

COTTON YIELD ESTIMATION IN UZBEKISTAN INTEGRATING MODIS, LANDSAT ETM+ AND FIELD DATA

G. R. Ruecker^{a,*}, Z. Shi^b, M. Mueller^c, C. Conrad^a, N. Ibragimov^d,
J. P. A. Lamers^c, C. Martius^c, G. Strunz^a, S.W. Dech^a

^a German Remote Sensing Data Center (DFD), German Aerospace Center (DLR), 82234 Wessling, Germany - (gerd.ruecker, christopher.conrad, guenter.strunz, stefan.dech)@dlr.de

^b Institute of Agricultural Remote Sensing and Information System, Zhejiang University, Hangzhou 310029, China - shizhou@zju.edu.cn

^c Center for Development Research (ZEF), University of Bonn, Walter-Flex-Str. 3, 53113 Bonn, Germany - (marc.mueller, c.martius, jlammers)@uni-bonn.de

^d Uzbekistan National Cotton Growing Research Institute, Tashkent, Uzbekistan - nazar@zef.uzpak.uz

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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-

meteorological 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)

* Corresponding author.

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).

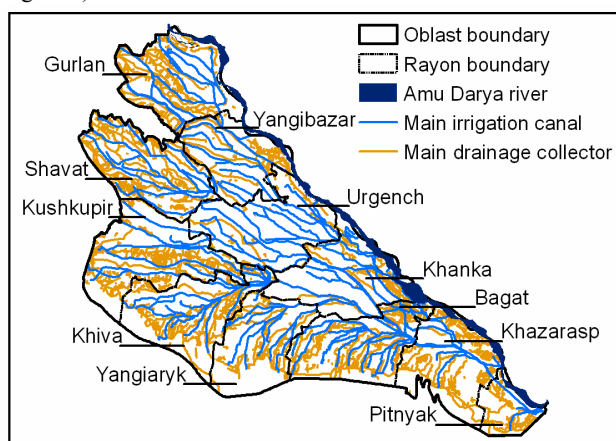


Figure 1. Study area

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).

$$Y = H_i \times \sum (\varepsilon \times PAR \times FPAR) \Delta t \quad (1)$$

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 ($0.4\text{--}0.7\ \mu m$) is part of the short-wave solar radiation ($0.3\text{--}3.0\ \mu m$), 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).

$$\varepsilon = \varepsilon' \times T' \times V' \quad (2)$$

where ε' is the maximum light-use efficiency, T' is a daily minimum temperature (TMIN) scalar value ($^{\circ}C$), 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).

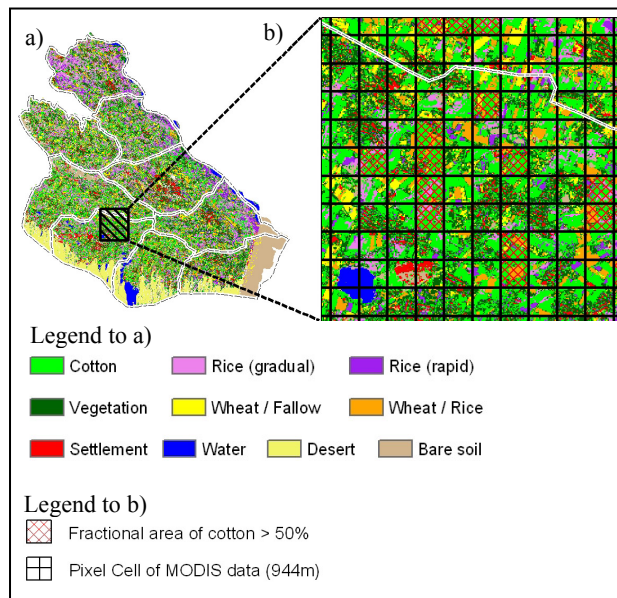


Figure 2. The land use map at 30m pixel resolution (a) and one enlarged landscape overlaid with MODIS pixel cell of ca. 1 km resolