satellite data. Relative Deviation (RD) of the RS estimates in comparison to DOA estimates, as provided in Figure 6, has significantly improved since the beginning of the project. Presently remote sensing technology is able to provide district level acreage and production estimates with 95 % accuracy.

Fig. 6. Relative Deviation of Wheat Estimates in Haryana
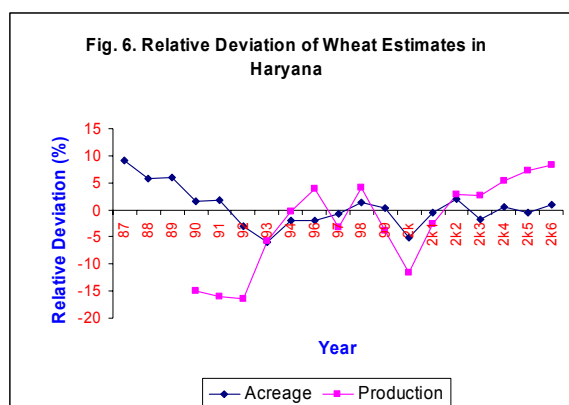
5.4. Timeliness

The crop forecasts to be really useful in the planning process need to be provided well before the harvest of the crop. Since the major objective of the current project was to operationalize the crop forecast, efforts were made to improve the timeliness of the forecasts over the years. Figure 7 indicates that the timeliness of the remote sensing wheat estimates have improved substantially over the years due to availability of efficient hardware/ software and high frequency of getting timely satellite data. The target dates for finalization of the wheat estimates i.e. the mid March is about a month in advance than the harvest of the crop i.e. mid April.

6.0 CONCLUSIONS

The accuracy and timeliness of the remote sensing estimates in comparison to BES/ DOA estimates has significantly improved since the beginning of the project. Presently remote sensing technology is able to provide district level acreage and production estimates much before the harvest of the crop with 95 % accuracy. Both the accuracy and timeliness of the estimates are likely to improve further with the availability of very high resolution (6 meter) satellite data through LISS-IV sensor of Resourcesat launched by India in October, 2003. This data may revolutionize the way agricultural systems are managed in the country. This high-resolution data could be used

for the assessment of minor crops, horticultural and vegetable crops for which no information is currently available with the government or any other agency. Besides this satellite data would be helpful in carrying out various agricultural operations and optimization of agricultural inputs through the concept of precision farming. Following major research areas have been identified for improving crop production forecasts

The research efforts related to yield models for forecasting, needs to be directed towards from the statistical approach to model based approach, which will use crop growth functions as well as model based crop parameter retrieval from satellite data (Dadhwal, 1999).

The new procedures should incorporate operational atmospheric correction using the globally available geophysical derived products on ozone, water vapour and aerosols at coarse resolutions.

With increasing availability of thermal infrared and microwave data, procedures for their use alone or in combination with optical- Near Infrared regions need to be adapted for operational yield modelling.

Sensor-to-sensor and date normalization procedures need to develop when using data from any of the available sensors within-season or across-season for data analysis.

Generation of locally developed LAI-NDVI model for the satellite data is one of the important input in the wheat simulation model WTGROWS. This NDVI-LAI relation then is inverted to compute RS based LAI estimates. This suggests a need to develop an easy to use LAI retrieval procedure from satellite data.

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EXTRACTION OF PHENOLOGICAL PARAMETERS FROM TEMPORALLY SMOOTHED VEGETATION INDICES

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KEY WORDS: Agriculture, Remote Sensing, Vegetation Indices, temporal

ABSTRACT:

Within the MARS Crop Yield Forecasting System (MCYFS; Royer and Genovese, 2004) of the European Commission vegetation indicators like NDVI, SAVI and fAPAR are operationally derived for daily, decadal and monthly time steps. Besides low resolution sensors as SPOT-VGT and NOAA-AVHRR, medium resolution data from TERRA/AQUA-MODIS or ENVISAT-MERIS are used at pan-European level. In case of available time series, esp. NOAA-AVHRR (since 1981) and SPOT-VGT (since 1998) difference values of the indicators (e.g. relative or absolute differences) and frequency analysis of the indicators (e.g. position in historical range or distribution) are calculated. The exploitation of the data is performed at full resolution, at grid level of the MCYFS or regional unmixed means (C-indicators) are used. Therefore a database has been set-up in order to provide the indicators based on a weighted average for each CORINE land cover class within an area of interest.

The current work aims to develop a strategy for an optimal use of the different sensors and thus derived indicators at different aggregation levels for the ingestion into the MCYFS. As a first step smoothing algorithms have to be applied to the time series to diminish noise effects. Therefore, existing methods as simple sliding windows, piecewise linear regression or fitting of polynomial functions are employed and compared. Thereafter, the time series analysis is performed with the aim to establish relationships between indicators profile features and the crop phenology.

1. INTRODUCTION

Simple vegetation indicators like the Normalised Difference Vegetation Index (NDVI) or the Soil Adjusted Difference Vegetation Index (SAVI) are used since a long time to establish empirical relationships between spectral reflectance and biophysical parameters (e.g. biomass, leaf area or vegetation cover) or the spectral reflectance is used to estimate the amount of absorbed photo-synthetically active radiation (APAR).

Within the MARS Crop Yield Forecasting System (MCYFS) of the European Commission the indicators NDVI, SAVI, Dry Matter Productivity (DMP) and fraction of APAR (fAPAR) are operationally derived for daily, decadal and monthly time steps. Besides low resolution sensors as SPOT-VGT, NOAA-AVHRR and MSG-SEVIRI, medium resolution data from TERRA/AQUA-MODIS or ENVISAT-MERIS are used at pan-European level. In case of available time series, esp. NOAA AVHRR (since 1981) and SPOT-VGT (since 1998) difference values of the indicators (e.g. relative or absolute differences) and frequency analysis of the indicators (e.g. position in historical range or distribution) are calculated.

These vegetation indicators are intended to be employed at three ingestion levels :
- independent source of information to confirm crop growth indicators and identify area with anomalies,
- ingestion in the crop model to calibrate agrophenological parameters like leaf area index or development stages,
- crop yield estimation by means of scenarios and regression analysis.

According to the different ingestion levels, the exploitation of the data is performed at full resolution, at grid level of the Crop Yield Forecasting System (50 km) (Lazar and Genovese, 2004) or regional unmixed means (C-indicators) are used. For the latter a specific aggregation scheme has been set-up based on a weighted average for each CORINE land cover class (De Lima, 2005) within an area of interest as administrative boundaries (Genovese et al., 2001).

The overall objective of the study is to develop a strategy for an optimal use of the different sensors and thus derived indicators at pixel and aggregation level for the ingestion into the MCYFS. It can be separated into the following tasks:
1. Identification of an optimal strategy for the preparation of the satellite based time profiles (noise filtering and curves features extraction).
2. Identification of vegetation parameters to be used at the different ingestion levels.
3. Analysis of the impact of different sensors according to the spatial resolution and different time periods on the different ingestion levels.

The present paper covers mainly issue 1 and partly issue 2. As a first step smoothing algorithms have to be applied to the time series to diminish noise effects (e.g. clouds, snow, bidirectional effects). Therefore, existing methods as simple sliding windows, piecewise linear regression or fitting of polynomial functions are employed and compared. These methods have been reviewed by several authors recently (e.g. Pettorelli et al., 2005; Swets et al., 1992).

Thereafter the analysis of the time series is performed with the aim to extract features of the temporal profiles (e.g. start of growth, max NDVI, end of cycle) and to establish regional relationships with the biomass development.

2. METHODS

2.1 Smoothing of NDVI Time Series

The available remote sensing time series are pre-processed in terms of sensor calibration, degradation, atmospheric conditions and geometry. However noise still exists in the data and biases the data exploitation. It can be grouped as follows (Pettorelli et al., 2005):

- decrease of NDVI values due to clouds, water, snow, shadow, bidirectional effects,
- less frequent false highs due to high solar or scan angles, transmission errors.

In the case of NDVI time series, smoothing methods have to meet special requirements due to the fact, that most errors are decreasing the NDVI and the error structure can vary in time and space (Pettorelli et al., 2005). On the other hand they have to keep the general shape of the profile or the low frequency characteristics in terms of intensity and phasing. It should improve the biophysical relation of the NDVI profiles, which is an important precondition for the extraction of curve features and derivation of phenological parameters.

2.1.1 Smoothing Methods

A review of the most common smoothing methods as well as their main advantages and disadvantages is given by Swets et al., 1992; Pettorelli et al., 2005; Curnel and Oger 2007.

Within this study, the following methods have been analysed:

- Best Index Slope Extraction – 'BISE' (Viovy et al., 1992),
- Weighted least-squares linear regression – 'SWETS' (Swets et al., 1999),
- Modified Swets approach – 'modSWETS',
- Savitzky-Golay filter – 'SAV-GOL' (Press et al., 1992),
- '4253H, twice' (Velleman and Hoaglin, 1981).
- Case sensitive filter – 'CASE-SENS'.

The case sensitive filter detects different configurations of consecutive NDVI values, which are represented by lows, highs and slopes depending on the window size. It applies linear interpolation to remove decreased NDVI values.

The Swets approach performs a linear regression for a moving window. It includes the weighting of points according to their configuration (lows, highs and slopes). The resulting family of regression lines for each point is averaged. The modification of the 'SWETS' algorithm presented by 'modSWETS' has been introduced to avoid too high resulting values before and after NDVI slopes (correction of peaks) and to keep the original high values due to the fact, that false highs are less frequent. The principle of the corrections is shown in figure 1.
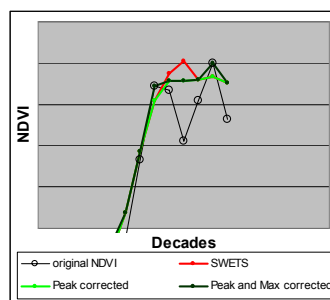

Figure 1. Principle of the modifications of the 'SWETS' approach ('modSWETS')

Moreover, the herein analysis was performed on different window sizes for each method as shown in table 1.

Methods	Time window size			
	3	4	5	6
BISE	x	x	x	x
SWETS	x	x	x	
modSWETS	x	x	x	x
SAV-GOL	-	x	x	x
'4253H, twice'	- *	- *	- *	- *
CASE-SENS	x	x	x	-

Table 1. Overview of the analysed methods and time window sizes; * window size is predefined

2.1.2 Criteria for Evaluation of Results

In order to compare the different smoothing methods and the respective time window sizes, following criteria are defined, which are specific to the requirements given by the objective of ingestion in the MCYFS and the application to the pan-European level for arable land and grassland:

1. High frequency noise should be diminished to the highest possible degree.
2. Overall intensity given by an area-specific NDVI profile (low frequency feature of profile) has to be retained.
3. High values should be retained to highest possible degree due to the low frequency of false highs.
4. Timing of profile features, e.g. start of cycle (see 2.2.1) should not be influenced by the smoothing or to the lowest possible degree.

Furthermore, it should be outlined, that it is not clear for every situation, up to which extent the smoothing has to be performed in order to get the best signal/noise ratio. Thus, the final decision can only be based on expert knowledge through visual comparison, which is to a certain degree subjective.

Local characteristics can appear as unimodal or bimodal distributions within a cycle due to the cultivation of different crops, as different intensities of NDVI for different countries / areas or as local maxima before the real start of growth due to winter cover (see figure 2).
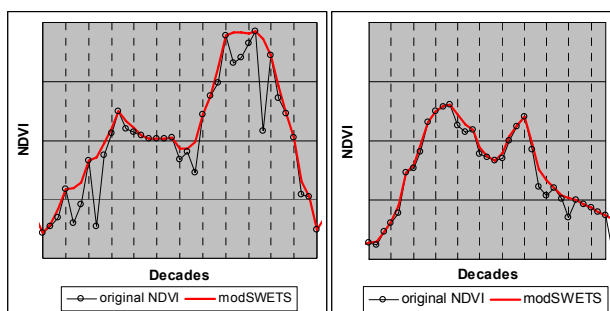
Figure 2.   Examples for local profile crop characteristics in Germany with winter cover (left) and in Romania with bimodal NDVI profile (right)

2.2   Extraction and Derivation of Parameters

2.2.1   NDVI Profile Features/Characteristics

Typical features that describe the annual cycle of the NDVI profile are given below (Pettorelli, 2005; Joensson and Eklundh, 2004):

*   date of start and end of growth,
*   maximum NDVI cycle and date of maximum NDVI,
*   rates of increase and decrease of NDVI within a cycle,
*   cumulated NDVI: sum of NDVI for a given time period (e.g. for whole year, from start to end of cycle).

Moreover, the above mentioned profile features of the current year are compared with the one of the available historical years for the use of satellite based indicators as independent source of information. It is realised by calculation of differences or by ranking of the current year feature within the whole time series.

The extraction of the profile features can be performed by means of empirical equations (Moulin et al., 1997), thresholds (Joensson and Eklundh, 2004) or derivatives (Zhang et al., 2003). The latter method is possible, if the NDVI profiles are smoothed by polynomial fitting or logistic curves. Within this analysis an approach is employed, which detects increases of NDVI country-specifically.

2.2.2   Agrophenological Parameters for Calibration

The agrophenological parameters are meant to be directly coupled with the crop growth monitoring system (CGMS) to realise the second ingestion level. The CGMS is based on the WOFOST model adapted to the European scale and LINGRA used for pastures. The main processes being modelled within WOFOST are phenological development, CO_2-assimilation, transpiration, respiration, partitioning of assimilates and dry matter formation (Lazar and Genovese, 2004).

It is therefore the objective to derive several agrophenological parameters, which are used in the CGMS. These can be the leaf area index (LAI), above ground biomass or crop development stages. There are several approaches, mostly empirical ones, which link vegetation indicators (e.g. NDVI, SAVI) to the LAI or to the biomass (DMP) (e.g. Baret and Guyot, 1991; Turner et al., 1999). The linkage between NDVI and possible development stages, which has to be set-up region-specific, are shown in figure 3.
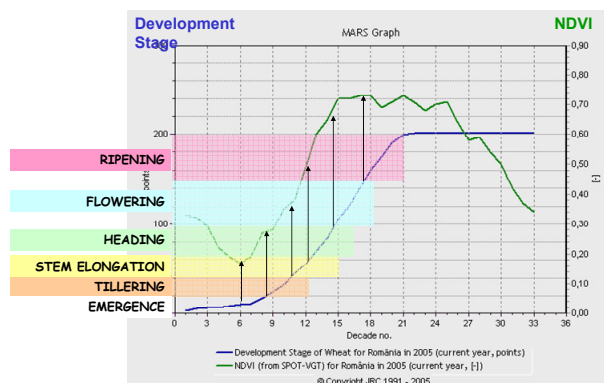

Figure 3.   Regional linkage between NDVI profile and crop specific development stages

3.   DATA BASES

The remote sensing data employed within the MCYFS for vegetation analysis are listed in table 2.

Platform	NOAA/ METOP	SPOT	ENVISAT	TERRA/ AQUA
Sensor	AVHRR 2 AVHRR 3	VGT 1 VGT 2	MERIS	MODIS
Pixel size (m)	1000	1000	300/1200	250/500
Existing from	1981	1998	2002	2000
MARS archive	1981	1998	2006	2004
Time period	d, t, m	t, m	t,m	d, t, m
NDVI	x	x	x	x
SAVI	x	x	x	x
fAPAR	x	x	x	x

Table 2.   Overview of remote sensing data within MCYFS (d - daily, t - 10-daily, 30 - monthly)

The herein used data are decadal NDVI values calculated from the reflectances of the SPOT-VGT satellite. The pre-processing takes place in three steps (Royer and Genovese, 2004):

*   spectral/radiometric: calibration and atmospheric correction; labelling of snow, cloud, sea,
*   spatial: geometric correction to template with European extent and INSPIRE – Lambert Azimuthal Equal-Area Projection,
*   temporal: synthetic images for different time periods by maximum value compositing (MVC).

The decadal NDVI profiles are corrected for snow and cloud values by linear interpolation between available values before and after snow or cloud occurrence. The extraction of arable land pixels for the analysis is carried out by means of the CORINE land cover 2000 (De Lima, 2005). The CLC data has been resampled to the extent and resolution of the SPOT-VGT data containing the percentage of class arable land according to the pixel size of 1km. Only pixels with more than 50% have been included in the analysis.

4.   RESULTS

4.1   Comparison of Smoothing Methods

The method comparison has been carried out for sample pixel in Romania, Germany, France, Italy, Spain and Poland. In a

first step for each location all methods for each window size have been analysed. At this level a pre-selection of methods has been done. Figure 4 shows the results of the different methods using time window size 5 for Germany.

The methods are first checked according to their ability to reduce high frequency noise (see 2.1.2 criteria 1). As shown in figure 4, the approaches '4253H,twice', 'SWETS' and 'modSWETS' fulfil this criteria very well. Whereas 'SAV-GOL' very often tends to insufficiently smooth the NDVI values. In contrary, the methods 'BISE' and 'CASE-SENS' appear to oversmooth the NDVI time series with increasing time window size.
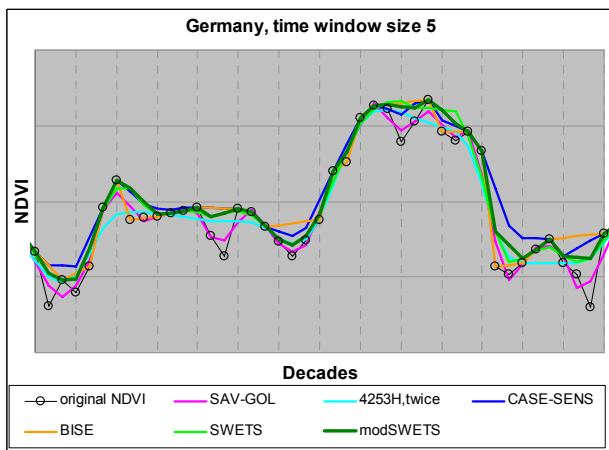
Figure 4. Smoothing methods for example Germany

The second criteria, which is keeping the overall intensity, is well fulfilled by all approaches. In figure 4 it is clearly visible, that the methods 'SAV-GOL' and '4253H,twice' (magenta and turquoise) manage to smooth high frequency noise.

At the same time these methods tend to depress the intensity of the local maximum NDVI (criteria 3). This is due to the fact, that they are not adapted to the special situation that higher NDVI values are more reliable than lower ones. Whereas the other methods ('CASE-SENS', 'BISE', 'modSWETS') are better able to keep the maximum values. The 'SWETS' method (light green) seems to be a transition between these two groups of approaches, because it fits better in the NDVI situation due to its point weighting for the linear regression. But it is several times below the maximum values (see figure 4).

For the further analysis, the methods 'CASE-SENS', 'BISE', 'modSWETS' are taken into consideration. They are now compared for different time window sizes. In figure 5 the different behaviour for some critical decades are shown.
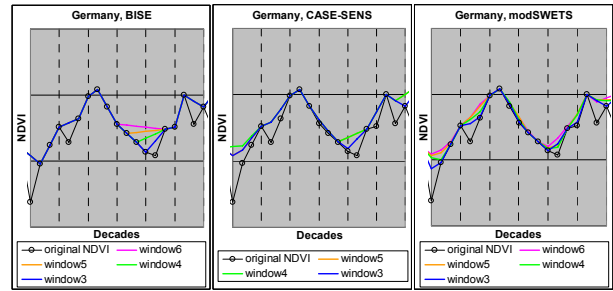

Figure 5. Pre-selected smoothing methods for different time window sizes

Considering the fourth criteria, the method 'BISE' (left) tends to smooth valleys too roughly depending on the window size and thus changes the phasing or timing of profile features like the start of cycle. A similar but less severe situation is given by 'CASE-SENS' (middle), whereas window size 5 behaves very similar to 4. The approach 'modSWETS' (right) apparently keeps the timing of the profile feature in a better way throughout all window sizes. Here it is of importance to find the optimal extent, up to which smoothing has to be performed.

A survey of the previous defined criteria and their fulfilment by the different methods is given in table 3.

Methods	Evaluation criteria (see 2.1.2)			
	1	2	3	4
BISE	xx	xx	xxx	x
SWETS	xxx	xx	xx	xx
modSWETS	xxx	xx	xxx	xx
SAV-GOL	x	xx	x	xx
'4253H, twice'	xxx	xx	x	x
CASE-SENS	xx	xx	xxx	x

Table 3. Overview of the analysed methods and time window sizes; degree of fulfilment: x poor, xx good, xxx very good

4.2 Extracted Curve Parameters

As a first step, start of crop cycle and maximum NDVI value have been extracted from the NDVI time profiles. The SPOT-VGT data have smoothed with 'modSWETS' and a window size of 5 decades. The results are presented for a sample area in Central Europe in figure 6. Light to dark green colors indicate in most of the cases the start of regrowth for winter crops, which is initialised mainly between January and March. Light blue colours (April to June) are related to the start of growth for prevailing summer crops.

The above mentioned phasing behaviour of NDVI profiles after application of the smoothing methods can cause differences in the estimated start of growth. The impact of the differences strongly depends on the used time composite, which is in the present analysis 10-daily. It will be less severe for daily composites but more severe for monthly NDVI.

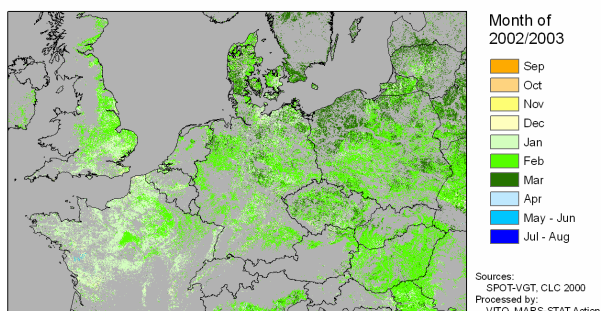**Start of Growth / Regrowth for Arable Land**

Figure 6. Estimated month of start of growth / regrowth based on 'modSWETS' smoothing for 2002/2003

Furthermore, in future the approaches will be applied to different indicators like SAVI and different sensors. According the latter point medium resolution sensors (MODIS, MERIS) will play an important role to improve the mixed pixel situation.

5. CONCLUSIONS AND PROSPECTS

The ingestion of satellite based data into the MARS crop yield forecasting system requires an adequate preparation and approaches for parameter extraction. Within the present study different smoothing methods have been analysed. It could be shown, that existing methods are no panacea. Their limits mainly consist in the capability to adjust to local characteristics due to agricultural practices. Within this study the 'modSWETS' approach was selected as the best method according to the given requirements. It is an efficient approach in reducing high frequency noise, but it retains the general curve shape, intensity as well as high values. At the same time 'modSWETS' is able to retain the phase of curve features. Moreover it appears, that the time window sizes 4 and 5 present the best compromise.

The smoothed NDVI profiles have been successfully used to extract curve features like the start of growth and the maximum NDVI for European countries. These curve features have to be linked to agrophenological parameters contained in the MARS Crop Yield Forecasting System. In order to establish this link a number of ground truth data sources will be employed, which is available for main crops in Europe.

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NEW METHODS AND SATELLITES: A PROGRAM UPDATE ON THE NASS CROPLAND DATA LAYER ACREAGE PROGRAM

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ABSTRACT:

The United States Department of Agriculture (USDA), National Agricultural Statistics Service (NASS) annually produces crop specific classifications and acreage estimates over the major growing regions of the United States using medium resolution satellite imagery. The classifications are published in the public domain as the Cropland Data Layer (CDL) after the release of official county estimates. This program previously used; Landsat TM and ETM+ imagery, the NASS June Agricultural Survey (JAS) segments for ground truth information, and Peditor software for producing the classification and regression estimates. The unpredictability of the Landsat program, the labor intensive nature of JAS digitizing for the CDL program, and the potential efficiencies gained by using commercial software warranted investigations into new program methods. NASS began investigating alternative sensors to the Landsat platform in 2004, acquiring ResourceSat-1 Advanced Wide Field Sensor (AWiFS) data over the active CDL states. Additionally, evaluations were performed on alternative ground truth methodologies using data collected through the USDA/Farm Service Agency (FSA) Common Land Unit (CLU) program and testing began with See5 software to produce the CDL.
NASS began pilot AWiFS studies for the State of Nebraska in 2004 and followed up with studies of Arkansas, Louisiana, Mississippi, Missouri, Nebraska and North Dakota in 2005. Accuracy assessments and acreage indications determined that the AWiFS results positively reduced the statistical variance of acreage indications from the JAS area frame, delivering a potential successor to the Landsat platform. In 2006 pilot testing was complete and the AWiFS sensor was selected as the exclusive source of imagery for the production of the CDL and acreage estimates. The FSA CLU program provides a comprehensive national digitized and attributed GIS dataset collected annually for inclusion into programs like the CDL. Commercial image processing programs such as See5 were tested in 2006 against the AWiFS imagery and CLU datasets, providing evidence of efficiency gains in statistical accuracy, scope of coverage and time of delivery to make further investigation warranted. The results of these program updates are presented.

INTRODUCTION

The Cropland Data Layer (CDL) Program at the National Agricultural Statistics Service (NASS) has been in production for over 10 years in its present state. The CDL is produced annually using available medium resolution satellite imagery such as the Landsat 5, Landsat 7 and IRS-1C LISS 3 satellites, the NASS June Agricultural Survey (JAS) for ground truth training data, and NASS developed and maintained public domain image processing software Peditor. The CDL program has expanded into many States through partnerships and cooperative agreements with interested federal and state governments and universities. Expansion has been supported by efficiencies with faster microcomputers, enhanced Peditor algorithms (Ozga 2000, Mueller and Ozga 2002) optimum staffing and employee training. This has allowed NASS to expand coverage while maintaining requirements of timely, accurate, unbiased state and county level acreage estimates delivered to decision makers in NASS with measurable error.

The program is a public domain product after publication of official county estimates. It is released in mid-March of the following year for wheat, corn and soybean States of the Midwest and in early July for the Mississippi Delta States with rice and cotton estimates. The uses of the CDL product are diverse and unique such as: agribusiness planning, environmental and ecological modelling, land use studies, crop rotational analysis, water usage, precision farming, epidemiological, alternative fuels, demographic, carbon, nutrient, pesticide and conservation research to name a few. The NASS CDL is widely viewed in the geospatial community as a one-of-a kind product useful for identifying crop specific land use cover types and can be used to mask out agricultural lands for modelling purposes.

The complete inventory of CDL states is depicted in Figure 1. The shade of green indicates if the program was a one time, annual, or potential project state, while the year shows either the crop year that the program started or the one year that it was performed. The dark green states are repeated annually, while the medium green states were performed either under contract or with program cooperators who created the CDL product. NASS is currently seeking active partnerships with the light green states.

The CDL program is moving to expand to additional states. New expansion efforts will prioritize states based on an individual crop's value of production. The following is a list of commodities ranked in order of importance to the U.S. agricultural economy: 1. corn, 2. soybeans, 3. winter wheat, 4.

cotton, 5. spring wheat and 6. durum wheat. These commodities are traded on U.S. commodity markets and are one of the USDA's "Program Crops". These crops total production and/or value of production for a state places it within the top 5-10 producing states for the U.S. Based on this economic data, future efforts will target the remaining non-CDL corn and soybean states listed in Table 1 to capture the high value States of Kansas, Minnesota, and Ohio for corn and South Dakota for soybeans.
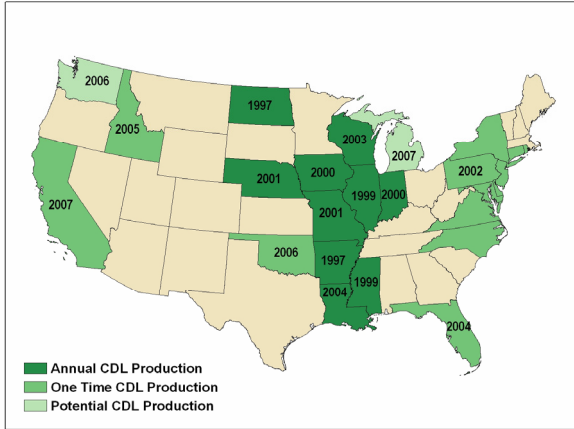

Figure 1. Cropland Data Layer inventory. Note the year indicates project start-up and the shade of green indicates project status.

Recent advancements in commercial software applications, newer multispectral satellite systems, ground truth alternatives to the JAS, and the ability to integrate other ancillary data sets into the analysis have offered research opportunities to improve on the recent CDL program efficiencies. See5[*] software integrated with ERDAS Imagine offers the opportunity to perform rapid state wide classifications and spatial smoothing of results and provide estimates to decision makers in NASS for consideration in setting early season state level estimates.

The launch of the IRS-P6 Resourcesat-1 Advanced Wide Field Sensor (AWiFS) in October of 2003 offered an alternative to the failing Landsat program. Research efforts began in 2004 to move CDL operations from the Landsat platform to that of the AWiFS. The Resourcesat-1 sensor is an operational program where the USDA is receiving domestic AWiFS imagery within five days of acquisition from commercial vendor GeoEye.

The JAS has been the backbone of the acreage estimation and CDL program since its inception in the 1970's (Allen and Hanuschak 1988, and Ozga and Craig 1995). The Farm Service Agency (FSA) of USDA partnered with NASS to deliver their enterprise-type GIS data layer called the Common Land Unit (CLU) program. The CLU layer is part of a national program that includes all farms that voluntarily participate in the program. The CLU program supports farm commodity and conservation programs and disaster response (Boryan 2007). The CLU is a comprehensive alternative ground truth dataset that can be utilized earlier than the JAS.

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[*] Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the US Government.

These new developments have created a variety of research opportunities to shorten the delivery times of acreage estimates, from mid-December to mid-October and to expand coverage to additional states as capacity is built out, while AWiFS offers new capabilities not previously experienced in the medium resolution marketplace.

Numerous Midwestern and Mississippi Delta States were processed with these new methods, techniques and data sources for crop year 2006. The various methods, procedures and estimation tests are discussed in detail for Iowa. Iowa is currently ranked number one in corn acreage with over 4.5 million hectares and second in soybean acreage with over 4.1 million hectares in the U.S.

CORN	SOYBEAN
Illinois	**Arkansas**
Indiana	**Illinois**
Iowa	**Indiana**
Kansas	**Iowa**
Minnesota	Kansas
Nebraska	Minnesota
Ohio	**Missouri**
Wisconsin	**Nebraska**
	North Dakota
	Ohio
	South Dakota

Table 1. The "Program Crops" corn and soybean states. Bolded states are already in the CDL program.

METHODOLOGY

AWiFS Studies

There have been numerous studies by NASS remote sensing analysts evaluating the possibility of using AWiFS imagery for the CDL program. In 2004, 142 scenes were collected by SpaceImaging Inc. on behalf of USDA during the month of August and NASS performed a feasibility study to determine if the AWiFS sensor would be a suitable Landsat replacement. In 2005, SpaceImaging Inc. collected 100 AWiFS scenes over the U.S. to use for comparisons with TM classifications. In 2006, USDA moved all image acquisition activities to AWiFS, collecting over 1,400 images and ceased active acquisition of Landsat imagery.

A Nebraska 2004 study, (Boryan and Craig 2005) compared a unitemporal AWiFS with a multitemporal and unitemporal TM classification. The results demonstrated that the TM multitemporal classification was the most accurate as expected. The unitemporal AWiFS classification while not as accurate as the unitemporal TM showed that despite lower accuracy assessments the AWiFS performed well for acreage estimation of corn and soybeans and the coefficients of variation (CV's) were only slightly worse than those of the TM sensor, and AWiFS performed better than the initial JAS estimates. In a pending article (Johnson 2007) discussed three co-incident AWiFS and TM collections in the central and southern parts of the U.S. in 2005. The classification assessments demonstrated that TM outperformed AWiFS in two out of three assessments with the exception of one area in Iowa. The Iowa case was the

smallest of the three study areas, had extreme AWiFS viewing geometry and was angled toward the sun. An analysis of Nebraska 2005 (Seffrin 2007) produced separate AWiFS and TM classifications that showed both sensors produced equally good estimates for corn and soybeans when compared to the official crop estimates. However, the state level CV's were larger for AWiFS than Landsat, but closer than the initial JAS estimate. These results were consistent with each other, and demonstrate that AWiFS crop indications were useful for crop acreage estimation, especially at the state and county level.

The AWiFS satellite was launched in October of 2003 and is backed by the Indian Space Research Organization and commercial partner GeoEye. This satellite provided an opportunity for breaching the Landsat data gap that is now in existence. Despite lower spatial and spectral resolution, the benefits of AWiFS outweigh the drawbacks; with the large swath width (740 km), an orbital repeat path of 24 days with repeat coverage every five days over 80 percent of the path, increasing the potential for in-growing season cloud free imagery, the ability to analyze larger amounts of training data that were not previously available with other systems with smaller coverage footprints, and near Landsat like spectral resolution (TM bands 2, 3, 4, 5) including the critical SWIR band, makes the AWiFS sensor an attractive Landsat alternative. The 56 meter spatial resolution does not appear to impact classification accuracy and acreage estimates while not as accurate as TM, they are statistically relevant. There also appears to be no negative affects (i.e., distortion) at the edges of the large AWiFS footprints (Johnson 2007). One potential limiting factor could be field size, as the CDL program typically targets states that contain large fields, usually with the average size greater than 20 acres and areas with smaller fields could provide less than optimum results, because of spatial resolution.

FSA/CLU Data

The USDA/Farm Service Agency (FSA) has established a Common Land Unit (CLU) standardized national GIS layer that managers land records, field locations and soils information. This program is maintained at the county level in over 2,300 FSA field offices, in a distributed data environment. The program's goal is to map and track all fields included in FSA programs on a near real time basis in part for compliance and administration purposes.

During the growing season, producers report their growing intentions, crops and acreage to the FSA offices and it is input into the GIS. A CLU is defined as the smallest unit of land with a permanent contiguous boundary and land cover. The CLU's are digitized in ESRI's shapefile format, while associated administrative attribute information is maintained in a separate database known as 578 Administrative Data. There are five main drawbacks to using the FSA CLU/578 datasets: 1) many CLU's have multiple crop types (mixed fields) within each field and are not suitable for training, only single use fields are used for training, 2) not all crop types are included in the program, only "program crops" are included and specialty crops are excluded, where the CLU program is not a true probability based sample of land cover and has bias toward subsidized "program crops", 3) every producer does not sign up for this program and non-agricultural areas are excluded too, leaving holes in the dataset, and 4) since the CLU's are maintained at the county level, a producer can report all of their farming operations in one office, regardless if their operations reside

physically onto adjacent counties (Boryan 2007) and 5) the ability to data mine through multiple years of CLU data, is not possible at this juncture, as the CLU's are a live dynamic GIS dataset and are updated each year as producers report on their operations, overwriting the prior year's CLU dataset. However, this comprehensive and robust CLU/578 dataset is timely and accurate enough to support NASS' remote sensing operations, reduce labor costs and potentially speed up analysis.

In order to obtain the current years' CLU information, a request is sent out by NASS through a liaison agent, who then sends the request to each FSA county field office within a state to pull their CLU datasets and send them back to NASS Headquarters for distribution. This request is quite burdensome for the FSA offices, and requests are limited to August and January of each year. The data is organized in ESRI shapefile format by county. The 578 Administrative Data is maintained in a separate centralized database, and NASS can query and extract data directly at any time. The merging of the CLU and 578 datasets occurs through a common Administrative ID, allowing for prior years' CLU's to be joined to the current years' 578 data using ArcGIS scripts.

The FSA comprehensive CLU dataset provides for the opportunity to have both an independent training and testing dataset that NASS never had with the JAS, as all JAS segments were previously used for both operations. The CDL program was operational in ten states in 2006, with the potential of even more in 2007. Each NASS Field Office that participates in the CDL program contributes hundreds of hours to digitizing the JAS field boundaries annually. While the JAS provides systematic probability based random samples, the CLU's include nearly the whole agricultural domain (Figure 2), and only require a few hours of an experienced GIS analyst to merge the CLU and 578 datasets together for each state. Once the datasets are merged, only single use fields with a one to one correspondence between polygon and field record are retained, multi-use CLU fields are omitted. The labor and cost savings to NASS are significant, and the remote sensing program will benefit from this comprehensive dataset. The JAS outer field boundaries are still needed for the remote sensing regression estimator, and that is already being maintained and provided by the NASS Area Sampling Frame Section to support the JAS.
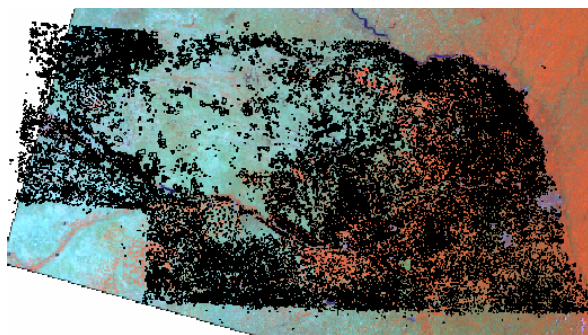

Figure 2. FSA CLU layer draped onto a July 15, 2006 Nebraska single date AWiFS image.

NASS' remote sensing intentions are to leverage the 578 data in mid-July with database queries from the liaison agent, and merge the current year's records with prior year's CLU's, as the likelihood of the Administrative ID changing is small, and the chances of a successful match are high. Preliminary selection of useable AWiFS scenes will begin at this point. An early

season classification can be run, to check ground truth validity and evaluate scene quality. In prior years, JAS digitizing would finish in September or October depending on available resources at the NASS Field Offices, thereby prohibiting an early season estimate. The new year's CLU's will be updated with the most recent certified 578 data in mid-August, and processing will begin on the mid-season estimate.

Ancillary Data

There are a variety of raster based data layers available from the U.S. Geological Survey (USGS) and now prior CDL products that can be included in the remote sensing analysis. Ancillary datasets from the U.S. Geological Survey, National Land Cover Dataset program (Homer 2004) were incorporated into the process to help separate non-agricultural land uses. The following data layers were utilized for the production of the 2006 CDL: elevation, forest canopy, impervious surfaces, the 2001 National Land Cover Dataset (NLCD) and prior CDL's. New program methods allow for the inclusion of these datasets improving classification accuracy especially in the non-agricultural areas.

The National Elevation Dataset (NED) (seamless.usgs.gov) is 30 meters in resolution, with the elevation model deriving slope, aspect, and topographic positional index (TPI) layers that can be used for training. The NED can be used to derive rules on whether potential agriculture production could exist based on topography and elevation data. The 2001 NLCD (www.mrlc.gov) was a national product completed in January of 2007, and included 21 land cover classes; percent tree canopy and percent urban imperviousness derived from Landsat imagery at 30 meters resolution. These products were used to derive extra signatures to improve the non-agricultural classification. Prior CDL's were used to focus the classifier on crop production/intensive areas and crop rotational patterns could be used for decision support. These datasets were resampled to 56 meters resolution using nearest neighbour rigorous transformation to match the native AWiFS pixel resolution.

Software Updates

NASS began using See5 (www.rulequest.com) software for the production of the 2005 Mississippi Delta CDL. For testing purposes only the agriculturally intensive Delta Region was classified with See5, as the rest of the domain was stamped in with Peditor classifications. The Florida 2004 CDL was produced next and it was the first full state CDL to be processed using See5. From the success of these pilot projects, additional See5 CDL's were processed for crop year 2006. The CDL States of Iowa, Nebraska, North Dakota, Washington and Wisconsin were tested with See5. Additionally, Nebraska and North Dakota were produced with FSA/CLU data only, while Iowa was produced with both Peditor and See5 software and JAS and FSA CLU training data.

Investigations began in late 2004 to determine if there existed an affordable, efficient and accurate classification alternative methodology to Peditor. Decision tree software was investigated based on recommendations from EROS Data Center researchers and literature reviews (Hansen et al., 1996; Friedl and Brodley, 1997 and Lawrence et al., 2004). Decision trees offer several advantages over the more traditional maximum likelihood classification method. The advantages include being: 1) non-parametric by nature and thus not reliant

on the assumption of the input data being normally distributed, 2) efficient to construct and thus capable handling large and complex data sets, 3) able to incorporate missing and non-continuous data, and 4) able to sort out non-linear relationships. These reasons combined usually lead to improved classifications over the maximum likelihood method. Additionally, there are several varieties of decision tree classifiers but See5.0 stands out because it further employs a statistical technique known as "boosting" which has been shown to improve results even further.

IOWA PROGRAM RESULTS

Ancillary Data Preparation

To prepare for the remote sensing analysis of Iowa, the ancillary data incorporated into the analysis was downloaded, including: forest canopy, impervious surfaces, and land cover. The project study area was defined by a polygon that extended 10,000 meters beyond the Iowa state boundary. This was used to clip subsequent data sets to the same extent. To capture the extent of Iowa and beyond, the USGS grouped the continental US into 17 zonal areas for ease of downloading and distribution. The ancillary layers covering Iowa in superzones 6, 8, 9, and 11 were downloaded from ftp://edcftp.cr.usgs.gov/pub/data/landcover/nlcd2001/superzones/ and were then mosaicked, resampled to 56 meters using a nearest neighbor rigorous transformation, and clipped to the study area. The NLCD land cover layer was used as ground truth for non-agricultural areas. These data sets were projected in Albers and no reprojection was necesary. The elevation data was downloaded in 1.5º x 2.0º tiles from the seamless data server (seamless.usgs.gov) in BIL format to cover Iowa and the surrounding area. It was then mosaicked, reprojected to Albers, resampled to 56 meters using bilinear interpolation using rigorous transformation, to a 16-bit unsigned integer ERDAS Imagine format image. This formatted Digital Elevation Model (DEM) was an input to deriving slope, aspect, and topographic positional index (TPI) layers that were also used for training.

AWiFS Scene Preparation

There were ten AWiFS scenes chosen to cover Iowa for crop year 2006. Figure 3 shows the AWiFS scene footprints divided into two Analysis Districts. Analysis District 01 (blue) was observed on May 19 and July 30 and Analyst District 02 (red) had observation dates of July 16 and September 26.

IOWA - 2006
Analysis Districts and
AWiFS Scene Observation Dates

**Analysis Districts &
Scene Dates**
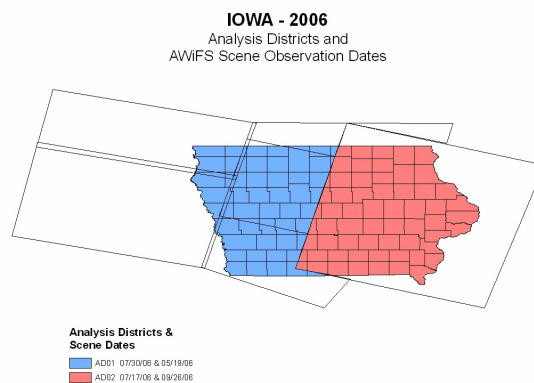AD01 07/30/06 & 05/19/06
AD02 07/17/06 & 09/26/06

Figure3. Iowa 2006 AWiFS Analysis District map.

All AWiFS scenes were purchased ortho-rectified from GeoEye. The individual AWiFS scenes were reprojected to Albers from the native Lambert Conformal Conic projection, using nearest neighbor resampling. Scenes of the same date were mosaicked and clipped to the study area using ERDAS Imagine.

FSA/CLU Ground Truth

The FSA common land unit (CLU) data were used as ground truth. Preprocessing of the shapefile data removed duplicate polygons and correctly assigned state and county identifiers. The shapefile attributes and the 578 crop data were imported into Statistical Analysis Software (SAS) and filtered for usable CLUs. CLUs were excluded if they had more than one crop type, were smaller than 10 acres, or had a difference in size of more than 10 percent between the shapefile and 578 data. A sample of the data was created by selecting one-fifth of the CLUs if a crop had more the 10,000 usable CLUs and selecting one-half of all other covers. To improve the classification of a severe drought area and the valley along the west of the state, the counties of Ida, Sac, Woodbury, Monona, Crawford, and Harrison had three-fifths of the corn and soybean CLUs sampled. The selected CLUs were rasterized to 56 meters and the categories recoded to match the published set of CDL master categories.

To calculate the number of non-agricultural training pixels to collect, the NLCD land cover layer was clipped to the state boundary and pixels tabulated by category. The proportion of agricultural to non-agricultural pixels was used to determine the number of non-agricultural pixels to select after the agricultural sample was selected. This will reduce the possibility that a category will over classify because it is disproportionately represented in the training data.

See5 Classification

Training data were created using the NLCD Sampling Tool in ERDAS Imagine for the entire state all at once. All of the sampled crop pixels were chosen for training. The sampling tool was run again to select a stratified sample from the non-agricultural categories of the NLCD land cover layer. The data files were merged and the names file adjusted to include dependent categories from both inputs.

See5 was run on the training data using the boost 10 option (Quinlan 1996). The resulting decision tree was input to the NLCD See5 classifier in Imagine to create a classification and confidence map. The classification results were post processed using a minimum mapping unit (MMU) filter to eliminate individual misclassified pixels. The Imagine NLCD "Smart Eliminate" tool was applied with a MMU of 20 acres (26 AWIFS pixels) for corn and soybeans and a MMU of 2 acres was used for all other covers for the final CDL and estimates.

See5 decision tree results can appear quite complex and difficult to interpret, the operations appear to be "black box" like, as the results are accurate, and there are hundreds if not thousands of "leaves" which represent box-like containments of pixels and no tools to manipulate them directly. However, there are ways to edit and improve the See5 classification. When a classification was run using the See5 classifier tool under the NLCD menu in ERDAS Imagine, the option to "Create Error or Confidence Layer" was chosen. This was the predicted

confidence associated with each output pixel based on the input rules (MDA Federal Inc. 2006) Bad ground truth could be reduced by only keeping ground truth pixels in the next See5 training where the input and output class match and have a high confidence.

For the Iowa 2006 project using FSA training data, the See5 boost function had the effect of reducing the decision tree error from 5.8% to 0.4% and reducing the size of the tree file to one-third the size of the original. Visually this made no change or improvement in the classification besides shifting a few pixels around. This may be a more useful technique when there is limited imagery (unitemporal) or less ground truth. In the future, development of a two step process may be required: step one evaluates all of the reps of ground truth based on the training of one rep of data; and step two retrains and reclassifies on a separate rep of data than used in the first training (with 'bad' ground truth eliminated during the first step).

Acreage Estimates

Pocahontas County (Figure 4), is located in northwestern Iowa, where agriculture is the dominant land use. Pocahontas land area encompasses a total of 150 hectares, with 71 and 62 hectares of corn and soybeans respectively in 2006 leaving only 13 hectares for other land usage, with 89 percent of the total land cover in either corn or soybean production.
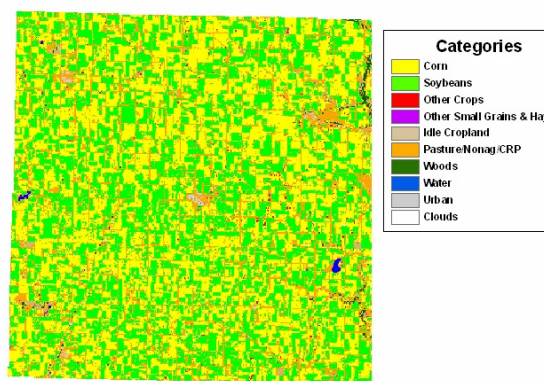

Figure 4. The Pocahontas County, Iowa 2006 Cropland Data Layer.

A comparison of the JAS and AWiFS estimates is depicted in Figure 5 using JAS and Peditor, JAS and See5, FSA and See5, FSA and See5 with smart eliminate set to 20. The zero line is the ASB Iowa State level final number with +/- 2% CV. All estimates are compared to the ASB for analysis purposes. For each of the estimates and crops in Figure 5 the black line represents the percentage difference that the estimate was from the ASB number. The yellow and green lines surrounding the bars are the +/- 2% CV's centered from the black line. The JAS for corn was quite accurate while the soybean number was around four percent under. The CV range difference between the JAS and remote sensing estimates are because of the benefits of the regression estimator. The FSA/See5-smart eliminate 20 produced the most accurate remote sensing corn estimate, while the JAS/Peditor estimate was a close second. The JAS/Peditor estimate performed best of all estimators for soybeans. The JAS/See5 estimate was the least accurate remote

sensing estimate, While the JAS/Peditor and FSA/See5 were the most accurate overall of all estimates.
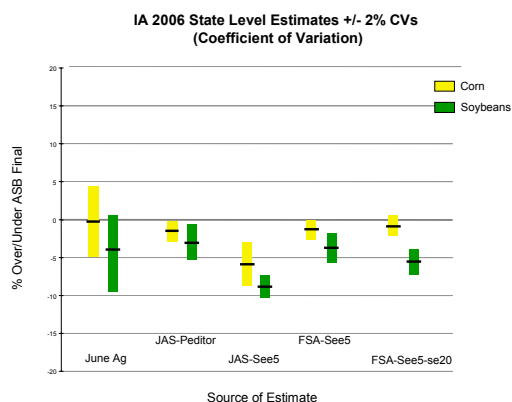

Figure 5: A comparison of the June Agricultural Survey and AWiFS estimates for Iowa crop acreage.

Numerous state level estimation tests were run on the Iowa 2006 dataset, to measure the accuracy of remote sensing estimates versus the JAS and the final Agricultural Statistics Board (ASB) results. All estimates for corn and soybeans were calculated by importing and processing the data in Peditor. After regression analysis at the Analysis District level, estimates were accumulated to the state level.

CONCLUSION

The opportunity to expand the remote sensing program to the "Program Crops" corn and soybean states and deliver operational state level estimates two months earlier would not be possible without a major overhaul in technologies and methods. The Resourcesat-1 AWiFS sensor was critical in proving rapid revisit times, large footprints, near Landsat like spectral bands and adequate spatial resolution. The ability to obtain the FSA CLU layer in early July and a final certified CLU in mid-August will enhance the program's chances of delivering an early season estimate and relieve the NASS Field Office from digitizing duties. The ability to include ancillary data for training, such as elevation, and non-agricultural land covers improves overall classification accuracy and appearance. The utility of See5 software provides a means for efficiently and accurately producing acreage estimates at the state level to the Agricultural Statistics Board a month or two earlier. It is hoped that the modernization effort will improve the estimate delivery time, accuracy and expand the program scope to include the major "Program Crops" of US agriculture, and make the NASS remote sensing program truly operational.

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CROP AREA ESTIMATES WITH RADARSAT

FEASIBILITY STUDY IN THE TOSCANA REGION – ITALY

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KEY WORDS: SAR, Backscattering, Land use, Rule base classification, Forward-chaining,

EXTENDED ABSTRACT

Early crop estimates for the Common Agricultural Policy of the European Union (EU), are a key point to manage future intervention on stocks. The current study project has the goal of assessing the suitability of SAR imagery, for such a task A constraint given to the project is that the information extraction stage must involve radar data exclusively (i.e., no optical imagery) and the information provided in near to real time using exclusively SAR without any ground truth.

Base data: SAR images and a set of ancillary data sets: Corinne land cover, DEM, meteorological data, point frame surveys, statistical information and generic information on the Tuscany agricultural and cropping system. On the base of the available data the following land use classes were considered as reference: Autumn and Winter Cereals (AWC); spring and Summer Crops (SSC) crops, Trees (T), Permanent Pastures (PP) and Rotation Forage (RF.

Methodological approach: SAR measures backscattering from soil and/or vegetation and these are function mostly of the surface roughness, the moisture contents and the crop structure in the first layers of the soil (2-3 cm)[1]. These capacities are at the same time SAR potential and limits. In general if the surface roughness changes (e.g. ploughing and sowing) so does radar backscattering. Noise to this is the contemporary presence of both surface and volume scattering. Noise is also due to air moisture contents, temperature, free water and snow.

A number of alternative classification methods were excluded a priori by the set constraints. However since a sequence of SAR images were available, the chosen route was to attempt the identification of land use classes through the analysis of backscattering profiles evolving along the time series. These can be connected to events such as agricultural practices and crop cycles which are locally specific. They are a stable element of reference and only require the knowledge of the agricultural specifics of an area. Such information does not require a "learning phase" for each date and location and is therefore uncoupled from ground truth.

A fixed link between backscattering and the agricultural "events" is labelled as "**RULE**" and such an approach to classification, defined as "**RULE–based**". The classification is essentially an inference function ("if-then") where the "RULES" are the backscattering values characterizing each land use class crop at each distinct time step. There are two main methods of reasoning when using inference rules: "**BACKWARD-CHAINING**" and "**FORWARD-**

CHAINING". "BACKWARD-CHAINING" starts with a list of goals and works backwards to see if there is data which will allow it to conclude any of these goals. "FORWARD-CHAINING" implies that the "then-clause" is known and used to build the inference with the "if–clause".

This last approach was chosen on the basis that the "then-clause" is the expected surface roughness of each land use class and the "if-clause" is their backscattering. The "FORWARD CHAINING" analysis runs a loop comparing options of backscattering values with known surface roughness values. It moves to the next date when it achieves an acceptable level of match *provided by as set indicator*. The achievement of a best match however provides a first hypothesis of a stable rule for classification. This rule is coded in the form of a LUT and the images are classified by comparing backscattering to the LUT with minimum-distance logic. The process of identification of the best and most stable RULE can continue in time as more information is acquired, including the efficiency of past classifications. The advantages of such an approach are that it provides consistent answers for repetitive decisions. Disadvantages are that reference ground-truth must in any case be used, at least to set up the rule base itself. Some times human common sense is ignored. In practice once the inferences are established there is no space for 'interpretation. A further limit is the adaptation to changing environments that requires a revision of the inferences (rules).

Implementation: The preliminary implementation work was the preparation of the GIS and the database of reference for the analysis and accuracy assessment. The following phases were:

1) SAR data processing: this was an external activity given out on contract

2) Analysis and identification of the RULES: This implied several investigation activities which found a systematic coding only once accomplished. The first was the analysis of the available data bases, especially the point survey data, to identify the target land use classes. The backscattering values for each image were extracted from the sample points and a t-test was applied to verify if it actually discriminated the 5 chosen classes. Surface roughness and backscattering are independent and in order to be analyzed on a common reference base they required the identification of a common unit of measure. This measure, defined **"SCORE",** relates to features which have the same dimension for both; ranking order of the values at a set date and the rate of change from date to date. The score of backscattering and surface roughness on the known points were subject to a preliminary analysis to verify if there actually was a functional link between them. Results were encouraging for the continuation of the analysis. A forward–chaining program was

implemented which ran for several days and provided a LUT for the classification. A sample of the available point data was used as reference.

3) Classification of the images: The SAR images were converted to the score value and the LUT was applied for the minimum distance classification.

Analysis of the results: The results of the classification were object of an accuracy assessment using confusion matrices. The reference was the JRC point frame survey (576 points). The analysis was run separately for each image of the time series and for each trek. It considered the accuracy of alternative aggregation scenarios for the land use classes. A first scenario kept the used the 5 original land use classes. The second excluded from the trees (4 classes). Derived from this one, a third scenario grouped rotation forage crops and permanent pastures crops (3 classes). A fourth scenario grouped winter cereals with rotation forage and permanent pastures. The results were that the accuracy of classification changed along the time series and with different precision for the 3 scenarios.

DATE of the image	5 classes 1/2/3/4/5	4 Classes 1/2/4/5	3 classes 1/2/(4+5)	2 classes 1+4+5/2
3/10/04	25.00%	30.61%	43.67%	71.84%
27/10/04	26.27%	31.85%	45.56%	77.82%
20/11/04	25.63%	30.86%	46.50%	74.07%
14/12/04	24.05%	29.34%	41.74%	66.12%
7/1/05	21.52%	25.00%	38.14%	64.83%
31/1/05	21.52%	27.43%	38.50%	66.81%
24/2/05	26.27%	31.62%	44.87%	76.50%
20/3/05	25.32%	32.03%	43.29%	73.59%
13/4/05	26.98%	34.63%	47.19%	84.85%
7/5/05	20.32%	25.22%	36.96%	56.52%
31/5/05	16.83%	23.81%	38.62%	64.02%
7/1/05	22.47%	29.60%	43.05%	80.27%

Conclusions

Analysis of backscattering data: Backscattering values fro winter and spring crops were not clearly distinct at the beginning of November and from December to January. The same can be observed in late spring for winter, forage crops, permanent pastures and trees. The values were plotted on a graph and, in order to help the interpretation, meteorological data from local weather stations were also plotted; specifically precipitation (mm), snow depth (mm) and minimum temperatures (º C).. Noticeable is the effect of precipitation and especially snow cover, on the signal. In January the intense snowfall caused the backscattering to be completely confused, the level converge and overlap and the land use classes cannot be discriminated. Meteorological events should not affect the "facts" that link the crop surface roughness to backscattering. These events however, may be local but are certainly not occasional and their interference in the possibility of establishing a direct connection between surface scattering and crop specific surface roughness is a limit to the use of SAR for crop classification. A first comment on this is that the all-weather capability of SAR data is at least questionable.

Classification: The applied methodology eventually brought to a classification of the images. The results are not encouraging concerning the recognisability of even broad land use classes. However a rather accurate discrimination appears between the grouping of winter cereal/rotation forages/pasture and spring crops. The accuracy of such a classification is around 78% between October and November it decrease during winter and reaches again and peak with an accuracy of more that 80 % in April. This period coincides with the most important cultivation practices and especially land preparation. The trend of classification accuracy may relate to a good response to surface scattering while the distinction between the land use classes is probably more related to volume scattering and this is appears to be significantly more relevant.

OPERATIONAL MAIZE YIELD MODEL DEVELOPMENT AND VALIDATION BASED ON REMOTE SENSING AND AGRO-METEOROLOGICAL DATA IN KENYA*

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ABSTRACT:

Remote sensing (RS) data acquired by satellite have wide scope for agricultural applications owing to their synoptic and repetitive coverage. On the one hand, spectral indices deduced from visible and near-infrared RS data have been extensively used for crop characterization, biomass estimation and crop yield monitoring and forecasting. On the other hand, extensive research has been conducted using agrometeorological models to estimate soil moisture to produce indicators of plant-water stress. This paper reports the development of an operational spectro-agrometeorological yield model for maize using a spectral index, the Normalized Difference Vegetation Index (NDVI) derived from SPOT-VEGETATION, meteorological data obtained from the European Centre for Medium-Range Weather Forecast (ECMWF) model and crop-water status indicators estimated by the Crop Specific Water Balance model (CSWB). Official figures produced by the Government of Kenya (GoK) on crop yield, area planted and production were used in the model. The statistical multiple regression linear model has been developed for six large maize-growing provinces in Kenya. The spectro-agrometeorological yield model was validated by comparing the predicted province-level yields with those estimated by GoK. The performance of the NDVI and land cover weighted NDVI (CNDVI) on the yield model was tested. Using CNDVI instead of NDVI in the model reduces 26% of the unknown variance. Of the output indicators of the CSWB model, the actual evapotranspiration (ETA) performs best. CNDVI and ETA in the model explain 83% of the maize crop yield variance with a root square mean error (RMSE) of 0.3298 t/ha. Very encouraging results were obtained when the Jack-knife re-sampling technique was applied proving the validity of the forecast capability of the model (r^2= 0.81 and RMSE= 0.359 t/ha). The optimal prediction capability of the independent variables is 20 days and 30 days for the short and long maize crop cycles respectively. The national maize production during the first crop season for the years 1998 to 2003 was estimated with a RMSE of 185 060 tons and coefficient of variation of 9 %.

1. INTRODUCTION

Crop-weather models had long been used for crop monitoring and yield forecasting before the advent of remote sensing products, like the Normalized Difference Vegetation Index (NDVI). More than 50 years have passed since the first paper on mathematical modeling of photosynthesis and productivity in plant communities was published in Japan (Monsi and Saeki, 1953) and these kinds of studies were later continued by research groups formed in Netherlands (de Wit et al., 1970; de Wit and Goudriaan, 1974). In the USA, McCree (1970), Curry (1971), and Loomis et al. (1979) published outstanding papers along the same lines. Interesting research was undertaken in Poland by using statistical empirical models (Górski et al., 1994).

In 1975, during the major world food crisis produced by climatic events, including the Sahelian droughts of 1972 and 1973, FAO established the Global Information and Early Warning System for Food and Agriculture (GIEWS). The absence of low-cost methods applicable to large regions oriented FAO to use the Crop Specific Water Balance (CSWB) model (Frère and Popov, 1979; Gommes, 1993) as a tool for monitoring and yield forecasting in African countries. In those countries, the insufficient information on weather and crops precluded applying more complex models.

In Europe, the crop-weather model, WOFOST, was adapted for monitoring and yield forecasting in European countries; the model represents the engine of the Crop Growth Monitoring System established in 1998 by the Monitoring Agriculture with Remote Sensing (MARS) project at the Joint Research Centre (JRC) (Meyer-roux and Vossen, 1994). WOFOST is a member of the family of models developed in Wageningen by the C.T. de Wit school (de Wit et al., 1970; de Wit and Goudriaan, 1974).

The introduction of remote sensing and the derived vegetation indices in the early 80's was considered a potential tool to improve simulations by objective observations in real-time. NDVI has been used as an indicator of the vigour of vegetative activity as represented by indirectly observable chlorophyll activity (Hastings and Emery, 1992). Low values of NDVI have been associated with the lack of vegetation, dormant states of existing vegetation or stress caused by drought, over-irrigation, or diseases (Hastings, 2005). Remote sensing products alone

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have been used in different parts of the world to estimate crop yield (Lewis, et al, 1998; Hochheim and Barber, 1998, Wang, et al, 2005).

Potdar et al (1999) observed for some cereal crops grown in rain-fed conditions that rainfall distribution parameters in space and time need to be incorporated into crop yield models in addition to vegetation indices deduced from remote sensing data. Such hybrid models show higher correlation and predictive capability than the simple models (Manjunath and Potdar, 2002). The agro-meteorological models introduce information about solar radiation, temperature, air humidity and soil water availability while the spectral component introduces information about crop management, varieties and stresses not taken into consideration by the agro-meteorological models (Rudorff and Batista; 1990). The purpose of this research is to improve the spatial estimation of yield by combining crop-weather models and satellite observations.

Using Kenya as an Eastern Africa case study, this paper presents the methodological approach employed to build and validate a maize yield model using remote sensing data from SPOT VEGETATION and the outputs of the FAO-CSWB model. Kenya was chosen as a trial study area for developing the model because Kenya is relatively rich in data, and agriculture is practiced in coastal, low land, and high land areas which have diverse climates and are representative of most regions in Eastern Africa. Maize is a major food crop cultivated in Kenya. It represents 90% of national cereal production. Between 1998 and 2003, the average area cultivated with maize was 1 574 370 hectares with a total national production of above 2 475 947 tons and a national average yield of 1.57 tons by hectare. Maize is mainly cultivated in the South-Western part of the country, in the provinces of Rift Valley, Nyanza and Western. The three provinces together produce more than 80% of the national maize production. Nyanza, Western and Rift Valley provinces have a mono-modal rainfall distribution while Central, Eastern and Coast provinces exhibit on average a bi-modal distribution of rainfall with the possibility of having two crop seasons each year. The first crop season historically extends from February to August, producing more than 82% of the national maize production, while the second crop season, from September to January, represents 18%.

2. MATERIALS AND METHODS

2.1 Real-time input data

2.1.1 Meteorological data

The rainfall and potential evapotranspiration (PET) data used in this study are products of the European Centre for Medium-Range Weather Forecast (ECMWF model) at Reading in the UK. The data were interpolated from the original 1-degree grid to a final resolution of 0.5 degree (approximately 55 km). Dekadal rainfall and ETP were then spatially averaged for each area comprised in the maize crop mask using ArcMap GIS tools.

2.2.2 Remote-sensing data

The products of SPOT VEGETATION acquired by MARS are 10-day NDVI (Normalized Difference Vegetation Index) synthesis (S10) images, obtained through Maximum Value Compositing (MVC). The images are corrected for radiometry, geometry and atmospheric effects. The 10-day images are delivered to the JRC with a delay of around 2-3 days.

2.2. The CSWB model

The FAO CSWB is a very simple but physically sound soil water balance model which is used to assess the impact of weather conditions on crops (Frère and Popov, 1979; Gommes, 1993, Rojas et al., 2005). The water balance of the specific crop is calculated in time increments, usually 10-days. The equation of the water balance is:

$$W_t = W_{t-1} + R - ETA - (r + i) \qquad (1)$$

Where,

W_t: amount of water stored in the soil at the time t.
W_{t-1}: amount of water stored in the soil at the end of the previous period (t-1).
R: cumulated rainfall during the dekad or t-period of time.
ETA: actual evapotranspiration in the t-period time
r: represents the water losses due to runoff in the t-period time
i: represents the water losses due to deep percolation in the t-period time

Two main outputs of the CSWB model are demonstrated to be positively correlated with the crop yield: the Actual evapotranspiration (ETA) and the Water Satisfaction Index (WSI). ETA has the advantage to include the radiation, which is an important climatic variable susceptible to influence the crop yield in the region. The influence of factors other than water stress which can reduce crop yields such as water logging, mechanical damage produced by strong winds, or biological factors, such as locusts, birds, insects or plant diseases are not considered by the CSWB model. The WSI is an index of the CSWB model to assess the amount of water received by the crop during any time of the season. Normally, the WSI is used for defining qualitative yield classes (i.e. good, average, and poor) or in relative figures (percent of an optimal yield crop). When the WSI is equal to 100, it indicates no water stress and good crop yields, while a WSI of 50 corresponds to poor crop yield or crop failures. The estimation of the actual evapotranspiration (ETA) was done using Agromet-Shell[2] (Hoefsloot, 2005). The crop information needed to run the water balance model (water holding capacity and cycle length) was taken from the Crop production system zones database (CPSZ) (Van Velthuizen et al, 1995).

2.3 Planting date estimation model

To start the simulation, the CSWB model requires the current planting date of each crop season. The criterion followed to define the planting dekad was the 1st dekad with at least 20 mm of rainfall followed by two dekads with at least 20 mm of total rain. The same planting date was used to start accumulating NDVI values up to the end of the crop cycle (Table 1).

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[2] AgrometShell is a software that integrates the main tools used in the Early Warning System such as SUIVI (agrometeorological database), FAOINDEX (Crop specific water balance), and the most common tools of data interpolation. Agromet-Shell was designed for storing agrometeorological information on meteorological stations base. In the present study the information from the crop mask units (spatially averaged of the polygon) was inserted in lieu of meteorological stations with the objective to run the water balance model. AgrometShell has been developed by the Agrometeorological Group at FAO and programmed by Peter Hoelsloot.

2.4 Crop statistics

The Kenyan government started collecting disaggregated agricultural statistics by crop season in 1997. However, since the SPOT VEGETATION sensor was launched on board the SPOT 4 satellite later, in 1998, crop data was analyzed between 1998 and 2003. The statistics are collected at district level and aggregated by province[*].

Table 1. Maize crop cycle length and phenological phases in dekads

Province	crop cycle dekads*	Initial dekads	Vegetative dekads	Flowering dekads	Ripening dekads
Central	16	3	3	7	3
Coast	11	2	2	5	2
Eastern	9	2	2	3	2
Nyanza	13	3	2	5	3
Rift Valley	16	3	3	7	3
Western	16	3	3	7	3

*10-days period

2.5 Maize crop mask

In this study, two levels of maize crop mask were defined. The first level, the 'general' maize crop mask was created using only statistical information; the second one is the result of intersecting the first level of crop mask with the Africover land cover information (Di Gregorio et al, 2000). The first level of crop mask was used for area-averaging of the meteorological and NDVI information. The second one was used for extracting the land cover weighted NDVI (CNDVI) (see point 2.7). To define the first level of crop mask the statistical information about the area planted with maize at district level was used. For each district, we calculated the percentage of the total provincial area planted with maize. The districts with no maize planted and those with less than 6% of the area planted with maize were masked-out from each province. As a result a general maize crop mask was used, constituting all the districts with more than 6% of area planted with maize for each province. The final resolution of this crop mask is at province level. To obtain a more precise maize crop mask we used two classes from the Africover land cover database: the isolated small fields and continuous small fields that were considered to better represent the traditional maize farms of Kenya. The first maize crop mask at province level was intersected by AFRICOVER classes. The result is a better delimitation of the areas cultivated with maize in each province. Unfortunately, the polygons resulting are too small to be used for extracting meteorological information at 0.5 degrees resolution.

2.6 NDVI

The Normalized Difference Vegetation Index (NDVI) has been the most frequently used vegetation index within agrometeorological analysis. It is defined as:

$$NDVI = (NIR - RED)/(NIR + RED) \qquad (2)$$

NIR and RED are, respectively, the reflectance (%) in the near-infrared and in the red channels. It is easy to understand the index when the characteristics of absorption and reflection of the radiation by green leaves is studied. The chlorophyll of the plant absorbs the majority of the radiation in the visible part of the spectrum, principally the red portion (0.6-07 μm), and is highly reflective in the near-infrared. Thanks to this property of green vegetation, NDVI is a direct indicator of the plant's photosynthetic activity. Therefore parameters such as water stress can be monitored successfully by analysing the NDVI values. The NDVI values were spatially averaged for each area comprised in the maize crop mask. Three variables were created when aggregating the NDVI values on a temporal scale: cumulated NDVI values starting from planting date up to the end of the length of the crop cycle (NDVIc), maximum NDVI during the crop cycle (NDVIx) and 3 dekad-averages around the maximum NDVI (NDVIa) to smooth the curve when an isolated peak represents the maximum.

2.7 CNDVI methodology

Despite the fact that it is not possible to eliminate all spectral responses from non-agricultural vegetation in the African parcels, any improvement of the crop mask will reduce the influence of natural vegetation and show a higher correlation of the remote sensing indices with crop yield. Therefore, it was decided to include the Land cover weighted NDVI method (CNDVI[*]) using Africover land cover (Di Gregorio et al, 2000). The CNDVI method has been developed to extract NDVI profiles from low resolution satellite imagery. It is currently in use for agricultural monitoring in Europe, with two main objectives: a) to aggregate NDVI information by administrative regions in order to give synthetic and manageable information; b) to focus on agricultural land only, owing to the integration of land cover information. The CNDVI method is fully documented by Genovese et al, 2001. The method was originally designed and tested for NOAA-AVHRR (with a 4.4 km resolution) and CO-ordination of Information on the Environment (CORINE) land cover data (Perdigao and Annoni, 1997), but can theoretically be applied to all combinations of low resolution images and higher resolution land cover data. Negre et al, 2001, have adopted the methodology to work in Africa using SPOT-VEGETATION instead of NOAA-AVHRR and AFRICOVER land cover classes (Di Gregorio et al, 2000) instead of CORINE Land cover. For the CNDVI extraction itself, the regrouped agricultural classes are re-scaled to the same resolution as the VGT images (1km), creating so called abundance images. In these images the value of each 1 km pixel expresses the percentage which is covered by an Africover class. The NDVI of each 10-day image pixel is weighted following the abundance image and the final NDVI profiles are class specific. Aggregation is done at a regional level to obtain a single CNDVI value per region, through a weighted average of NDVI values. The agricultural AFRICOVER classes are not crop specific but provide information about field size and field distribution. In this study two classes were selected: the isolated small fields and continuous small fields that were considered to better represent the traditional maize farms of Kenya.

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[*] MARS-FOOD received the Kenya statistics of area planted, yield and production aggregated at national level of maize and sorghum for the period 1985-2003, and disaggregated by crop season ('Long rains' and "Short rains") at district level for the period 1997-2003 from Nancy Mutunga, FEWS-NET Country Representative of Kenya.

[*] CNDVI: 'C' for Land cover information that in the case of Europe represents CORINE land cover and in Africa mainly AFRICOVER land cover and 'NDVI' for Normalised Difference Vegetation Index.

AFRICOVER classes were used to refine the crop mask by province, by selecting specific agricultural areas, supposed to be maize areas within each district. As done with the NDVI, three variables were created aggregating the CNDVI values on a temporal scale: using cumulative CNDVI values starting from planting date up to the end of the crop cycle (CNDVIc), maximum CNDVI during the crop cycle (CNDVIx) and 3 dekad-averages around the maximum CNDVI (CNDVIa) to smooth the curve when an isolated peak represents the maximum.

2.8 Crop yield model development and validation

A multiple linear regression analysis was used in the development of the crop yield model testing the following independent variables: WSI, cumulated ETA during the whole maize cycle, ETA cumulated by phenological phase (initial, vegetative, flowering and ripening), cumulated soil water deficit and surplus, NDVIc, NDVIx, NDVIa, CNDVIc, CNDVIx, CNDVIa and total cumulated rainfall during the crop cycle. To increase the number of observations and hence the net degree of freedom, the model was developed considering all the observations from all regions together. The Jack-knife re-sampling technique (leaving one data value out each time) was applied to test the forecast capability of the model. To avoid a strong influence of climatic conditions given by a specific year each time it excluded a set of observations belonging to the same year. To assess the prediction capacity of the model, a correlation matrix with the independent variables accumulated during the phenological phase of maize was tested. To study the evolution of the r-square and RMSE, 4 multiple linear regression models were built at provincial level whereby each model represents a phenological phase of maize (initial, vegetative, flowering and ripening) using the most correlated variables. The Jack-knife technique was applied to each model to validate its forecasting capability.

The methodology flow chart describing briefly the steps involved in digital data analysis, the agrometeorological model outputs and the development of the spectro-agrometeorological yield model is given in Figure 1.

2.9 Estimation of national maize production during the first crop season

Although our main scope was the development of a crop yield forecasting model, due to the fact that the area planted with maize has a strong time-trend in Kenya, it is possible to obtain an estimate of the national maize production during the first crop season. The maize crop yield was estimated by province using the spectro-agrometeorological yield model. To obtain the national maize yield average, the provincial yields obtained by the spectro-agrometeorological model were weighted by the percentage of contribution of each province to the total national area planted with maize. The national area planted with maize was estimated using the time-trend equation of Figure 3 (b). Between 1998 and 2003, the area planted with maize during the first crop season represented above 71% of the national area planted with maize. A correction factor from the statistics of 71% was applied to estimate the area planted during the first crop season. The weighted national yield was multiplied by the estimated area planted during the first crop season with maize to obtain the national production figures for the first crop season. Finally, comparison was made between the estimated production and the observed national production figures of Kenya.

3. Results
3.1 Maize crop masks

Figure 2 (a) shows the districts in each province that represent more than 6% of the area planted with maize. The districts with
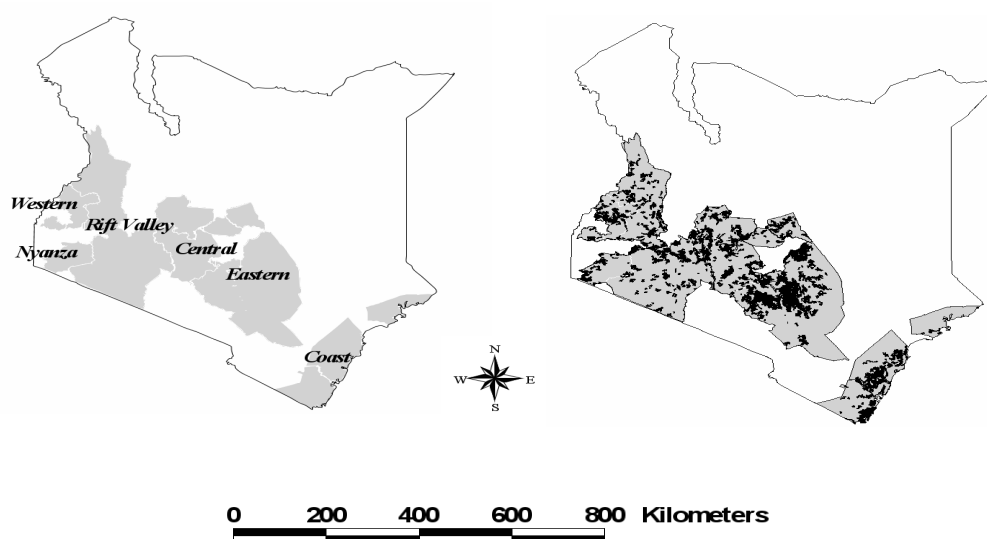

Figure 2. (a) Maize crop mask done based on the percentage of area planted with maize at district level (districts with less than 6% of area planted with maize have been masked-out). (b) In black the isolated small fields and continuous small fields from the Africover database; in gray the maize crop mask done based on the percentage of area planted with maize at district level. The Africover classes outside the general maize crop mask have been masked-out.
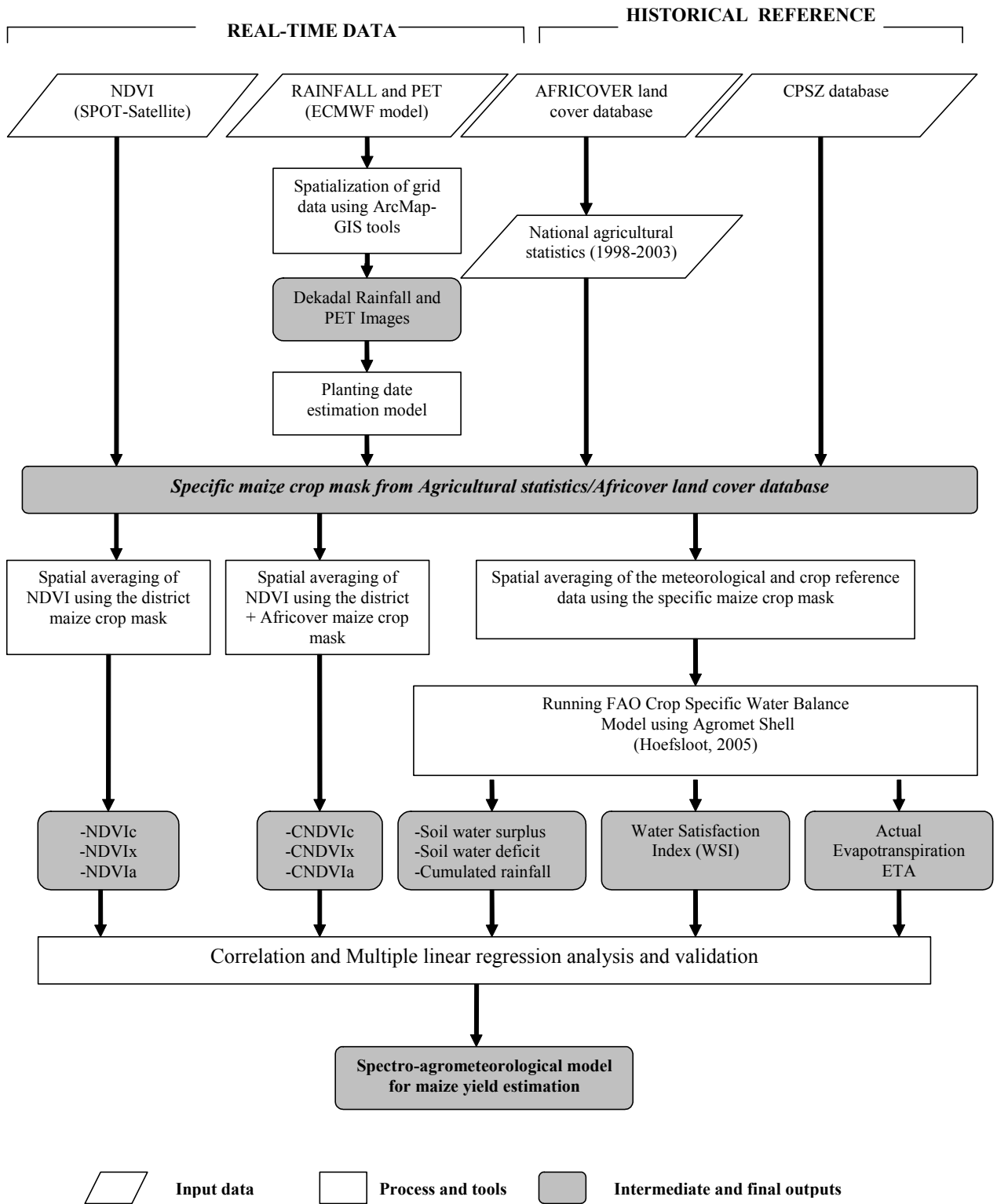
Figure 1 Methodology flow chart describing input data, process and tools for the development of the spectro-agrometerological yield model.

less than 6% have been masked-out. This crop mask was used in order to extract the NDVI and the meteorological values needed to run the CSWB model. Figure 2 *(b)* shows the two classes of Africover land cover considered in this study: isolated small fields and continuous small fields. The Africover classes outside the general crop mask were not considered during the extraction of the CNDVI values.

3.2 Trend analysis

The trend in rainfall, area planted, yield and production of maize during the first crop season was studied. The results of the analysis carried out at the province level are presented in Table 2. The maize yield exhibits a negative trend in Coast, Nyanza and Western provinces; the data was not de-trended due to the fact that this tendency can be explained by the trend in rainfall. Considering the objective of the study, we de-trend when the tendency is explained by variables other than climate, such as technological improvements. Nyanza and Rift Valley have a very positive trend in area planted during the 'Long rains' crop season. Due to the fact that 6-years is a short series to have a conclusive trend analysis, we used the longest series of national aggregated data of Kenya (1985-2003) and analyzed the production, area planted and yield of maize at national level.

The statistics shown in Figure 3 *(a)* illustrate that maize production has no trend. The average production is above 2.5 million tons with a minimum production of 1.7 million tons which occurred in 1993 followed by a maximum production of 3.0 million tons in 1994. Figure 3 *(b)* shows that the area planted has a strong positive trend while maize yield has a negative one. Kenya has increased the area planted to compensate for decreased productivity and the growing demand for maize. The results of our trend analyses undertaken during the first crop season suggest that the increase in area planted has been concentrated mainly in the Nyanza and Rift Valley provinces, and less extensively in the Coast province. Eastern is the only province that shows a negative trend in area planted during 1998-2003 period (Table 2). Figure 4 shows the trend in annual rainfall (1989-2005), first crop season (1989-2005) and maize yield aggregated at national level (1985-2003).

Figure 3 *(a)* Maize production for the period 1985-2003. *(b)* Area planted and yield for maize during the period 1985-2003. Data from Government of Kenya.

3.3 NDVI and CNDVI

Figure 5 shows the difference between the spatially-averaged NDVI and CNDVI for the different provinces and years. The differences are smaller in Coast and Eastern province, suggesting little impact on the model. Meanwhile, the rest of the provinces have large differences. Negative differences could be explained by the addition of dry areas with low NDVI values in the general maize crop mask; meanwhile positive differences indicate that the general crop mask includes very dense natural vegetation with high NVDI values within the agricultural areas. We conclude that there is a difference between NDVI and CNDVI that spans from 0.01 to 1.08 when the variables are accumulated for the whole crop cycle.

Table 2. Trend analysis in rainfall, area planted and yield (1998-2003) and rainfall (1989-2005) by provinces during the first crop season in Kenya

Province	1998-2003						1989-2005	
	Rainfall	r^2	area plant	r^2	yield	r^2	Rainfall	r^2
Central	no trend	-	no trend	-	no trend	-	no trend	-
Coast	negative	0.56	positive	0.30	negative	0.87	no trend	-
Eastern	no trend	-	negative	0.23	no trend	-	no trend	-
Nyanza	negative	0.61	positive	0.84	negative	0.52	negative	0.49
Rift Valley	no trend	-	positive	0.79	no trend	-	negative	0.20
Western	negative	0.58	no trend	-	negative	0.52	negative	0.37

The trends of all three figures are negative. The trend in annual rainfall shows a small coefficient of determination (r^2= 0.13) when compared with the coefficient of the first crop season (r^2=0.34). The accumulated rainfall from September to January, second crop season (1989-2005) has no trend, signifying that the decrease in maize yields is due to reduced water availability during the main cropping season in Kenya.
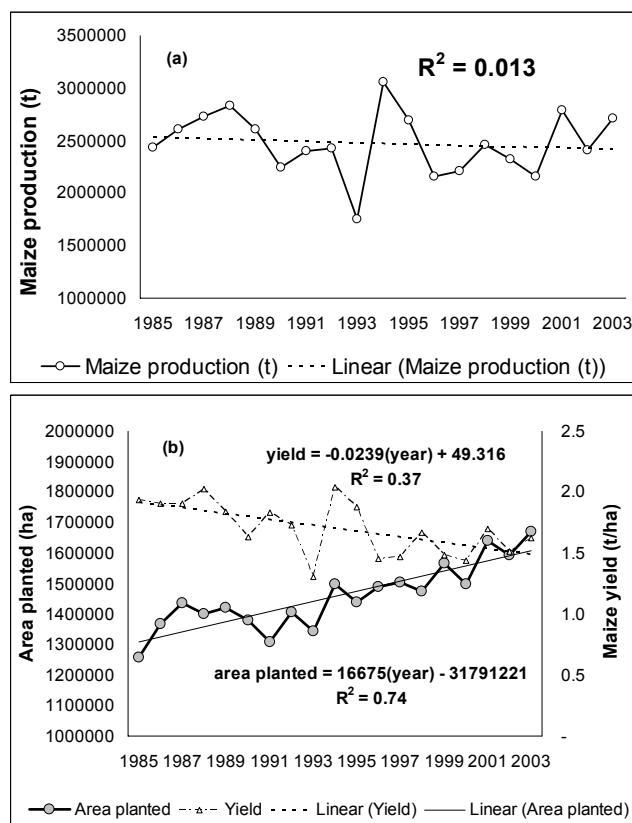
To assess the impact of such differences on the statistics of the model we calculated the reduction in per cent of the unknown variance using 1-r^2 (r from Table 3). The unknown-variance has been reduced by 26% when CNDVI is used in the model instead of NDVI. We conclude that the CNDVI gives a better spectral signal of maize crop areas than NDVI spatially averaged by the general crop mask.
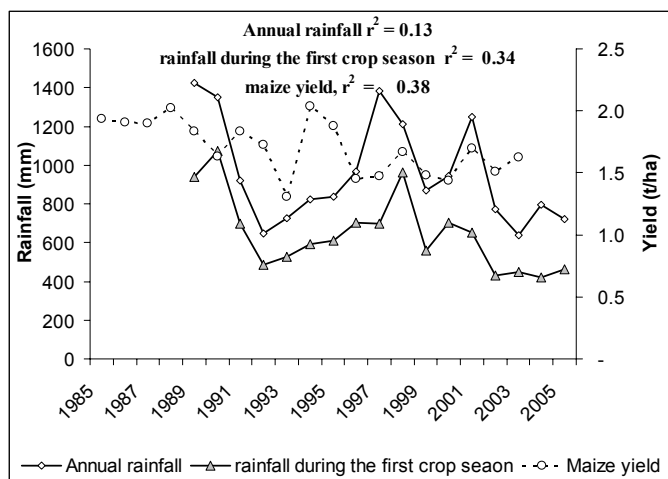
Figure 4 Negative trend in annual rainfall (1989-2005) and in the cumulated rainfall (February-August), first crop season, compared with the negative trend of the national maize yield.
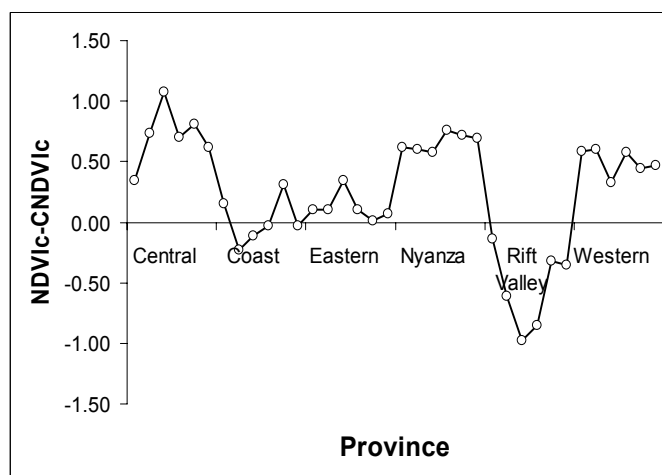

Figure 5 Difference between the spatially-averaged cumulated NDVI from planting dekad up to end of the crop cycle (NDVIc) and cumulated CNDVI for the same period (CNDVIc) by province.

Table 3 Correlation Matrix of maize yield and the independent variables

	WSI	WEXt	WDEFt	ETAi	ETAv	ETAf	ETAr	ETAt	Rain	CNDVIc	CNDVIx	CNDVIa	NDVIc	NDVIx	NDVIa
WSI	1														
WEXt	0.130	1													
WDEFt	0.921	0.283	1												
ETAi	0.298	-0.278	0.164	1											
ETAv	-0.402	-0.142	-0.382	0.107	1										
ETAf	0.852	0.265	0.795	0.309	-0.285	1									
ETAr	0.818	0.339	0.812	0.328	-0.278	0.764	1								
ETAt	0.860	0.275	0.811	0.386	-0.175	0.976	0.858	1							
Rain	0.381	0.947	0.494	-0.135	-0.215	0.502	0.551	0.517	1						
CNDVIc	0.237	0.290	0.122	0.585	0.144	0.517	0.408	0.560	0.405	1					
CNDVIx	0.395	0.320	0.361	0.613	0.148	0.433	0.505	0.523	0.423	0.700	1				
CNDVIa	0.383	0.268	0.338	0.610	0.081	0.381	0.463	0.462	0.358	0.675	0.954	1			
NDVIc	0.176	0.312	0.060	0.582	0.125	0.437	0.340	0.477	0.403	0.979	0.700	0.670	1		
NDVIx	0.186	0.253	0.161	0.560	0.092	0.170	0.278	0.244	0.288	0.582	0.901	0.868	0.656	1	
NDVIa	0.216	0.205	0.190	0.540	-0.011	0.141	0.248	0.200	0.238	0.512	0.825	0.829	0.602	0.960	1
Yield	0.511	0.350	0.463	0.574	0.057	0.663	0.649	0.731	0.525	0.869	0.782	0.771	0.818	0.594	0.525

Table 4. Multiple regression coefficients, Standard Error, t-Stat, P-value and 95% Confidence Inte

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Uppe
Intercept	-1.4429	0.2324	-6.2094	0.00000052164	-1.9157	
ETAt	0.0030	0.0007	4.2611	0.00015945560	0.0016	
NDVIc	0.2498	0.0312	8.0022	0.00000000312	0.1863	

3.4 Correlation matrix

Table 3 presents the correlation matrix of maize yield and the independent variables. There are three groups of independent variables: variables derived from remote sensing, climatic variables derived from the ECMWF model and variables derived from the CSWB model. The CNDVIc shows the highest value of correlation coefficients amongst remote sensing variables (r = 0.87). The average of 3-dekads around the maximum NDVI doesn't give a better correlation than the maximum itself, which means that smoothing the peaks of the NDVI curve does not improve the correlation with yield. Rainfall accumulated from planting date up to the end of crop cycle gives a correlation coefficient of 0.52 which is higher than some of the indicators produced by CSWB model such as the Water Satisfaction Index (WSI) and accumulated water excess (WEXt) and deficits (WDEFt). Amongst the CSWB model variables, the ETA shows a high correlation coefficient (r = 0.73). It is interesting to highlight that the results of ETA by phenological phases show good correlation during the initial, flowering and ripening phases and low correlation during the vegetative one. These results are in agreement with international research about impact of water stress on crop yield during different phenological phases (Doorenbos and Pruitt, 1977). Finally, we selected the two most correlated variables, ETA (total) and CNDVIc, to create the multiple linear regression model.

3.5 Spectro-agrometeorological model

Figure 6, shows the comparison between the estimated maize yields by the model and the observed ones. Table 4 shows the multiple regression coefficients of the intercept and independent variables, the t-Stat and the interval of confidence of the coefficients at 95% of probability of occurrence. The adjusted r-squared is 0.83. The root mean square error (RMSE) of the model is 0.3298 t/ha and the coefficient of variation is 21%[*]. [Insert table 4 about here] The following equation of the spectro-agrometeorological model was found:

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[*] Root mean square error (RMSE) examines the size of our forecast error. This measure assumes that larger forecast errors are of greater importance than smaller ones; hence they are given a more than proportionate penalty. The root mean square error (RMSE) is defined as:

$$\left(\frac{1}{T} \sum_{t=1}^{T} (F_t - A_t)^2 \right)^{1/2}$$

where: T = number of observations, F_t = forecast of component A_t = actual outturn

The coefficient of variation (CV) is a measure of relative dispersion and is given by (CV=standard deviation/mean). It is generally expressed as a percentage. In this study it was calculated using the standard deviation of the residual divided by the mean of the observed variable.

$$\text{Yield} = -1.4429 + 0.2498 \sum_{i=PD}^{t=EOCC} CNDVI(t) + 0.0030 \sum_{i=PD}^{t=EOCC} ETA(t) \quad (3)$$

Adjusted r-square = 0.83, n = 36, where t is dekad number;
EOCC = End of maize crop cycle;
PD = Planting dekad;
Yield = Maize crop yield expressed in tons by hectare;
CNDVI= Weighted NDVI using Africover land cover by dekad;
ETA= Actual Evapotranspiration in millimetres by dekad
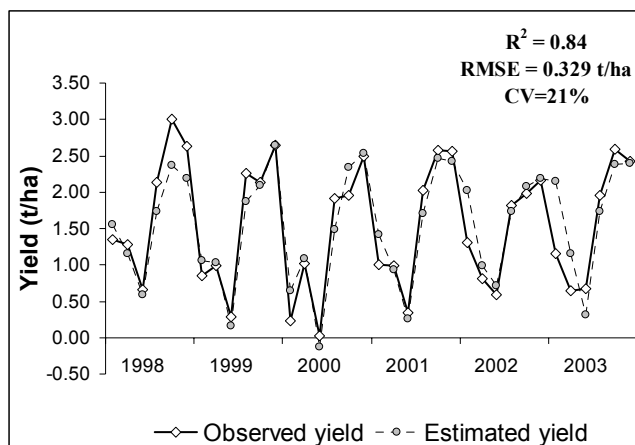
Figure 6 Comparison between the maize yield estimated by the spectro-agrometerological model and the observed yields for the different provinces.

3.6 Jack-knife re-sampling technique

To validate the forecast capability of the model the Jack-knife re-sampling technique was used. The impact of the difference on climatic conditions of each province was reduced leaving out each time a set of observations belonging to the same year. Figure 7 shows the comparison between the maize yields'

Figure 7 Comparison between maize yield estimated by the model using the Jack-knife re-sampling technique and the observed yield. The Root mean square error (RMSE) = 0.359 t/ha, coefficient of determination (0.81) and coefficient of variation of 23%.

estimates done by the model using the Jack-knife re-sampling technique and the observed yields. The r-square is 0.81, the root mean square error (RMSE) of the model is 0.359 t/ha and the coefficient of variation is 23%. Our results are encouraging when compared with those reported by Lewis *et al* (1998). They used a simple regression model with NDVI from NOAA-AVHRR for estimating maize production in Kenya and they obtained a Jack-knife r-square of 0.56.

3.7 Prediction capability of the independent variables

To study the prediction capability of the independent variables the correlation coefficient of CNDVI and ETA with maize yield was calculated. Figure 8 *(a)* shows the evolution of the correlation coefficient accumulated during the whole cycle and accumulated by phenological phases. CNDVI has a very strong correlation during the whole cycle. ETA shows low correlation only during the vegetative phase. The high correlation found in both variables requires further study. During the initial phase CNDVI has higher correlation than ETA, which can be explained by the fact that CNDVI integrates information about the pre-planting condition ("long memory") and is therefore better than simulations by the CSWB model. Also the spectral signal contains information about the characteristics of different soils that is difficult to introduce into the CSWB model. During the vegetative phase, the correlation of both variables by phenological phase decreases, this confirms the well-known low sensibility of yield when some stress happens during this phase (Doorenbos and Pruitt, 1977). The flowering phase shows a high correlation followed by the ripening phase. It was decided to build a multiple regression model using the CNDVI and ETA accumulated from the initial to ripening phases (that means by phenological phases). The Jack-knife re-sampling technique was used to avoid any strong influence of climatic conditions of a specific year. Figure 8 *(b)* shows the evolution of the adjusted r-square and RMSE after the Jack-knife technique had been applied. Even if the correlation during the initial phase is high in both variables, the adjusted r-square for this phase is 0.59. The variables at the early stage of the crop explain 59% of the variability of maize yields. Since the adjusted r-square is very high at the beginning of the crop season it should be tested once a longer time series is available to see if r-square remains high. Using the model at this early stage has a lot of uncertainty. Uncertainty decreases during the flowering period in which the adjusted r-square increases to 0.74 with a RMSE of 0.42 t/ha. We suggest that using the variables CNDVI and ETA accumulated from planting up to the end of flowering as a preliminary forecast and to refine it when the crop cycle reaches the end. The CNDVI and ETA accumulated for the whole crop cycle explains 81% of the maize yield variance with a RMSE of 0.36 t/ha when the Jack-knife technique is applied.

3.8 Estimation of national production during the first crop season

Although our main scope was the development of a crop yield forecasting model, due to the fact that the area planted with maize has a strong time-trend in Kenya, it is possible to obtain an estimate of the national maize production during the first crop season. We estimated the total area planted using the equation of time-trend (Figure 3 *(b)*). Using the spectro-agrometeorological model, the maize-yield was estimated at province level. Figure 9 shows the comparison of the observed production with the estimated production for the years

1998 to 2003. The RMSE is 185 096 tons with a coefficient of variation of 9%.
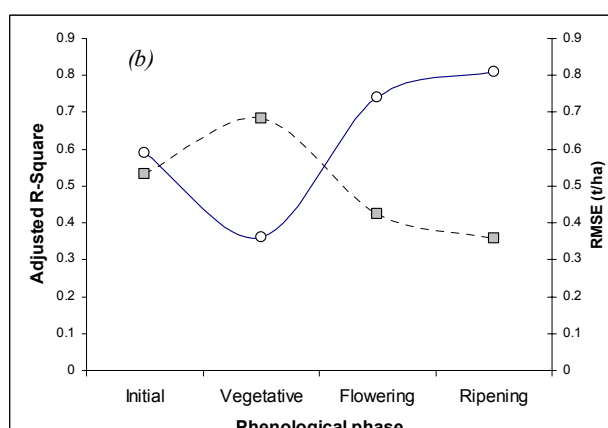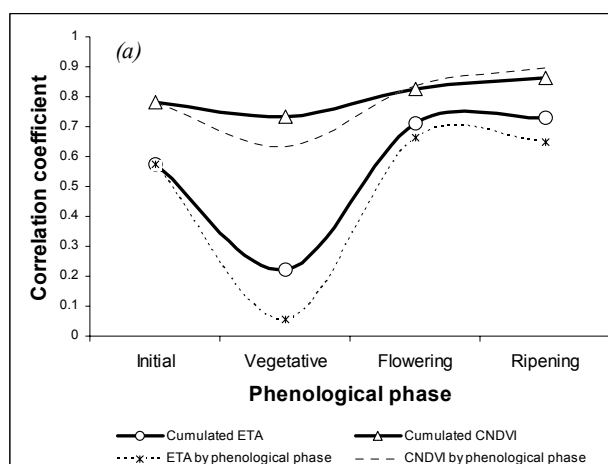
Figure 8 *(a)* Variation of the correlation coefficient (r) with the independent variables cumulated during the whole cycle and cumulated by phenological phases. *(b)* Variation of adjusted r-square and root mean square error in t/ha of the spectral-agrometeorological model using the cumulated CNDVI and ETA when applying the Jack-knife re-sampling technique.
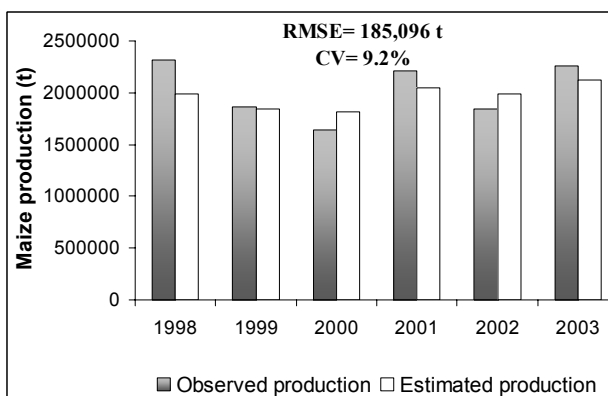
Figure 1 Comparison of the observed national maize production and the estimated maize production during the first crop season.

4. Conclusions and recommendations

It has been shown that it is possible to conduct operational maize yield forecasts using CNDVI derived from SPOT VEGETATION and ETA from the FAO CSWB model.

CNDVI showed to improve the spectral signal of the maize crop areas when compared with the simple spatially averaged NDVI using the general crop mask. CNDVI proved to be a simple and valid method for NDVI extraction with low resolution satellite images and highly fragmented high resolution land cover classes. However, significant improvements in extracting pure agricultural time profiles were primarily due to spatial refinements of the crop masks. The model showed a suitable prediction capability of 20 and 30 days before harvest for the short and long maize crop cycles, respectively. Thanks to this prediction capacity it is possible to obtain an early forecast using the CNDVI and ETA accumulated from planting dekad to the end of the flowering phenological phase. A more accurate estimate will be possible when the maize crop cycle reaches the end using the CNDVI and ETA accumulated for the whole length of the maize crop cycle. Even the second forecast using the variables accumulated up to the end of the crop cycle makes it possible to have reliable predictions 3 to 4 months earlier than the official estimates provided by national authorities and based on traditional field sampling surveys. As the time-series of the yield data was limited, some reservations for the model must be made, until a longer series of yield data will become available. The simplicity of the proposed regression yield model should allow an operational implementation in developing countries. Based on these encouraging results, regression models could be developed by MARS-FOOD for other geographical areas in Eastern Africa.

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METEOSAT BASED AGROMETEOROLOGICAL MONITORING AND CROP YIELD FORECASTING USING THE ENERGY AND WATER BALANCE MONITORING SYSTEM

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ABSTRACT:

This paper provides an overview of the Energy and Water Balance Monitoring System (EWBMS). This Meteosat based system provides continuous agrometeorological data fields over large regions at pixel spatial resolution (3 km) and daily temporal resolution. It is unique in being the first operational source of actual evapotranspiration, which data is the key to soil moisture, crop and pasture growth and regional water balances. In this paper we explain how the EWBMS data products may be used for crop yield forecasting. A dedicated crop yield model (ECGM) has been developed which uses the EWBMS radiation and actual evapotranspiration data to generate estimates of crop production and crop yield forecasts. Some activities carried out in the framework of the GMES projects Geoland and GMFS are introduced. Examples of products and results are shown.

INTRODUCTION

The EARS Energy and Water Balance Monitoring System (EWBMS) uses hourly geostationary meteorological satellite data to create daily data field of surface and air temperature, surface albedo, global and net radiation, actual and potential evapotranspiration and precipitation. The system is the first operational source of actual evapotranspiration data. These data are key to the two most important applications of the EWBMS: river basin water management and crop yield forecasting. This paper focusses on agrometeorological data provision and crop yield forecasting in Africa and Europe on the basis of Meteosat Second Generation (MSG) data. We use other geostationary satellites to cover Asia (FengYun-2c, Meteosat 7) and America (GOES).

SATELLITE DATA PROCESSING

MSG VIS and TIR data are received hourly with our MSG receiving station in Delft. They are pre-processed automatically to prepare for rainfall and energy balance processing. Clouds are identified, cloud top temperatures are measured and depending on these temperatures cloud heights classes are assigned. For each cloud height class the cloud frequency or "cloud duration" (CD_i) is count during a day. These cloud durations are input for the rainfall processing.

A second task during pre-processing is to create noon and midnight image composites as input for the energy balance calculations. For mathematical-physical reasons use is made of noond and midnight surface temperatures. However in a noon
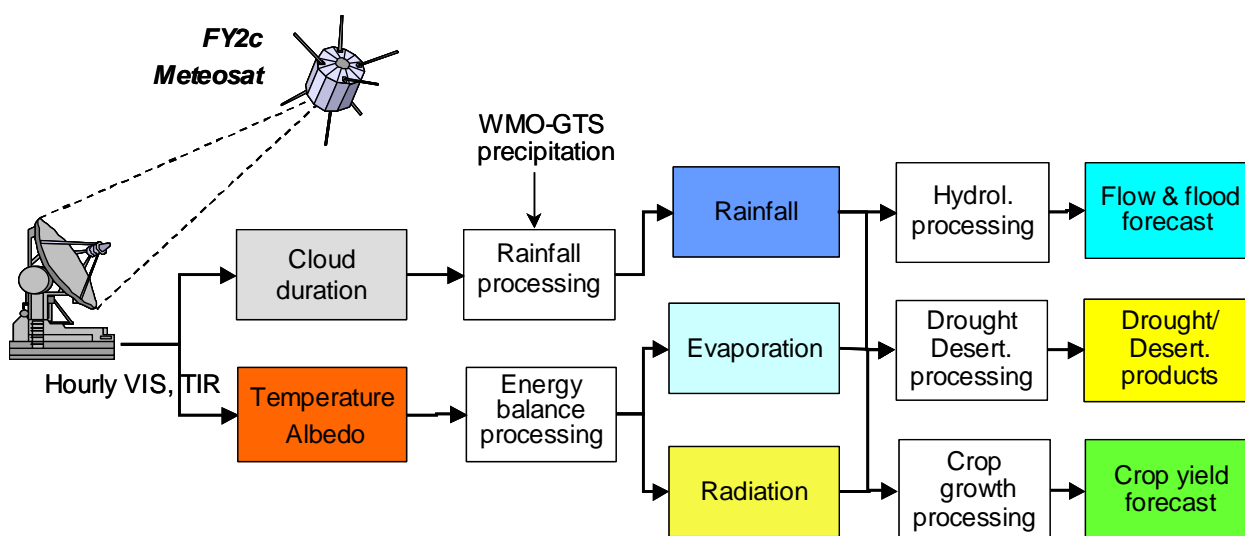
Figure 1: Overview of the Energy and Water Balance Monitoring System
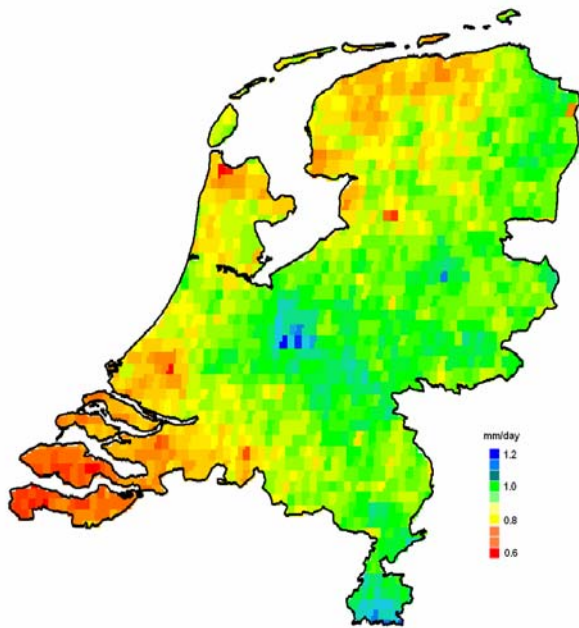
Figure 2: EWBMS average daily rainfall during the period January-April 2006 in the Netherlands, derived from MSG and WMO-GTS data
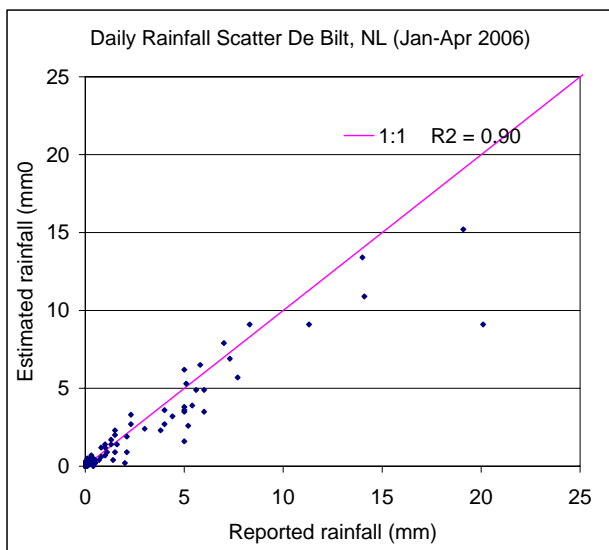
Figure 3: Comparison of predicted and reported daily rainfall as measured at the Royal Netherlands Meteorological Institute in De Bilt, Netherlands.

Meteosat slot the time varies from west to east and is only equal to noon at the centre. For this reason a series of hourly MSG images is used to create composite images where it is (close to) noon or midnight everywhere.

Rainfall processing

For the rainfall processing, besides the satellite data, we use WMO-GTS data that are received in near real time via the internet. We describe the relation between the precipitation field and the cloud durations by means of "local regression". It means that we select a set of 1 central and 11 surrounding rainfall stations. This provides a set of 12 samples of the precipitation field, for which we extract the corresponding

cloud durations. Subsequently a regression equation is calculated which characterizes the relation between rainfall R and cloud durations at the central rainfall station:

$$R = a_0 + a_1.CD_1 + a_2.CD_2 + \ldots\ldots\ldots \qquad (1)$$

The coefficients of the regression equation (a_0, a_1…) are assigned to the central rainfall station. Then we consider the next rainfall station and the procedure is repeated untill for each rainfall station a set of regression coefficients has been determined which characterizes the local rainfall field. Finally each regression coefficient is interpolated by means of inverse distance weighing so as to obtain values of the regression coefficients for each pixel. Hereafter the precipitation in each pixel can be calculated using the regression equation above.

In our rainfall mapping methodology a validation procedure is included. Validation is done by "Jack-knifing". It means that the whole rainfall mapping is done as many times as there are GTS rainfall stations, but each time leaving another single rainfall station. Each run then provides a single pair of measured and satellite derived rainfall values which are mutually independent. At the end there are as many validation data pairs as there are GTS rainfall stations. The quality of the relation is then determined by calculating the correllation coefficient and standard error of estimate. An example for daily rainfall in the Netherlands is shown in figures 2 and 3.

Energy balance processing

Processing for the surface energy balance components is based on physical laws, rather than statistical relations. First calibration equations are applied to convert the thermal infrared and visual digital values to planetary temperature (T_0') and planetary albedo (A'), i.e. the temperature and albedo as observed through the atmosphere. We use a "2-flux" atmospheric transmission model to convert the planetary values to values of the surface temperature (T_0) and surface albedo (A). No information on atmospheric composition is needed. In stead use is made of within image references like lowest albedo and highest surface temperature.

A new methodology has been developed to derive the boundary layer air temperature (T_b). The regression between observed noon and midnight surface temperatures in a sub-window usually shows a linear relation:

$$T_{12} = a.T_{24} + b \qquad (2)$$

Where regression is not accurate enough, the coefficient a in (2) is derived on the basis of a model of the course of the daily surface temperature. For the case of perfect heat transfer to the atmosphere, the noon and midnight surface temperature would be equal to the boundary layer air temperature, i.e.

$$T_{12} = T_{24} = T_b \qquad (3)$$

From (2) and (3) we may solve the boundary layer air temperature T_b. A boundary layer air temperature map is obtained by shifting the window pixel by pixel across the satellite data fields. By combination of the observed surface temperature T_0 and the boundary layer temperature T_b we can make an estimate of the air temperature at observation height (T_a). Observation height air temperature is a by-product of the EWBMS system that is also used for validation, whereas such air temperatures are also available from GTS reports.
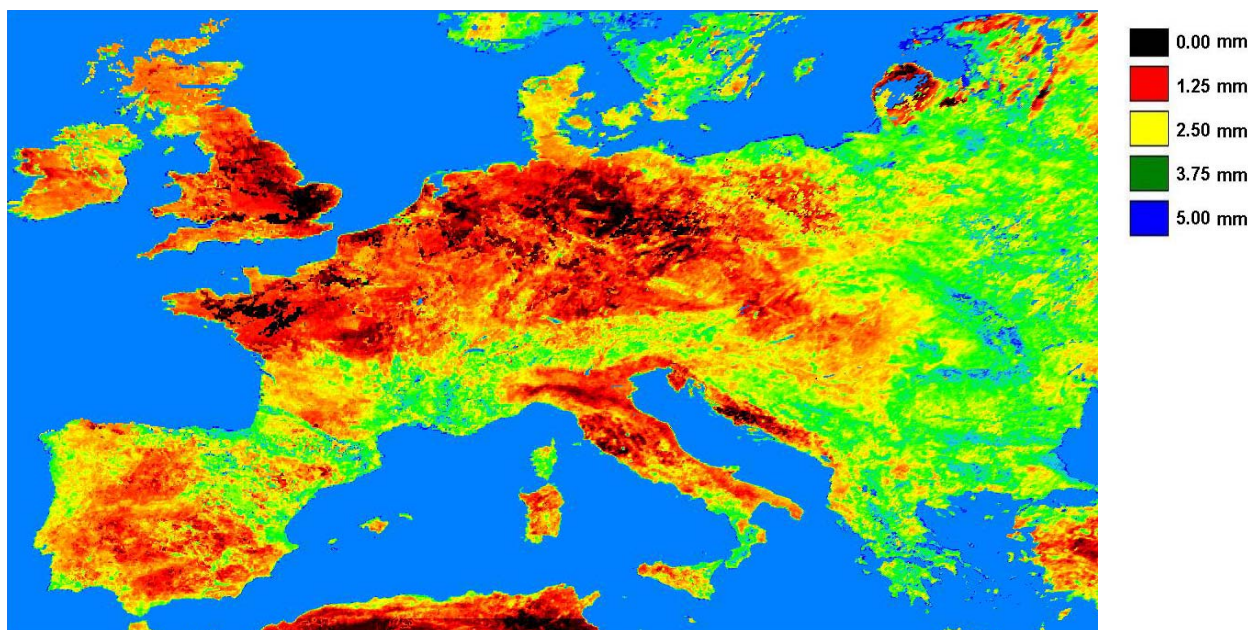
Figure 4: EWBMS actual evaporation during 18-20 July 2006, showing this summers intense drought in NW Europe

Hereafter we calculate the global radiation at noon. This involves the earlier mentioned 2-flux model of atmospheric transmission to calculate the global radiation at the ground surface. The noon value is then converted to a daily average value of the global radiation (I_g) using Fourier analysis of the daily solar cycle. Hereafter the upgoing thermal radiation flux (I_u) is estimated from the surface temperature, and the downgoing radiation flux from the boundary layer air temperature (I_d). The net radiation (I_n) is then obtained with:

$$I_n = (1-A)\ I_g + I_d - I_u \qquad (4)$$

The next step of the energy balance processing is the calculation of the sensible heat flux into the atmosphere (H) with:

$$H = \alpha\ (T_0 - T_b) \qquad (5)$$

Where α is the atmospheric heat transfer coeffient. Having determined the daily average values of the net radiation I_n and the sensible heat flux H, we can find the latent energy LE, i.e. the energy used for evaporating water, from

$$LE = I_n - H \qquad (6)$$

Our research has shown that for vegetation it is necessary to involve an adittional term in the energy balance, which represents the energy used for photosynthetic electron transport. The value is in the order of 5-10% of the global radiation. From the latent energy flux LE (in W/m^2) we can determine the actual evaporation (E) in mm/day. About 28 W/m^2 is required for evaporating 1 mm of water. An actual evapotranspiration map for Europe, July 2006, is shown in figure 4. This map clearly depicts this summer's drought in NW Europe.

If sufficient water is available the evaporation is potential (LE_P). By means of the Penman-Monteith equation it can be shown that:

$$LE_P \approx 0.8\ I_n \qquad (7)$$

The relative evapotranspiration (RE) is then defined as

$$RE = LE / LE_p \qquad (8)$$

The relative evapotranspiration is also a product of the EWBMS. It is an important agricultural drought indicator (because it is radiation independent) and, as we will see, is directly related to crop growth. It represents actual crop water use and therefore is a better indicator of crop growth then rainfall.

CROP GROWTH SIMULATION

The EWBMS data fields of rainfall, actual evapotranspiration and radiation may be used for crop yield forecasting in several ways. The most direct approach would be to use the accumulated rainfall or actual evapotranspiration during the crop growing period as crop growth indicator and then to establish an enpirical relation between such indicators and reported crop yields. A multi year data set will be required. The required satellite data are available, as we are receiving and archiving Meteosat data since 1993.

A more sophisticated approach to crop yield is the use of deterministic crop growth models. Many crop growth models use rainfall data as input, because in the past only such data were available. A source of inaccuracy in this approach is the estimation of amount of water available to the crop. This involves a number of assumptions in relation to rainfall runoff and rainfall storage in the soil. Crude simplications of unsaturated zone soil moisture storage and transport are made.

In Africa rainfall measurements are scarce and in some areas not available at all. Nowadays some use is made of distributed rainfall data generated by weather prediction models. However rainfall prediction is usually the weakest part of such models. Actual rainfall fields are usually dislocated relative to their forecast. A much better source of data for crop yield estimation is available from the EWBMS system.

The EWBMS provides continent wide data fields of actual evapotranspiration at daily temporal and 3 km spatial resolution. It is well established that actual evapotranspiration closely represents the actual water use by plants (*Doorenbos and Kassam 1979*). Although Meteosat cannot resolve each individual field, it has been shown that Meteosat derivded actual evapotranspiration is very useful for estimation crop growth and forecasting yield. The evapotranspiration data avoid the inaccurate soil moisture budget component in classical rainfed crop growth models. Moreover the evapotranspiration data are available for each 3*3 km pixel of Africa and Europe in near real time.

EARS Crop Growth Model (ECGM)

In this section we explain how a simple dedicated crop growth model may be developed and used, which is fed by the EWBMS actual evapotranspiration and radiation data. This model is based on three main principles:

(1) Crop growth depends mainly on radiation interception and hardly on species (*Monteith 1977*),
(2) Crop growth is proportional the actual evapotranspiration (*Stewart 1973, Doorenbos & Kassam 1979*),
(3) Crop growth is CO_2 limited, which leads to a radiation use efficiency, which decreases hyperbolically with increasing radiation (*Rosema et al. 1998*)

In the ECGM the daily gross photosynthesis (P) is calculated with:

$$P = c.\varepsilon.C.RP.I_g \qquad (9)$$

Where "c" is a conversion factor, ε is the photosynthetic efficiency of radiation, C is the crop coverage, RP the relative production and I_g the global radiation. In the above expression the crop coverage is estimated from the crop biomass with:

$$C = B/B_c \qquad (C=1 \text{ for } B \geq B_c) \qquad (10)$$

Here B_C is the biomass at crop closure. This equation corresponds to exponential initial growth. The calculation of the relative production as a result of water limitation is based on the well-known relation developed by *Stewart (1973)* and extensively documented in *Doorenbos & Kassam (1979)*:

$$RP = 1 - k_y (1 - RE) \qquad (11)$$

The yield respons factor k_y depends on the drought resistivity of the crop and is for example 1.25 for maize, 1.0 for winter wheat and 0.8 for sorghum and millet.

The formulation of the photosynthetic efficiency results from our research on the relation between chlorophyll fluorescence and photosynthetic electron transport. Equilibrium between photosystem reaction centre charging an drainage leads to the following relation

$$\varepsilon = 1/(1.25 + r_e.I_g) \qquad (12)$$

where r_e is a the resistance for electron transport (~0.01). We have discussed the factors determining gross photosynthesis rate. The main quantities determining this rate are the global radiation I_g and the relative evapotranspiration RE. These data can be obtained from the EWBMS system.

A part of the sugar stored as a result of the photosynthesis process is burned again to provide energy for crop biomass maintenance. This maintenance respiration (Re) is calculated on the basis of the relation provided by Supit (1994)

$$Re = c_r B q_{10}^{(T-Tref)/10} \qquad (13)$$

For our purpose this relation has been adapted as follows

$$Re = c_r B q^{RE} \qquad (14)$$

Now the net daily biomass production is given by

$$\Delta B = P - Re \qquad (15)$$

Using the daily EWBMS radiation and relative evapotranspiration products as input we may now accumulate the biomass during the growing season on a day-by-day basis.

$$B_{i+1} = B_i + \Delta B \qquad (16)$$

The ECGM software requires the specification of the start of the growing season. This may be done in several ways: fixed date, starting dekad map, or an automatic start. The automatic start requires that the relative evapotranspiration exceeds a specified treshold (RE>RE_c). We can also run the crop growth model for non water limited conditions, i.e. for RE=RP=1. This leads to the potential biomass B_P. We define the relative biomass at any moment of the growing season (RB) as the ratio of the actual over the potential biomass:

$$RB = B / B_P \qquad (17)$$

CROP YIELD FORECASTING

The absolute value of the biomass simulated with a crop growth model is usually not very accurate. The reason is that models are relatively simpel, or, when they are more complex, require too much input data, which data is not available across large areas. For this reason we follow a "relative" approach to crop yield forecasting, which makes use of more yearly satellite derived and reported yield. The following approach is often used. It is first assumed that the economic yield is proportional to the crop biomass and that consequently the relative biomass equals the relative yield: RY=RB. We determine from 5 years of satellite data the average relative biomass:

$$RB^@ = \Sigma RB_i /5 \approx \Sigma (B_i) / (5.B_P) \qquad (18)$$

The current years relative biomass as derived from the satellite is given by (17). We now define the difference biomass as the fractional difference of the current year simulated biomass relative to the average biomass of the previous 5 years:

$$DB = RB/RB^@ - 1 \qquad (19)$$

Assuming that we have the observed yields of the previous five year available, we can calculate the average observed yield $Y^@$. Rather than the absolute biomass B, the ECGM produces the relative biomass RB and the difference biomass DB as standard products because they are more accurate than the absolute biomass B. From the DB product we may obtain the crop yield forecast (Y) with:
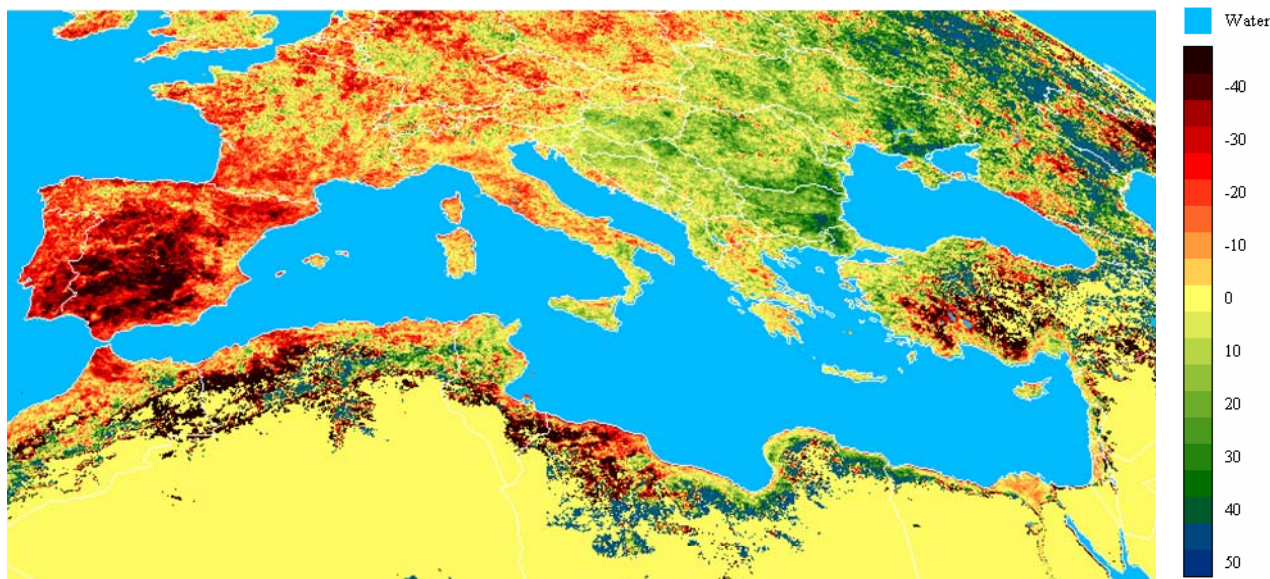
$$Y = (DB+1).Y^@ \qquad (20)$$

Figure 5: EWBMS difference biomass for wheat in the Euromed region, August 2005. The deviation from average (yellow) is quantified by the scale on the right. Western Europe and particularlyPortugal and Spain had an unfavorable growing season (red, black). The Balkan countries and Oekraine show above average yield expectation (green)

Country	Difference from avrg(%)	Forecasted Wheat yield (Hg/Ha)
Albania	5	31302
Austria	-3	48462
Belarus	3	26425
Belgium	-13	72736
Bosnia Herzeg.	8	31589
Bulgaria	24	37337
Croatia	7	41730
Cyprus	0	20180
Czech Rep.	-7	43760
France	-10	63024
Germany	-7	68322
Greece	1	23684
Hungary	10	42259
Italy	-4	29947
Macedonia	-2	25400
Moldavia	11	22666
Netherlands	-9	77521
Poland	-6	33697
Portugal	-29	9249
Rumania	17	29434
Serbia Mont.	13	34644
Slovakia	0	38018
Spain	-32	19549
Switzerland	-5	54459
Turkey	-6	20094
Ukraine	15	29327
United Kingdom	-2	75968

Table 1: Wheat yield forecast European countries Sept. 2005

It is noted that the difference biomass DB may be determined at any moment during the growing season from the simulated actual and potential biomass according to (19). It also means that we can make a crop yield forecast with (20) at any moment of the growing season. It has been shown that a reliable yield forecast is possible from about 70 days after planting/sowing. As we usually have to produce crop yield forecasts for adminstrative units (for which we have historic yield data) the procedure is usually such that we use the EWBMS and ECGM to generate RB and DB image products. Hereafter we spatially average the results for the crop growing area within the specific administrative unit. Finally we calculate the forecasted yield with (20). The better the crop mask that is used, the better the results will be.

Another approach to crop yield forecasting, as usually followed at JRC, makes use of regression between the observed yields (Y) and satellite derived yield indicators (I). Based on the historic data a regression equation is determined:
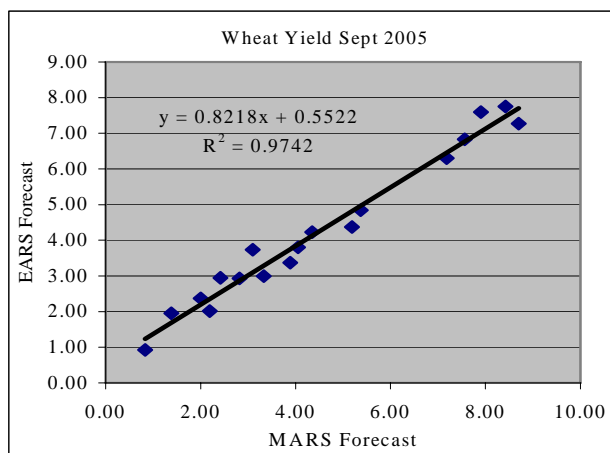
Figure 6: Comparison of EARS and MARS yield forecast in 2005 (courtesy Jacques Delincé,JRC Agrifish unit)

$$Y = a_0 + a_1.I_1 + a_2.I_2 + a_3.I_3 + \ldots \qquad (21)$$

Yield indicators from the EWBMS system can be: the rainfall (R), the actual or relative evapotranspiration (E, RE), and the simulated or relative biomass (B, RB). All these indicators are accumulated or simulated up to the current moment of the growing season and are spatially averaged for the relevant crop growing areas and administrative units. Once a regression equation has been determined for each administrative unit, this equation may be used for yield forecasting in the next year.

Geoland project

In the framework of the Geoland-OFM project we have prepared maize and wheat yield indicators for Spain, Belgium and Poland at the level of NUTS-2 administrative units. Similar yield indicators have been generated for a large number of counties in the provinces Hebei, Shanxi, Henan, Shandong, Beijing and Tianjin in China, using data from the Japanese GMS satellite of the years 1999-2001. All indicators have been provided to OFM coordinator Alterra. Results have been analyzed in detail by the AGRIFISH unit of the EU Joint Research Centre in Ispra (*Genovese, Bettio and Fritz, 2006*) following the regression approach of equation (17). Results may be discussed in other presentations at this conference.

In addition to the previous activities we have carried out a crop yield forecast for a large number of European countries (NUTS-1 level) at the end of August 2005. See figures 5, 6 and table 1 on the previous page. This forecast was compared by the JRC-Agrifish unit with the their own forecast based on weather data and the CGMS model. The results for wheat and barley were very much the same ($r^2 \approx 0.95$, see figure 6).

GMFS project

In the framework of the GMES project Global Monitoring for Food Security we have produced operational crop yield forecasts for Africa. These "FAST" activities (*Food Assessment by Satellite Technology*) consisted of (i) providing timely EWBMS crop growth and yield forecast data fields to partners and users by ftp, and (ii) preparing region and country specific crop yield forecasting bulletins in support of FAO/WFP Crop and Food Supply Assessment Missions. Such missions are usually undertaken on request of countries, which have an emerging food production problem and want to apply for food aid. We have produced 24 regional and national crop yield forecast bulletins. The FAST bulletins were their earliest source of quantitative crop yield information.

Concluding remarks

The EWBMS system is an abundant source of agro-meteorological information relevant for crop yield forecasting. The data products have some explicit advantages. They are: quantitative, continuous in space and time, synoptic, uniform, objective, validated and economic. In the framework of the Geoland and GMFS projects we have demonstrated being able to make reliable and timely crop yield forecasts for every province in Europe and Africa from halfway the growing season. The economic aspect should not be neglected. The system is based on low cost satellite receiving and processing technology. Generating a crop yield forecast for most European countries and creating and distributing the corresponding early warning bulletin took 5 person days.
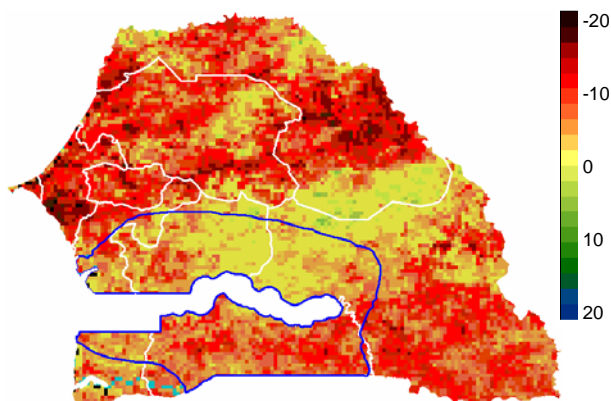
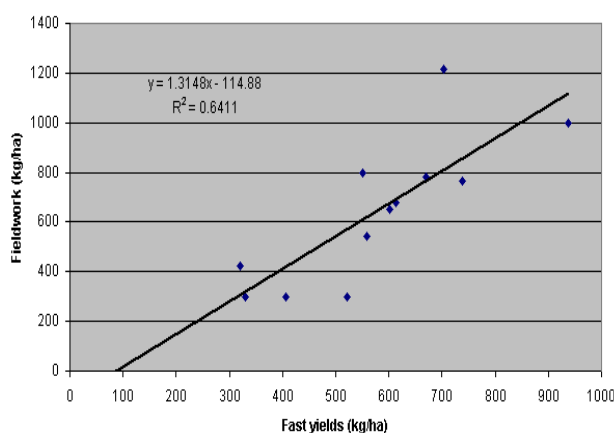Figure 7: Sorghum difference yield (%), Senegal 2004, GMFS

Figure 8: Validation of FAST yields by fieldwork in GMFS.(Courtesy Synoptics, Wageningen)

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COTTON YIELD ESTIMATION IN UZBEKISTAN INTEGRATING MODIS, LANDSAT ETM+ AND FIELD DATA

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ABSTRACT:

Estimating crop yields is critical for regions in the Aral Sea Basin, where agriculture, predominantly cotton (Gossypium hirsutum L.) production, is the main source of income. Monitoring the spatial distribution of cotton yields helps identifying sites with yield constraints, so that appropriate counteractions such as the application of targeted agricultural inputs or land use restructuring can be taken. An agro-meteorological model evolved from Monteith's biomass production model was developed for estimating spatially distributed cotton yield in Uzbekistan using multi-temporal MODIS-derived parameters from 2002 as primary data inputs. Local meteorological data was used for estimating the photosynthetically active radiation (PAR) and the environmental stress scalars, including air temperature stress and vapor pressure deficit stress on crop development. High spatial resolution Landsat 7 ETM+ images were applied to extract the area under cotton cultivation within the landscape and to determine the cotton fraction among other land uses within the coarse spatial resolution MODIS pixels. The spatial resolution of the MODIS FPAR data was upgraded by using an established relationship to the higher resolution MODIS NDVI data. The estimated raw cotton yield reached an average of 2.38 t ha-1 and ranged from 1.09 to 3.76 t ha-1. The pixel-based modeling revealed a general spatial trend of higher yield in upstream areas and in locations closer to the irrigation channels and lower yields in downstream area and sites more distant to irrigation channels. The validated yield estimations showed a ca. 10 % deviation from official governmental statistics at district level. The established agro-meteorological model with minimum data input, and mainly based on multi-temporal, freely available MODIS data is a promising strategy for economic and operational late season estimation of spatially distributed cotton yield over large regions.

1. INTRODUCTION

In Uzbekistan cotton production plays a dominant role in the economy and covers 46 % of all irrigated land in the country. However, the volume of water from the Amu Darya River, which is one of the major sources of water for irrigation, gradually becomes limited due to increasing water demand in upstream irrigation regions and in neighbouring countries (Ressl et al., 1998, Vlek et al., 2003). The estimation of cotton yield is of importance for better targeting water allocation and planning of land use restructuring.

Remote sensing is the one technology that can give an unbiased view of large areas, with spatially explicit information distribution and time repetition, and has thus been widely used to estimate crop yields at a regional scale (Quarmby et al., 1993; Baez-Gonzalez et al., 2002; Doraiswamy et al., 2003). The agro-meteorological model based on solar radiation and leaf development (Monteith, 1972) has great potential for estimating crop yield using mainly satellite and agro-

metereological data as inputs (Moulin et al., 1998; Lobell et al., 2003). Satellite data such as those from NOAA-AVHRR (National Oceanic and Atmospheric Administration - Advanced Very High Resolution Radiometer) and MODIS (Moderate Resolution Imaging Spectroradiometer) with high temporal frequency have so far mainly been used for model runs at a daily time step. Bastiaanssen and Ali (2003), for example, applied the linear relationship between the fraction of photosynthetically active radiation (FPAR) and NDVI derived from AVHRR to estimate the fraction of photosynthetically active radiation absorbed (FPAR) for the Monteith model.

The newly available satellite images from the MODIS sensor provide enhanced atmospheric correction, cloud detection, improved geo-referencing, comprehensive data quality control and the enhanced ability to monitor vegetation development (Running et al., 1999; Huete et al., 2002). Moreover, a series of standard MODIS products such as FPAR, vegetation index (VI), leaf area index (LAI), and net primary productivity (NPP)

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is provided by the MODIS land science team. The MODIS land data have mainly been the focus in global scale change research, but the regional application and validation of these data are only in the initial stage (Justice et al., 2002).

The aim of this research is to estimate the spatially distributed cotton yields in the Khorezm region located in Northwest Uzbekistan by an agro-meteorological model that uses remote sensing and field data. More specific research objectives are: 1) to upgrade the spatial resolution of the MODIS FPAR data by using an established relationship with the higher resolution MODIS NDVI data and cotton area information derived from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) classification; and 2) to integrate from these pixels time series of the FPAR MODIS product, crop and climatic specific information in an agro-meteorological model for estimating spatially distributed cotton yield in Khorezm in 2002.

2. DATA AND METHODS

2.1 Study Area

The study area, the Khorezm region of Uzbekistan, is located at the lower Amu Darya River at about 250 km south of the present shores of the Aral Sea. The irrigated area covers approximately 275,000 ha, is bounded by latitudes 40° 34′N - 42°59′N and longitudes 60°02′E – 62° 28′°E, at 113-138 m above sea level and has 11 rayons (districts in Uzbekistan; Figure 1).
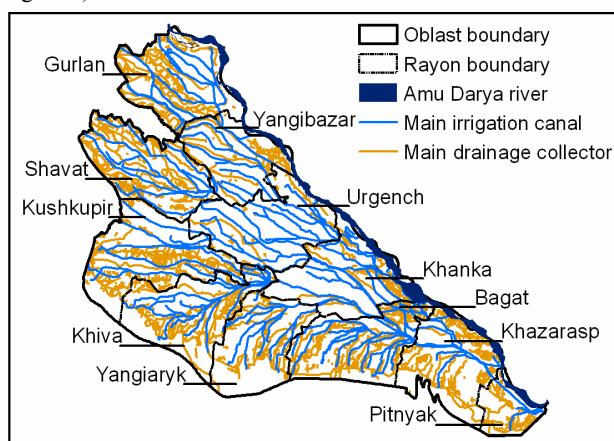
Figure 1. Study area

Agriculture plays a dominant role in the economy of the Khorezm region. The most important crop of Khorezm is cotton, which covered ca. 60 % of the irrigated land (ca. 165,000 of 275,000 ha) in 1999, while rice, winter wheat and other crops have a markedly smaller area share (OblStat, 2002). These crops are grown on a patchwork of fields that vary in size from ca. 1 ha to ca. 25 ha. Generally, the cotton growing season in Khorezm extends from mid-April to the end of September. With an average annual precipitation of only 92 mm, crop cultivation in Khorezm requires intensive irrigation using water from the Amu Darya River. During the cotton season of 2002 there was only 78 mm of precipitation, whereas the total daily potential evapotranspiration (ET_0), calculated with the Penman-Monteith equation (Smith et al., 1991), amounted to 460 mm.

2.2 Data

In this study data from the MODIS land discipline group product comprising biophysical parameters such as the FPAR (MOD15) and vegetation indices (MOD13) (Justice et al., 2002) were used. MOD15A2 products are 8-day composites with 1 km nadir resolution at global scale. These products were generated from the atmospherically corrected surface reflectance product (MOD09), the six biome map which is stored in the land cover product (MOD12) and ancillary information on surface characteristics using a three dimensional radiative transfer model (Myneni et al. 2002). MODIS MOD13Q1 products contain 250 m ground resolution 16-day composites of the NDVI. A bidirectional reflectance distribution function (BRDF) composition algorithm is used to obtain NDVI values based on couple of optimum atmospheric conditions within 16 days. Otherwise a maximum value composition is performed on the highest quality MOD09 data within this period to generate the NDVI product (Huete et al., 2002). Both MODIS FPAR 8-day composite scenes from April 7 till September 30, 2002 and all MODIS MOD 13 NDVI 16-day composites from 2002 were downloaded from the Earth Observing System data gateway. The analysis of the quality assessment science data sets assigned to each MODIS product resulted in the selection and linear temporal interpolation of pixel values with minimum atmospheric or other influences (Conrad et al., 2004).

2.3 Concept for Crop Yield Modeling

The conceptual framework for modeling cotton yields within the Khorezm region includes the following five principal components: 1) data input; 2) cotton area detection; 3) cotton yield estimation per pixel; 4) cotton yield estimation per administrative unit and validation; 5) data output.

The data on cotton area was extracted from an existing land use classification of 2002 (Schweitzer et al., 2002). This classification was generated by using multi-temporal MODIS and Landsat 7 ETM+ NDVI data and polygon boundaries on the spatially different hydrological conditions in Khorezm in a knowledge-based classification approach. From the NDVI time series, reference temporal signatures of the major land uses were extracted based on 478 training data of the main land uses, which were collected in Khorezm during 2002. Investigations of the leaf area index development and field observations indicated that the crops' phenological development varies spatially within Khorezm. This might be due to temporal variations in water supply depending on the distance of the fields to the Amu Darya and the major irrigation channels (Ruecker and Conrad, 2003). Another often reported reason for different LAI development is due to different planting time within the region which is again mainly determined by water availability. Thus, the spatial knowledge on different water supply was incorporated into the classification by a GIS-based pre-stratification of Khorezm into hydrological zones, using the major drainage channels as boundary criteria. The satellite images, stratification boundaries and ground truth data were combined with expert knowledge on phenological crop development to design specific rules for land use classification and for the detection of cotton fields. The total classification accuracy was calculated by confusion matrix and amounted to 81.6 % with an accuracy of 89.5 % regarding the classification of cotton (Schweitzer, 2005). The detailed land use classification approach and resulting map are described elsewhere (Ruecker and Conrad, 2003).

The yield for the extracted cotton area was estimated by assimilating multi-temporal MODIS, meteorological and crop specific data into an agro-meteorological model (see below). The pixel-based cotton yield was aggregated to the administrative levels of rayons, validated against existing yield statistics and presented in the form of maps.

2.4 Crop Yield Model Description

Crop growth and yield were considered to be dependent on the radiation received by the crop throughout the growth cycle. According to Monteith (1977), there is a strong relationship between the cumulative radiation quantity absorbed by the foliage during the crop growth period and the biomass production. Based on this relationship, a model for estimating yield was elaborated as shown elsewhere (Lobell et al., 2003).

$$Y = H_i \times \sum (\varepsilon \times PAR \times FPAR) \Delta t \qquad (1)$$

where Y is the cotton lint yield (g m^{-2}), H_i represents the harvest index, ε is the light-use efficiency in units of g biomass MJ^{1} PAR. PAR is the photosynthetically active radiation (MJ m^{-2}). $FPAR$ is the fraction of PAR absorbed by the plants. $FPAR$ values were derived from MODIS data. Δt represents the daily time step during the whole cotton growth period.

PAR (0.4–0.7 μm) is part of the short-wave solar radiation (0.3–3.0 μm), which is absorbed by chlorophyll for photosynthesis in the crops. PAR is thus a fraction of the incoming global solar radiation R_g. The value of PAR/R_g fraction does not vary much with place, climatic conditions and integration time over the growing period; generally a constant of 0.48 is used (Varlet-Grancher, et al.1982). R_g is calculated using the formula of Hargreaves (1985). The value of the light-use efficiency was adjusted to local conditions by including the environmental stress terms ambient air temperature, vapor pressure deficit (VPD) and soil moisture cumulative stress index (Goetz, et al., 1999). The simplified algorithm used for the generation of MODIS net primary production data was adopted (Eq.(3)) (MODIS land team, 2003).

$$\varepsilon = \varepsilon' \times T' \times V' \qquad (2)$$

where ε' is the maximum light-use efficiency, T' is a daily minimum temperature (TMIN) scalar value (°C), V' is a VPD scalar value (Pa). The attenuation scalars are linear ramp functions of TMIN and VPD. VPD is the difference between saturated vapor pressure and actual vapor pressure. The daily saturated vapor pressure is related to air temperature and the daily actual vapor pressure can be approximated from the daily relative humidity data (Allen et al, 1998). The details on the model parameterization can be found elsewhere (Shi et al., 2007)

2.5 Spatial Downscaling of MODIS FPAR Data

Due to the spatially fragmented land use distribution and the relatively small field sizes in the agricultural landscape of Khorezm, the 1 km resolution MODIS time-series FPAR data is rather coarse, so that every pixel covers several different land uses (Figure 2). This was confirmed by a spatial overlay of MODIS pixels on the Landsat 7 ETM+ classified land use map of 30 m pixel resolution, which revealed only 32 MODIS pixels at a 1 km resolution covering cotton fields with more than 50 % area share. Thus, the coarse MODIS data resolution required a spatial downscaling for a more accurate estimation of cotton yield that is adjusted to the field sizes (Moulin et al., 1998).
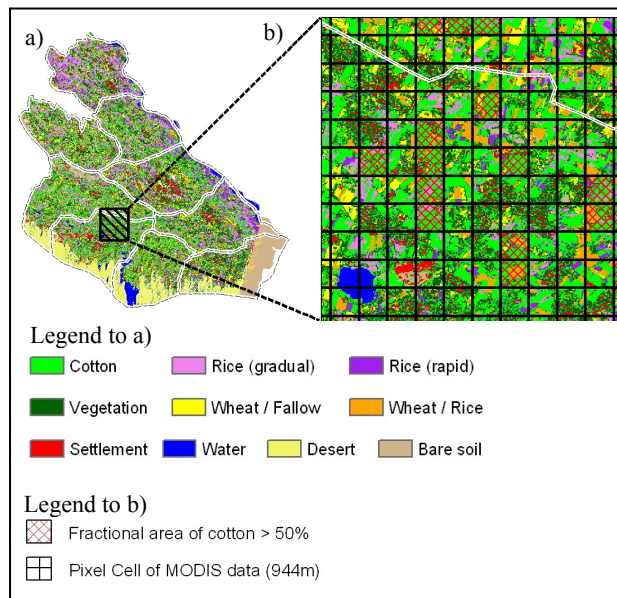
Figure 2. The land use map at 30m pixel resolution (a) and one enlarged landscape overlaid with MODIS pixel cell of ca. 1 km resolution (dark grid, a) and selected pixels with fractional area larger than 50% (red cross lattice, b).

The empirically determined relationship between the coarse MODIS FPAR (1 km resolution) and the more detailed MODIS NDVI (250 m resolution) data for green vegetation was applied as spatial downscaling strategy (Prince and Goward, 1995; Fensholt et al., 2004) to the MODIS data covering the Khorezm region. The spatial overlay of the MODIS NDVI pixels on the 30 m resolution land use map revealed 1187 MODIS NDVI pixels covering more than 80 % of the area share of cotton fields. Therefore, the MODIS FPAR pixels with greater than 50 % cotton area were selected as the primary sampling points (N = 32). Within each FPAR pixel the corresponding MODIS NDVI pixels with 250 m resolution were determined and the mean NDVI value per FPAR pixel was calculated.

2.6 Cotton Yield Validation Approach

In order to validate the model, the modeled yield outputs were tested against actual cotton yields in Khorezm based on official data for yields of raw cotton

3. RESULTS AND DISCUSSION

3.1 Spatial Downscaling and Selection of FPAR Data

In the spatially fragmented agricultural area of Khorezm with different land uses and land covers, a direct application of the cotton yield estimation model to the relatively coarse MODIS pixels at 1 km resolution would cause yield estimations of low accuracy. Most 1 km MODIS pixels represented a mixed land

surface reflectance from cotton, rice, wheat areas or bare soil. There were only 32 FPAR MODIS pixels at 1 km resolution which covered > 50 % of the area share of cotton fields. However considering NDVI MODIS pixels of 250 m resolution, there were 1187 pixels with > 80 % cotton area. In the rayons closer to the Amu Darya River (northeast) and in the lower central area of Khorezm where the main irrigation channels pass through, generally larger cotton fields are found than in the more desert-like areas or areas further downstream of irrigation channels (compare Figure 1).

For establishing the relationship between the coarse MODIS FPAR data with the more detailed MODIS NDVI data, the FPAR values and corresponding NDVI values were extracted from 32 selected pixels in twelve 16-day intervals during the cotton growth period (Figure 3).
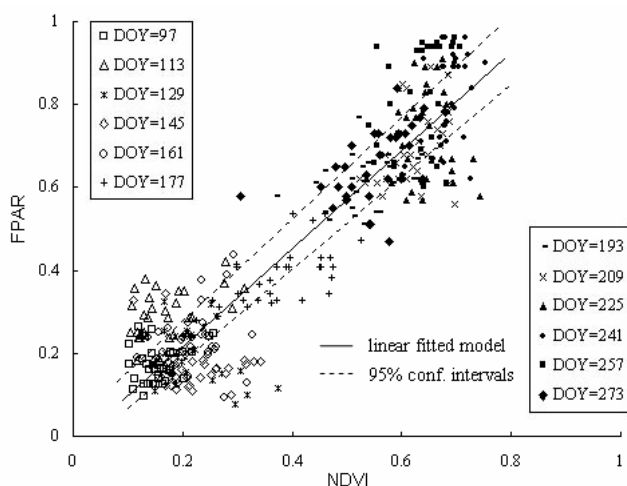
Figure 3. Scattergram of MODIS NDVI and FPAR data for different days of year (DOY) during the cotton growth period in Khorezm, and their linear fitted model and regression 95% confidence intervals.

The scattergram shows a good linear relationship between MODIS NDVI and FPAR data (N = 384) with:

$$FPAR = -0.0187 + 1.1799 * NDVI \qquad (3)$$

In this study, the whole FPAR and NDVI data of the selected pixels during the cotton growth period were used to predict the linear model. Meanwhile, the spatial resolution of the estimation unit for the agro-meteorological model was downscaled. In the following, only 1187 MODIS pixels with 250 m resolution and a fractional cover of more than 80 % cotton were used for the yield estimation in the crop yield estimation model.

3.2 Parameterization of Model Input Data

The yield model parameters Hi (harvest index) and ε' (light use efficiency) were determined based on consultations with local agronomists and international references. The values may vary depending on climatic and soil conditions in each season, crop variety and applied fertilizers. This makes it difficult to choose an average factor that is representative for the whole region of Khorezm in the considered year, 2002. For lint cotton, several researchers defined Hi to be 0.06-0.12 (Sys et al., 1991), 0.08-

0.12 (FAO, 1979) and 0.12 (Bastiaanssen and Ali, 2003). Generally, lint cotton yield is considered one-third of the raw cotton yield, if no specific conversion factor is known (FAO, 2005). According to Uzbek agricultural ministry statistics in 2003, Uzbek farmers harvested 2,900,000 t of raw cotton of which 930,000 t of lint cotton were measured, thus, a turnout of approximately 32 % is estimated in Uzbekistan (BISNIS, 2004). Consequently, an average Hi of 0.36 for raw cotton and 0.12 for lint cotton were used. Regarding the value for light use efficiency of cotton, Bastiaanssen and Ali (2003) specified the permitted range to be 1.5-2.5 g MJ^{-1} and Rosenthal and Gerik (1991) recommended 1.44 g MJ^{-1}. In this study, a field experiment carried out in the Khiva district of the study area was used to calculate the approximate ε' value. Under optimum water supply practice with five irrigation events during cotton growth in 2002, the average yield of raw cotton was 2.99 t ha^{-1} (Forkutsa, 2006). Using the meteorological data and FPAR values from MODIS pixels in Khiva district in 2002, the Monteith model was applied to calculate the maximum light-use efficiency $\varepsilon' = 1.37$g MJ^{-1}, and the mean of light-use efficiency within cotton growth period is approximately 1.16 g MJ^{-1}. Since Khorezm is a flat plain with little spatial variability of the general weather conditions, the daily meteorological data from the Urgench weather station was used to represent the whole region and used to estimate the daily PAR, T' and V' values.

3.3 Spatial Cotton Yield Estimation in Khorezm

The agro-meteorological model was run to calculate cotton yield on the 1187 selected MODIS pixels. The estimated yield of raw cotton within 1187 MODIS pixels ranged from 1.09 t ha^{-1} to 3.76 t ha^{-1}, with an average of 2.38 t ha^{-1}. A final cotton yield map was masked by the cotton area image retrieved from the Landsat 7 ETM+ land use classification (Figure 4).
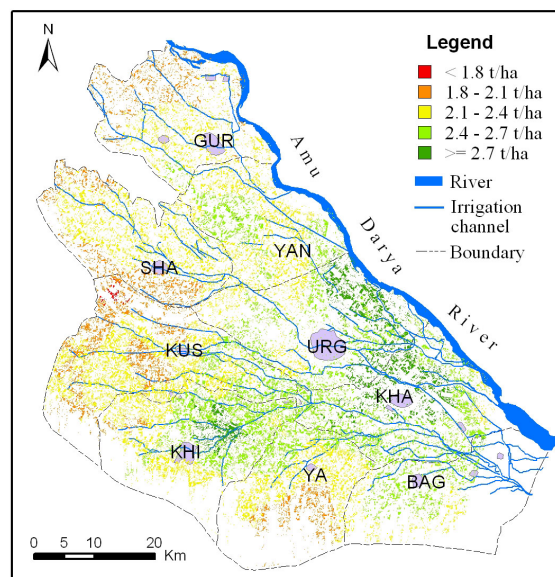

Figure 4. Cotton yield variation across Khorezm in 2002 after block-kriging interpolation from selected MODIS pixels.

In Khorezm, all irrigation water that is supplied by a canal system originates from the Amu Darya River. Therefore, the general spatial distribution of cotton yield coincides with the water supply pattern. Figure 4 shows that cotton growth is better in two types of rayons. Either, rayons such as Urgench (URG) and Khanka (KHA) have more efficient and plentiful

water supply as they are closer to the Amu Darya River, or, rayons such as Khiva (KHI) which are connected to the distant river through a strong canal system. In contrast, cotton yield is much lower in downstream areas (e.g. Shavat (SHA) or the northern parts of Gurlen (GUR)) or in areas farther away from the Amu Darya River where no strong primary irrigation water supply exists (e.g. Kushkupyr (KUS), Yangiarik (YA)).

3.4 Data Validation

Actual cotton yield data from the government statistics were used to validate the modeled yield data in Khorezm (Table 1).

District	Modeled yield lint pixels	Modeled yield lint area	Yield reported	Δ ‡ for selected pixels	Δ for whole cotton area %
	t ha⁻¹				
Gurlan (GUR)	0.70	0.68	0.72	-2.7	-4.9
Kushkupir (KUS)	0.71	0.70	0.86	-17.8	-18.5
Urganch (URG)	0.87	0.83	0.73	18.8	14.0
Khanka (KHA)	0.85	0.84	0.87	-1.8	-2.9
Khiva (KHI)	0.81	0.79	1.02	-20.6	-22.8
Shavat (SHA)	0.70	0.69	0.76	-8.2	-9.1
Yangibazar (YAN)	0.78	0.77	0.68	14.8	12.9
Bagat (BAG)	0.82	0.79	0.74	10.3	6.4
Yangiaryk (YA)	0.74	0.73	0.73	0.8	-0.5
Average §	0.77	0.76	0.79	10.6	10.2

‡ Δ: difference (%) = (modelled value – reported value) / reported value;

§ average of Δ is calculated on the absolute value of Δ.

Table 1 shows that the average differences between modeled yield and official reported yield are 10.7 % and 10.6 % for selected cotton pixels and the whole cotton area, respectively. However, in two rayons in the western region bordering the desert, Kushkupir and Khiva, the yield was significantly underestimated by the simulation, with -18.9 % and -22.2 %, respectively. In contrast the yield was, with 17 % and 13.4 %, moderately overestimated in two rayons that are bordering the Amu Darya River, Urgench and Yangibazar, respectively. The contrasting yield differences can be attributed to the spatial variability of MODIS FPAR data reflecting spatially variable crop growth within Khorezm. FPAR values which have a good relationship to NDVI values have mainly higher values in the areas near the Amu Darya River. As was stated above, these latter areas benefit from higher water availability than the desert-near regions (Figure 1).

Timely and adequate supply of water certainly will result in good and homogeneous cotton growth whereas on the marginal land, often late planting, retarded crop development, and heterogeneous cotton growth and field coverage are being observed (cf. also similar spatial plant coverage patterns observed in an assessment of leaf area index by Ruecker and Conrad (2003)). As a result, the FPAR value of the MODIS pixels and therefore also the yield estimated by the agro-meteorological model is greater in favorable than in marginal land. Since the yield estimations in Khorezm so far rely on the spatial distribution of the FPAR data, the focus of future research will be to further adapt the model by including more field-based spatially distributed information such as cotton varieties, agricultural practices, and irrigation procedures that all influence yields.

4. CONCLUSIONS

In this study, an agro-meteorological model with minimum field-based input data and freely available multi-temporal MODIS data was applied to estimate cotton yield in the Khorezm region of Uzbekistan. The modeled yield data showed a good correspondence with the actual yield values provided by government statistics at district level. The spatial yield distribution coincided with the overall pattern of the irrigation system and reflected dependencies on hydrological conditions upstream and downstream. A practical application of this approach is e.g. to provide yield distribution maps as basis for efficient land use planning. Thus, this yield estimation approach can be regarded as an economical and feasible way to achieve spatially distributed crop monitoring and yield estimation on a regional scale.

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6. ACKNOWLEDGEMENTS

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CROP YIELD PREDICTION WITH SPOT VGT
IN MEDITERRANEAN AND CENTRAL ASIAN COUNTRIES

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KEY WORDS: crop yield forecasting, SPOT VEGETATION, crop growth monitoring

ABSTRACT:

Some years ago the MARS-FOOD group was established to support the Food Aid and Food Security policies of the European Commission. The activities are aimed at improving methods and information on crop yield prospects. Russia, Central Asia, and non-European Mediterranean countries (MECA region), Eastern Africa (IGAD sub-region) and the MERCOSUR region in South America were selected as pilot areas. Crop growth indicators are produced based on low resolution remote sensing data, global meteorological modelling outputs (ECMWF model) and crop growth simulation models (CGMS and FAO-WSI). Crop yield forecasting is done using predictors selected from the crop growth indicators. Dekadal SPOT-VEGETATION data are used as a basis for calculation of remote sensing indicators of crop growth. The Normalized Difference Vegetation Index (NDVI) and results of Dry Matter Production modelling (DMP) applying the Monteith approach (Monteith, 1972) are used as a main source of remote sensing indicators for the MECA region. The indicators are used in aggregated for sub-national administrative unit form applying crop mask. Some indicators are derived for a network of representative points. The current dekadal indicators are compared with previous year dekadal values or with long-term average dekadal data. Additionally relative time mosaics of indicators are used as a tool for crop growth monitoring (Savin, Nègre, 2002). We analyze additionally seasonal cumulative values of indicators by comparing seasonal time profiles. As a result, near 10 remote sensing indicators can be derived for each crop for each dekad of growing season in aggregated form and the same amount for representative points. Crop yield forecasting starts from an attempt to build simple regression equation between statistical crop yield and crop growth indicators. We found that regression with high R^2 can be built for many administrative units of MECA region. During the second phase of crop yield prediction the similarity analysis is applied. The aim of analysis is to define a year-analogue for indicator time profiles. This operation is conducted mainly for the administrative units where regression analysis does not give acceptable results. The last phase is devoted to comparison of indicator's value with previous year or long-term average value. Final yield prediction is made by expert taking into consideration the results of all phases of indicators analysis. The crop yield can be predicted quantitatively based only on remote sensing indicators for many administrative units of the region. For some units only a sign of crop yield changes can be predicted. In some cases it is impossible to predict crop yield based only on remote sensing indicators. The time when crop yield prediction can be made differs from region to region. For the most part of administrative units of the region the best time for crop yield prediction is allocated near crop flowering. However, for some units the best time is shifted to earlier or to later period of crop growing season. The results of the crop growth monitoring and yield prediction are summarized in the form of agro-meteorological bulletins, issued bimonthly for Russia and Central Asia, and for the Mediterranean countries.

1. INTRODUCTION

In 2001, the MARS project started what is now called the MARS-FOOD Action aimed at giving support to the EU Food Security and Food Aid policy by improving information on crop prospects, particularly in regions of the world stricken by frequent food shortages. The main end users are the European Commission services directly involved in food aid (DG DEV, DG AIDCO and EU delegations). The activities are carried out in close collaboration with the Food and Agriculture Organization (FAO) of United Nations. After the initial development and demonstration phase (2003-2004) the developed methods and systems are now being tested on a pre-operational basis (2005-2006). One of the test areas includes non-European countries of Mediterranean basin, Russia, and Central Asian countries (MECA region).

A common problem in crop monitoring and yield forecasting in many countries of the world is generally represented by the difficulties in extending locally calibrated forecasting methods to other areas or to other scales. Several agro-meteorological and remote sensing based indicators have proven to be highly correlated with yield (Rasmussen 1997; Lewis et al., 1998; Reynolds et al. 2000) for certain crops in specific areas. Recommendations on how to use multiple regression analysis have been released by international organizations like FAO (Gommes 2001), but due to the large geographic variability of all yield indicators, no synthetic procedure is available yet for a general and simple operational yield estimation procedure, based on the data available for each single site or country.

The purpose of the method elaborated and used by MARS-FOOD (Rembold et al., 2006) is not to solve the dilemma of geographic variability in yield estimation, but to develop a simple method, which for any place of the world combines the

available data for producing the best possible yield forecast. Such a processing chain is necessarily a multi-step procedure, where each step is developed case by case, depending on data availability and local climatic and agronomic indicators. The results of each step are then retained and quality flagged for computing the most likely final estimate. All intermediate results are inserted into a final matrix in a way that the user can evaluate the reliability of each step. The basic principle here is that converging results obtained by different methods reduce the error of the final estimate, while if there is no agreement they have to be used with more caution. On the other hand, a certain degree of freedom is left to the analyst in evaluating the reliability of the different estimates, leaving room to his additional knowledge of the study area. The proposed steps are not necessarily sequential but do normally follow a certain order based mainly on their complexity and the number of input data they involve. Expert knowledge is needed in the choice of indicators and in the final weighting of the results by the analyst. In this paper we describe our experience in using this approach in MECA region based on remote sensing data.

2. METHODS

Dekadal SPOT-VEGETATION data are used as a basis for calculation of remote sensing indicators of crop growth. We use the ten-day synthesis (S10) product, which is computed from all the passes on each location acquired during 10 day periods. The periods are defined from 1st to 10th, from 11th to 20th, from 21st to the end of each month. The synthesis between different passes is performed selecting the best measurement of the period defined from the following criteria: a) it does not correspond to a blind or interpolated pixel; b) it does not be flagged as cloudy in the status map; c) it does correspond to the highest value of Top of Atmosphere NDVI. For each pixel the ground surface reflectance in the four spectral bands is computed, the atmospheric correction being performed using the annotations of the primary product corresponding data. Geometric viewing conditions, reference to the date and time of the measurement, and information on the composite status map are also given. For each data set, the references of all corrections applied for calibration, atmospheric correction and geometric processing are produced. After that, clouds and snow cover masks are applied to all images.

The Normalized Difference Vegetation Index (NDVI), and results of Dry Matter Production modelling (DMP) applying the Monteith approach (Monteith, 1972) are used as a main source of remote sensing indicators for the MECA region. The indicators are used in aggregated for sub-national administrative unit form applying crop mask. The crop masks were created based on GLC2000 database (Global …, 2007), common agronomical practice knowledge, regional and countries' crop distribution paper maps, publications in scientific journals and other auxiliary information on regional crop geography. Some indicators are derived for a network of representative points. The current dekadal indicators are compared with previous year dekadal values or with long-term average dekadal data. Additionally relative time mosaics of indicators are used as a tool for crop growth monitoring (Savin, Nègre, 2002). Crop development stage-specific (relative time) NDVI mosaic is a scene of NDVI pixels, corresponding to the same crop development stage. Over the scene NDVI pixels can refer to different calendar dekads. Dates of crop phenological phases have not spatial variability within small region or for a separate pixel. In such situation the NDVI value of the current year must be compared with those of other year, which had been received

for predefined crop phenological phase. In this way the NDVI values are normalized for the characteristic time of crop growth. We analyze additionally seasonal cumulative values of indicators by comparing seasonal time profiles. As a result, near 10 remote sensing indicators potentially can be derived for each crop for each dekad of growing season in aggregated form and the same amount for the representative points (fig.1).
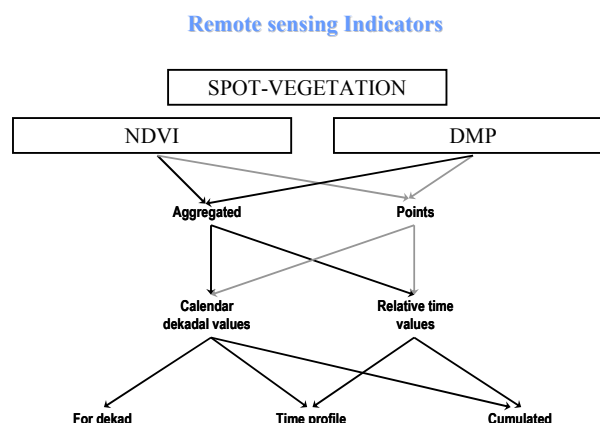

Figure 1. Diversity of potential remote sensing indicators of crop growth

Crop yield forecasting is done using predictors selected from the crop growth indicators. Crop yield forecasting starts from an attempt to build simple regression equation between statistical crop yield and crop growth indicators. We found that regression with high R^2 can be built for many administrative units of MECA region. The regression equations are updated after the end of crop growth season based on new coming crop yield statistical data. During the second phase of crop yield prediction the similarity analysis is applied. The aim of analysis is to define a year-analogue for indicator time profiles. This operation is conducted mainly for the administrative units where regression analysis does not give acceptable results. The similarity analysis was repeated 1 time every 2 months starting from the beginning of the growing season. The reliability of the results is increasing with each step until reaching a maximum on the middle of the season. The square sums of deviation between the indicator of the current and other seasons, as well as extreme deviation values were used for the definition of the year-analogue. The last phase is devoted to comparison of indicator's value with previous year or long-term average value. The results of all previous steps are resumed in a final matrix, which allows the analyst (and the users) to evaluate the quality of each single estimate. For the regression analysis the determination indices and prediction errors are retained for each of the examined indicators. Based on a final comparison of the results, by expert knowledge of the area and the qualitative use of any additional indicators (for example, analysis of local extremes of yield and indicator co-variation) available for the examined crop, the analyst finally decides a synthetic yield forecast. At the present stage, this evaluation procedure is driven mainly by expert evaluation. In the future the process could be partially automated by a higher harmonization of the single steps and a weighting system of their results.

3. RESULTS

The described above approach is used operationally for crop yield forecasting for the countries of MECA region since 2004. The approach is a part of crop yield forecasting system, where remote sensing indicators are used together with other crop growth indicators (meteorological, statistical and so on). The quality of crop yield forecasting can be observed from the table 1.

country	statistical wheat yield 2005 (t/ha) (available at FAOSTAT web site since 20.12.2005)	predicted 10.04.05	predicted 10.06.05
Algeria	1.4	1.3-1.5	1.1-1.3
Egypt	6.5	6.3-6.5	6.3-6.5
Israel	2.5	2.3-2.5	2.4-2.6
Jordan	1.4	1.3-1.5	1.3-1.5
Lebanon	2.6	2.5-2.7	2.6-2.8
Libya	0.8	0.7-0.9	0.8-1.0
Morocco	1.0	1.1-1.3	0.8-1.0
Palestine	2.3	2.2-2.4	2.2-2.4
Syria	2.5	1.9-2.1	2.3-2.5
Tunisia	1.6	1.6-1.8	1.4-1.6

Table 1. Example of wheat yield prediction for some countries from the MECA region

The significance of remote sensing indicators for crop yield prediction differs from country to country. In some regions crop yield can be predicted based only on regression analysis between yield and remote sensing indicators. In this case the R^2 of the regression models differs from 0.7-0.9 for Morocco, Algeria, Israel, Jordan, Saudi Arabia, Azerbaijan, Georgia, Iran, Uzbekistan, some regions of Russia, to 0.5-0.7 for Syria, Tajikistan, Armenia, Kyrgyzstan, and Afghanistan. Of course, the quality of regression models differs not only from country to country, but from crop to crop too (at given moment for the countries of MECA region a yield prediction is made for winter wheat, rice, maize, and potatoes).

Sometimes, analysis of similarity of the indicator behaviour between seasons can lead to receiving preliminary figures of crop yield. For example, figure 2 contains time profiles for a number of years of cumulated for the season DMP values for the areas with winter wheat in Stavropol region of Russia. As it can be deducted from the figure, two groups of profiles can be easy defined starting from the beginning of July: group with relatively high crop yield (seasons 2001/2002 and 2003/2004), and group with relatively low crop yield (other seasons). Thus, based on information in which group the time profile of the current season will be situated, it will be possible to deduct roughly the corresponding crop yield level.

The figures 3 and 4 demonstrate regions where winter wheat yield can be predicted based on only remote sensing indicators.

As can be resumed from these figures, for many administrative units the wheat yield can be predicted based only on remote sensing indicators. The usefulness of NDVI and DMP indicators depends mainly on specific of natural conditions, and varies from country to country. For some countries (for example, for Morocco and Uzbekistan) both indicators can be applied for crop yield prediction, for others – only one of these indicators can be used.
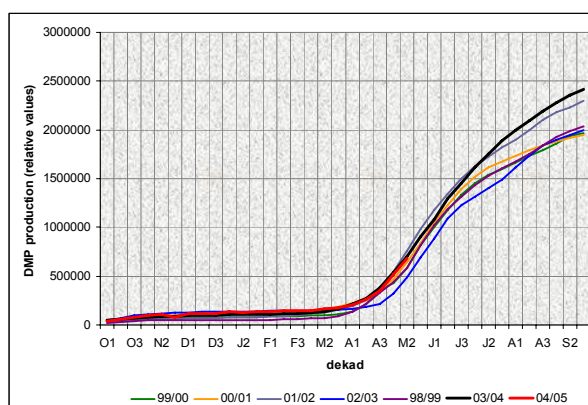
Figure 2. Time profiles of cumulated for growing season DMP values for winter wheat areas in Stavropol region of Russia (winter wheat yield (t/ha): 1999 – 2.4; 2000 – 2.3; 2001 – 2.8; 2002 – 3.3; 2003 – 2.4; 2004 – 3.5)
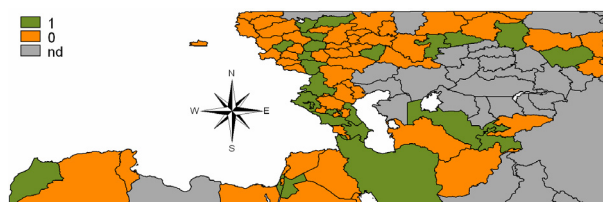
Figure 3. Administrative units within MECA region where winter wheat yield can be predicted using only NDVI based indicators (green units).
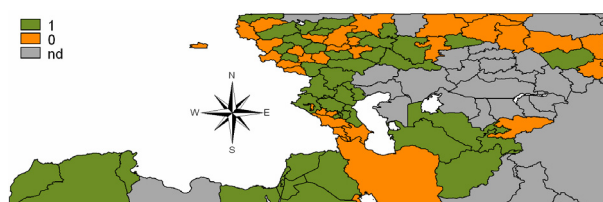
Figure 4. Administrative units within MECA region where winter wheat yield can be predicted using only DMP based indicators (green units).

Other important question is a time schedule for the yield prediction. Each step of the analysis can be implemented only at a given moment of the year, depending on statistical data availability for the previous season and on the results of the preliminary analysis of crop growth indicators. Based on analysis of crop growth predictors defined for the previous seasons, the optimal time schedule for crop yield prediction has been elaborated for each country of the region. For example,

best time for each step of the yield prediction for the Maghreb countries is resumed in Table 2.

Historical yield profiles can be analyzed only when the yield statistics for the previous season are available. In the FAOSTAT database data entries are made at different times of the year, but in general, preliminary yield data become available in December (for the previous season). Thus, the first step of the yield prediction procedure (analysis of historical yield profiles) can be implemented not earlier than December.

	Step of the analysis:				
	statistical yield time series	early yield indicator analysis	regression	similarity analysis	final prediction
Morocco	36*	13	10	13	13
Algeria	36*	1	7	13	13
Tunisia	36*	4	7	13	13

* - dekad of the previous year

Table 2. Earliest dekad of the year when each step of the analysis can be implemented

The comparison analysis of local extremes can be conducted for Morocco at the 13th dekad of the year, for Tunisia at the 4th dekad of the year, and for Algeria at the 1st dekad of the year. For example, in Tunisia there is a temporal resemblance between wheat yield and DMP extremes (fig.5). The local extremes of DMP in this country become evident starting from the 3[d] dekad of the year, after which the comparison analysis with historical yield data can be done. These findings are still based on a short time series and have to be used with caution. They are updated every year as soon as new data become available.

Regression analysis can be done at the 7th dekad of the year for Algeria and Tunisia, and at the 10th dekad for Morocco, when all necessary data for the calculation for the current season can be obtained.

Concerning the similarity analysis, it can be run every 2 months, but the most reliable results for these countries can be expected only after the last dekad of April.
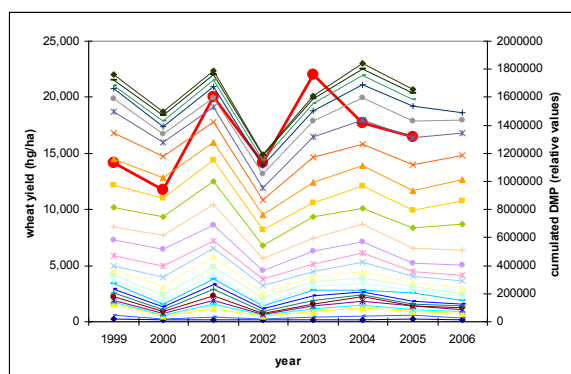
Figure 5. Co-variance between extremes of wheat yield in Tunisia (red line) and extremes of DMP indicator (each line corresponds to the dekad of the growing season)

Thus, preliminary yield prediction (mainly qualitative) can be implemented in different dekads of the year, while the final prediction based on the results of all steps can be done only when all of them are finalized. Thus, while the first results on wheat yield prediction in the Maghreb countries can be released already in December, the final prediction can be obtained only at the end of April.

4. CONCLUSIONS

Simple remote sensing indicators derived from SPOT-VEGETATION instrument can be successfully used as a source of crop yield predictors for the Mediterranean and Central Asian countries. In spite of low resolution of input data, the quality of crop yield forecasting is high enough. The quality varies from country to country, and from crop to crop. Potentially, the quality can be improved by adding into analysis other crop growth indicators (meteorological and statistical).

The elaborated methodology opens opportunity for simple quantitative crop yield forecasting for areas with relatively low data availability. It was developed for immediate operational use and each single phase can separately be improved by following the evidence of new studies in the field. Moreover, it can be successfully applied for other regions, and using remote sensing data of other spatial resolution. In the frame of this methodology the preliminary crop yield figures in many countries can be received during the crop flowering, and in some cases – before crop flowering.

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PILOT STUDY ON WHEAT AREA ESTIMATES IN TURKEY

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KEY WORDS: Remote sensing, wheat, area estimates, accuracy, area frame segment

ABSTRACT:

Cereal crops are very important plants just like any other country on the world supplying human food. It is important to know how much areas these crops cover for agricultural management and policy for sustainable food source. Recent advances showed that many countries have been using remote sensing technology as tool for estimation of agricultural production, yield and other related themes such as early warning, precision agriculture etc. This study aims to estimate cereal crop areas reliably in two different regions (Konya and Adana provinces) having different agricultural applications using satellite imagery and specific sampling method and to compare with farmers' declarations. The methodology for acreage estimation is based on the computation of proportional distribution of crop types in the segments (500 x 500 m), which were randomly selected over the agricultural areas and then extrapolating of this proportion to the rest of the area retrieved from classified satellite imagery. Crop type designation on segments was carried out by visiting the segments on the ground. The results were noticeable especially in comparing estimated acreages with the national statistics' figures which were coming from farmer declaration yielding an agreement of average 84 % for both regions.

1. INTRODUCTION

Agricultural policy plays a major role in the effective management of natural resources of a country. It is important that the acreage and condition of the various crop production sites, production amounts should be determined for a complete set up of agricultural planning. Agricultural statistics including yield, acreage, and other data is collected by local technical staff of Ministry of Agriculture from declarations of farmers in Turkey. These figures are sometimes subject to incoherencies year by year and generally considered as not reliable. This situation resulted in unfair treatment among the farmers who applied for subsidy given by throughout government's agricultural policy. There is also a requirement to know crop acreages for establishing good agricultural planning and management.

Considering these circumstances, there's always been a necessity to establish a methodology which is fast, consistent, as well as reliable for collecting agricultural data. Remote sensing has emerged as a revolution since 1970s and was considered valuable tool for extensive agriculture where land was remote and too large to observe from the ground (Rudd 1974). With the considerable development of computers, software, and new satellites the importance of remote sensing in agricultural applications has increased over the last ten to fifteen years. The Geographic Information Systems and Remote Sensing Department (CRIFC) of the Ministry of Agriculture and Rural Affairs (MARA) of Turkey was established in 1997 to collect information using such a technology. Since then,

CRIFC has carried out a number of national and pilot projects concerning agriculture and environment essence. This study is carried out under the FAO supported project named "Strengthening the Crop Yield and Production Forecasting Capability" between 2004 and 2006. This project was intended to build on the GIS and Remote Sensing capability available at MARA to improve area estimates, to combine it with agro meteorological yield estimates to routinely issue production estimates for wheat and barley. The main objective of this study was to determine a feasible methodology to estimate acreage of cereals (wheat & barley) in Konya and Adana provinces using satellite imagery. It was also expected to show that crop yield area estimated by remotely sensed imagery can be used for farmer subsidy payments.

2. MATERIAL AND METHOD

2.1 Study Area

Cereal production of Turkey is dependent upon mostly wheat and barley, which is concentrated in Central Anatolia. with rainfed conditions. With approximately 480 000 ha (SIS 2005) wheat acreage, Konya is the largest and the most wheat producer province in the country and located in central Anatolian Plateau. Konya province is therefore selected one of the study areas (Figure 1).
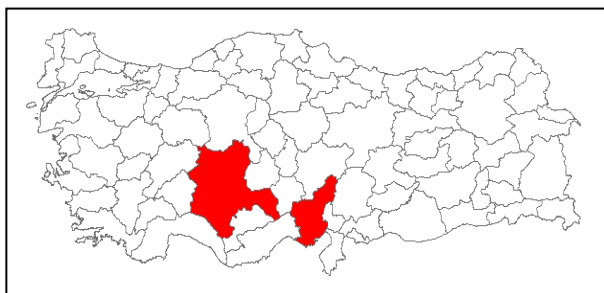
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* Corresponding author.

Figure 1. Study area

Cereal farming is habitual throughout the province. On the contrary, the other study area, Adana located at the south in Mediterranean coast, can be divided two sub-regions in terms of topography and climate. At the north, mountains cover the ground with dense forest, and very little agricultural activities are done (Figure 1). Climate is cold with dense snows in winter times. Unlike north, southern part of the province is entirely flat with various crops such as citrus, vegetable, maize, cotton and wheat as well. Mild climate conditions can be seen in winter with warm temperatures and plenty of rain which is typical for Mediterranean climate.

2.2 Image data

In the study, high spatial resolution imagery (HRV) and relatively low resolution image (Landsat TM and ATM) were used for both regions. HRV images were used for localize some of the segments and to prepare detailed sketch of crop distribution in segments. On the other hand, Landsat images were only used for classification procedure and thus producing thematic data of crops. Only four Landsat frames could cover regions. Two types of HRV images were purchased, SPOT 5 image for Konya province and two IKONOS images for Adana.

To determine the date of images a crop calendar was prepared based on the phenologic characters of the crops cultivated for both regions. Images procured are given in Table 1 below;

Imagery	Date	Path/Row
Landsat7	June 17, 2005	177-34
Landsat7	August 4, 2005	177-33
Landsat7	May 18, 2005	175-34
Landsat7	July 10, 2005	176-34

Table 1. Purchased imagery list

2.3 Method

In this study, methodology is a modified version of JRC's MARS (Monitoring Agriculture with Remote Sensing) project during 1990s (Gallego 1999) and JRC's Agrifish Unit web page, http://agrifish.jrc.it/marsstat/mini-sites.htm. An area frame was used to draw a sample of parcels from given segments with size of 500 by 500 meters. Landsat, Spot and Ikonos images, having different spatial resolution were used for the project. For crop acreage prediction Landsat images are used covering the whole terrain of the two provinces. VHR images such as Spot and Ikonos are used to determine the segment crop pattern and the proportional distribution of crops in the segments. 500x500 m dimensional grids namely area frame segments are prepared to ensure that they are all scattered over the study area without considering land use by means of GIS software.

For the selection of segments, an Area Fame Sampling method was used. Only the segments which fall in with the agricultural areas were selected from randomly scattered segments throughout the province. Out of those, 135 representative segments of agricultural areas in Konya and Adana provinces were selected for field visit, with the number of 85 and 50 segments respectively (Figure 2).

Field visits for selected segments were done by two teams in one week period for two regions. Field visits time schedules were last week of May 2006 for Adana and beginning of July for Konya. Segments were reached by their LL (lower left) coordinates recorded in GPS previously. During the field visits following tasks were realized: segments survey, recording of ground control points (GCPs) for landing marks and parcel visits. 116 points of collected GPS data were used for image rectification and reprojection.
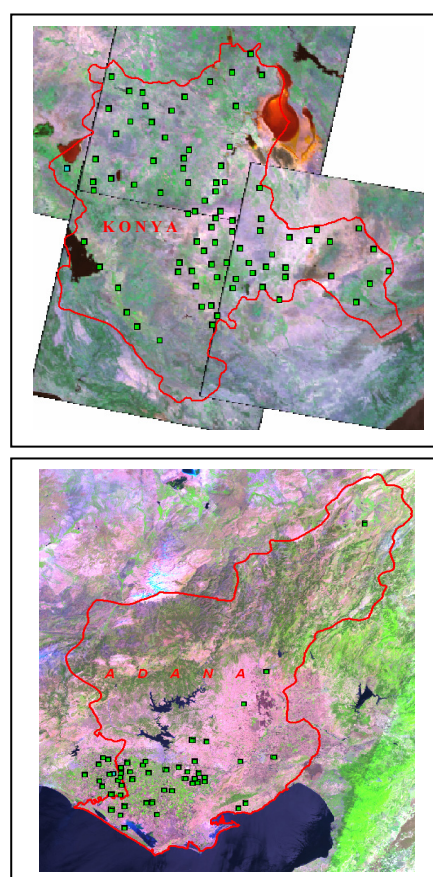
Figure 2. Segment locations

Crop pattern in the segments is identified and sketched (Figure 3). Surface area of the crops were determined and recorded over the sheets for extrapolating of this proportion to the agricultural area retrieved form satellite imagery. Parcel visits were also made to get land cover information which would be used for image classification. Image classification was performed using ground information from parcel visits to establish crop categories and develop clusters for the classification.
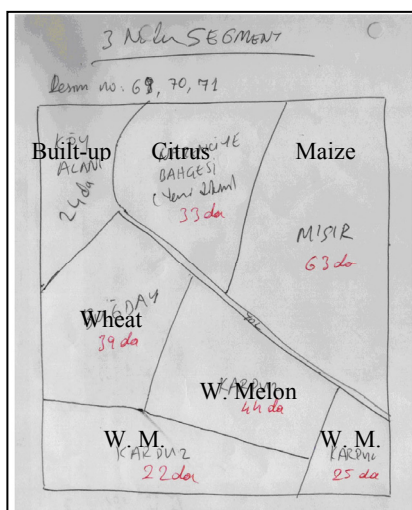
Figure 3. Sample segment sketch

3. RESULTS AND DISCUSSION

3.1 Results in Adana

Since northern part of the Adana is mostly forested and mountainous areas, selected segments are distributed over lowlands. There were 57 segments in Adana. Area of each segments were 25 ha totalling 1425 ha in 57 segments. Total wheat acreage in all of the segments was 494.4 ha which constitutes 36.2% of segment areas. The total agricultural area obtained by image classification of Adana was 438 000 ha, out of which 158,000 ha is wheat. This figure is found by extrapolating average wheat percentage (36.02%) obtained by segment visits to the whole agricultural area of the study region. On the other hand, wheat acreage obtained by image classification was 178 000 ha, which is higher than the acreage obtained by extrapolation. It should be noted that wheat acreage obtained by both extrapolation and image classification were less then official statistics.

Tot. W.A in Seg.	% of W.A in Seg.	Tot. A.A in Province	W.A by extrp.	W.A by Cls.	W.A by O.S
494.4	36.02	438,800	157,767	178,000	187,553

W.A - Wheat acreage   *Extrp - Extrapolation*
A.A – Agricultural area   *Cls.- Classification*
O.S – Official statistics

Table 2. Wheat area statistics (ha) for Adana.

3.2 Results in Konya

Unlike Adana, barley is also grown in Konya in addition to wheat. Since it is difficult to classify wheat and barley separately in satellite imagery, they were classified together and wheat and barley acreage figure was given together.

The number of the segments is 85 in Konya totalling 2125 ha. Total wheat acreage in all those segments was 730 ha which constitutes 34.4% of segment areas. If this proportion is applied to total agricultural area which was 1,818,000 ha derived from classified imagery, we find 618,150 ha wheat area. Total barley area in 85 segments was 552 ha, in other words 26% of the total segment areas. When we extrapolate barley percentage in segments to the whole agricultural area, we got 472,700 ha barley acreage. Total wheat and barley acreage obtained from extrapolation was 1,090,000 ha (Table 3a and 3b).

Tot. W.A in Seg.	% of W.A in Seg.	Tot. A.A in Province	W.A by extrp.	W.A by O.S (SIS, 2005)	W + B.A by O.S (SIS, 2005)
730	34.4	1,818,000	618,050	716,000	1,303,000

W + B.A – Wheat and Barley acreage

Table 3a. Wheat-barley area statistics (ha) for Konya

Tot. B.A in Seg.	% of B.A in Seg.	B.A by extrp.	W + B. A by extrp.	W + B. A by cls.	B.A by O.S (SIS, 2005)
552	26	472,700	1,090,000	951,000	587,000

Table 3a. Wheat-barley area statistics (ha) for Konya

Image classification results showed that total wheat-barley areas amount to 951,000 ha. Again total wheat-barley acreages obtained by both extrapolation and image classification were less then official statistics as was in Adana.

Crop area estimations obtained from segments were comparable to official statistics for both provinces, yielding an agreement of 83.7% for Adana and 87% for Konya.

In case of remote sensing area estimates; there was good agreement between area obtained through image classification and NS in Adana (95% correlation), but lower correlation (73% agreement) was found in Konya.

4. CONCLUSIONS

Segment visits produced comparable to official statistics but it is time consuming and costly. Image processing also requires high labour cost especially for larger areas. Use of data from farmer registration system requires may improve accuracy of RS results.

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AN OPTIMAL TEMPORAL RESOLUTION OF MULTISPECTRAL SATELLITE DATA FOR FIELD-SCALE AGRICULTURE

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KEY WORDS: Agriculture, Crop, Monitoring, Modelling, Estimation, Classification, Simulation, SPOT

ABSTRACT:

The objective of this study was to define the temporal resolution of future space missions dedicated to field-scale agriculture. The approach consisted in the assessment of the retrieval performance of the green area index (LAI) as a function of satellite revisit frequency. In this respect, different acquisition scenarios were simulated taking into consideration realistic LAI evolutions on large wheat fields, as well as realistic hypotheses: three levels of measurement errors and models uncertainties (10%, 20% and 25%), two probability levels of daily clouds occurrence (0.5 and 0.7), all these factors being combined with six scenarios of revisit frequency, covering the current capabilities of sensors (from 1 to 30 days). The high revisit frequency at high space resolution was routinely achieved by the concurrent use of three SPOT satellite sensors. The lack of continuous temporal coverage of estimated LAI values was overcome using a semi-empirical evolution model (MODLAI).

The results of the simulations indicated that RMSE between the estimated and reference LAI values are low, and quite similar, up to 7 days revisit frequency, regardless of the error level or the cloudiness probability. These results were explained by the very good temporal interpolation performances of MODLAI, when the number of good quality acquisitions allowed its fine adjustment.

1. INTRODUCTION

This paper presents results obtained during the ADAM Project (http://kalideos.cnes.fr/index.php?id=accueil-adam) investigating the "Assimilation of spatial Data by Agronomic Modelling". This project was an important scientific co-operation between France and Romania.

One of the major objectives of ADAM was to define the main characteristics, including the temporal resolution (i.e. revisit frequency), required for future space missions dedicated to field-scale agriculture. The investigation focused on the monitoring of the green leaf area index (LAI), which is related to productivity and can be estimated from the available multispectral data.

At present, LAI evolution is currently monitored only at *coarse and medium spatial resolution* by large swath sensors (e.g. AVHRR, VEGETATION, MODIS and MERIS) and used as input in global models of biosphere-atmosphere exchanges of energy, carbon dioxide, water vapour and other materials.

In the first stage of this study, the objective was to prove that knowledge and technology are mature enough to monitor the LAI evolution also at *high spatial resolution*, by using the depointing capability of SPOT series of satellites to increase the revisit frequency. Besides, a semi-empirical model of LAI evolution was used to exploit the high temporal consistency of crop growth. A subjacent result of the first stage was the generation of a "reference" LAI dataset to be further used for this investigation.

The second and main stage was focused on the definition of an optimal satellite revisit frequency that allows fulfilling a basic information need at the field scale, namely weekly estimates of LAI at a spatial resolution between 10 and 20 m.

2. DATA AND METHODS

Data. The ADAM site is dominated by large agriculture fields (15-40 ha) located in Fundulea, at about 35 km east of Bucharest.

Thirty nine SPOT satellite images were acquired in multispectral mode, from October 2000 to July 2001. The high temporal resolution was assured by the concurrent use of SPOT1, SPOT2 and SPOT4 satellites. The radiometric corrections implied sensor inter-calibration, as well as atmospheric corrections using data gathered by a sun-photometer connected to the AERONET network. The geometric corrections were performed by spatio-triangulation. The entire pre-processing phase was supervised by the French Space Agency and resulted in a high quality time series of 33 images expressed in "Top of Canopy reflectance" (ρ_{TOC}) values.

On the ground, LAI was frequently measured over 42 elementary sampling units (ESUs) by the destructive technique. Only wheat crops were monitored. The ESUs represented the largest range of crop conditions, accounting for variation in cultivar, sowing date, precedent crop, fertilization, and micro-topography. Each ESU covered 30m x 30m, being representative of a small number of SPOT XS contiguous pixels

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(about 1 ha total area). Ten more frequently sampled ESUs were intended for the method calibration, and the remaining 32 for its validation. The meteorological data were continuously gathered by an automatic station installed in the ADAM site centre.

Methods. Figure 1 illustrates the flow of procedures carried out throughout this study. For the clarity of explanations, the MODLAI model appearing several times in Figure 1 will be described at this point.

MODLAI was inspired by an evolution model first defined by Baret and Guyot (1986). In the present study, MODLAI describes the LAI evolution as a function of the "accumulated daily mean air temperature" (above 0°C for wheat) starting from sowing, variable named T in Equation (1):

$$LAI = K\left[\frac{1}{1 + e^{-b(T-T_i)}} - e^{a(T-T_s)}\right] \qquad (1)$$

The main advantages of MODLAI are the availability of T in practice and the reduced number of parameters, all the more so they have biological meanings:

K = amplitude of the maximal leaf area
Ti = accumulated temperature at the first inflexion point
b = relative growth rate at Ti temperature
a = relative senescence rate, and
Ts = accumulated temperature at the time of green leaves disappearance

Back to Figure 1, the top section (coded "I") shows the steps accomplished during the first stage of this study:
- The MODLAI parameters were estimated for each calibration unit (CU) by model inversion, using the look-up table (LUT) method for global optimization (Knyazikhin *et al.*, 1998).
- After adjustment, MODLAI was run in the forward direction to estimate LAI over the CUs at the satellite acquisition dates.
- Next, for each acquisition date, a transfer function was determined by multiple linear regression:

$$LAI(t) = \alpha_0 + \sum_{b=1}^{3} \alpha_b \rho_{TOC,b}(t) + \varepsilon \qquad (2)$$

where b = SPOT band number (G = 1, R = 2, and NIR = 3)

α_i (i = 0..3) = regression coefficients, and ε = residual
- MODLAI was adjusted again by the same LUT method, this time using the LAI values retrieved thanks to the transfer functions and the corresponding satellite data. This enabled the daily estimation of LAI on CUs.
- The performance of the LAI retrieval was evaluated by calculating the coefficient of determination (R^2) and the root mean square error (RMSE) between measured and estimated LAI at the dates of ground sampling on CUs. The very good performance, shown in the "Results" section (Figure 2), accounted for the next steps.
- The validation of the retrieval method started with a multitemporal classification applied over the wheat fields using the time series of SPOT images. In this respect, the ISODATA algorithm was used under the assumption that thirty TOC reflectance classes can adequately describe the spatial and temporal variability of the wheat fields.
- The estimation of the LAI values for each ISODATA class was achieved using the previous transfer functions.
- MODLAI was again readjusted based on the last LAI estimates and the corresponding satellite data; it was then run to estimate the daily LAI values over all wheat fields.
- The overall retrieval performance was evaluated calculating R^2 and RMSE between measured and estimated LAI at the

dates of ground sampling on the 32 validation units (VUs). The performance was again very good ("Results" section, Figure 3). Thus, it was demonstrated that knowledge and technology are sufficient mature to monitor LAI at high spatial resolution.

In particular, it was possible to regard the daily LAI estimates over the 42 ESUs as daily "true" values. Nevertheless, considering the actual updating need, which is once a week, the daily "true" LAI was sampled to generate a weekly data set to serve as "reference" LAI for the next stage of the project.

Figure 1 Methods diagram
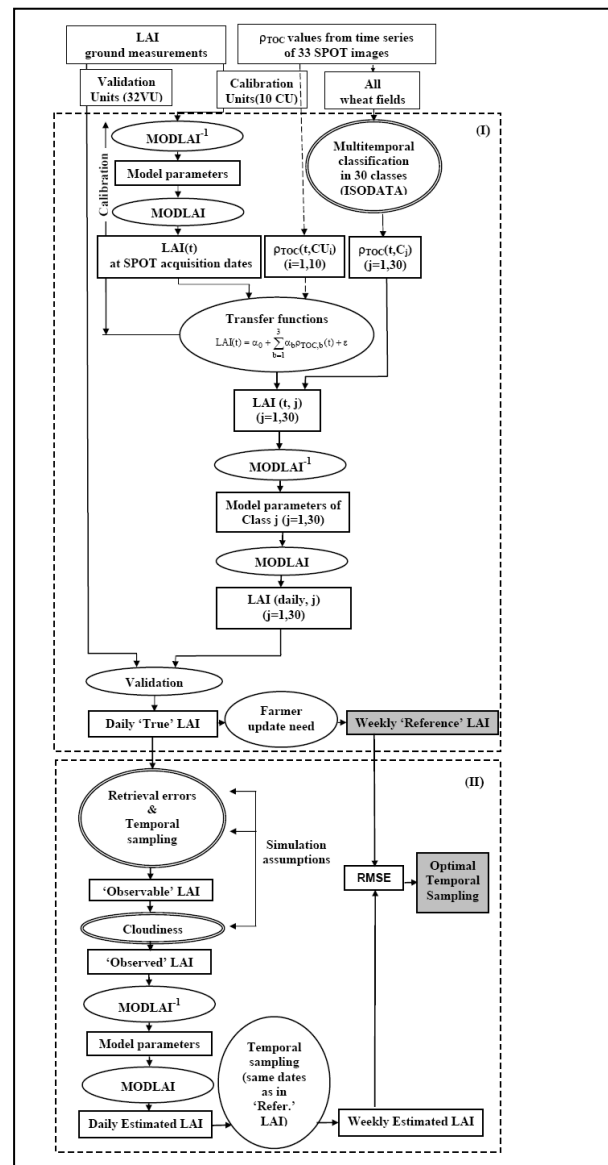
The objective of the second stage was to define an optimal temporal resolution of satellite data to fulfil the basic need at the field scale to dispose of weekly estimates of LAI at a spatial resolution between 10 and 20 m. The approach was based on the simulation of tens of thousands of acquisition scenarios over the 42 ESUs. The scenarios were defined under the following hypotheses: (i) 3 levels of LAI retrieval errors (modelled as additive white Gaussian noise): 10%, 20%, and 25%; (ii) 6 satellite revisit frequencies: 1, 2, 3, 7, 15, and 30 days; (iii) 2 probability levels of daily clouds occurrence: 0.5 and 0.7. The steps performed during this stage are shown in the bottom section of Figure 1 (coded "II"):

- According to the first hypothesis, several daily "noisy" LAI data sets were generated from the daily "true" LAI. Further, the hypothesis on the revisit frequencies, with the start day of the orbital cycle randomly selected, transformed the daily "noisy" LAI data sets into ad-hoc called "observable" LAI data sets.
- The third hypothesis on cloudiness further selected the ad hoc called "observed" LAI data sets.
- The continuous temporal coverage of LAI estimates was generated using again MODLAI.
- An optimal temporal resolution of satellite data was defined by evaluating the retrieval performance for all scenarios (Figure 4 below). RMSE was calculated between the estimated and reference LAI, for each fixed weekly date of the growth cycle.

3. RESULTS AND DISCUSSION

The good performance of LAI retrieval during the first stage of the study is illustrated below. Thus, it can be seen in Figure 2 that RMSE ≈ 0.28 between measured and estimated LAI on the calibration units, while R2 ≈ 0.96, and in Figure 3 that MODLAI has a good capacity to describe the LAI evolution on the validation units (performance shown for VU26).

The results of the second stage were obtained by repeating (3x6x2x42) scenarios 35 times, to get values statistically meaningful while accounting for the random character of clouds occurrence and individual LAI retrieval uncertainties. Figure 4 shows the overall retrieval performance as a function of satellite revisit frequency. Results indicate that the errors of the weekly LAI estimates as compared to the reference LAI are low and quite similar up to 7 days revisit frequency. MODLAI was always well adjusted to the dataset of individual observations, when their number was large enough (i.e. between 12 and 18 observations spanning over the 9 months growth cycle). For lower revisit frequencies, results show that the quality of individual LAI retrieval is very important, calling for improved radiometric accuracy, radiative transfer models and inversion procedures.
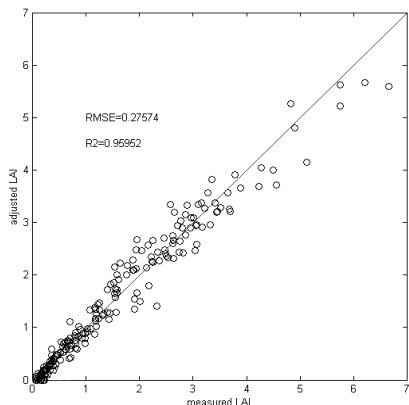
Figure 2   Calibration performance
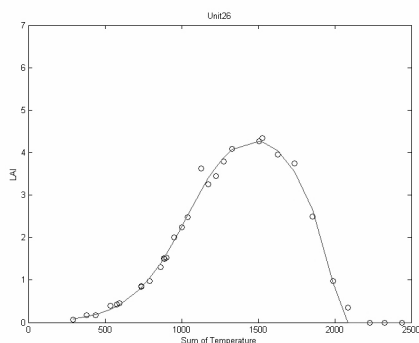
Figure 3   Example of validation

4. CONCLUSION AND PERSPECTIVES

The main conclusion of this study is that combining reasonably high temporal and spatial resolution satellite images - weekly
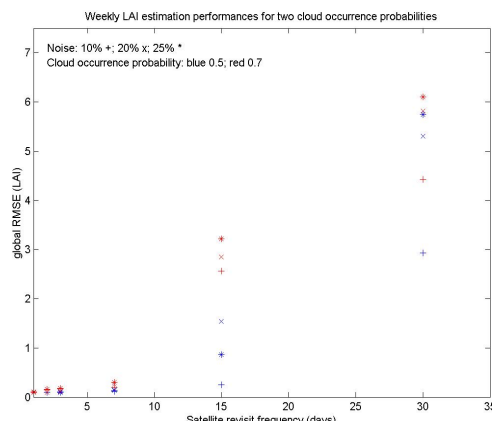
Figure 4   Overall performance of LAI

observations at 10-20m - with knowledge on canopy functioning may provide a pertinent information to decision makers at the field scale. This result was obtained by exploiting the temporal dimension of the remotely sensed data within an evolution model. The approach allowed adequate temporal interpolation, as well as smoothing out estimates from remotely sensed reflectance. These findings are in accordance with Kötz *et al.* (2005), who found significant improvement on maize LAI estimates by using the same MODLAI model.

A step ahead would be the replacement of this simple evolution model by a true crop functioning model (e.g. STICS), which may account for more detailed processes, resulting in higher accuracy and direct access to biomass, yield, water and nitrogen balance. Moreover, it is likely that the launching of space missions dedicated to field-scale agriculture will foster the advancement of techniques based on assimilation of remotely sensed data within crop functioning models (Lauvernet, 2005).

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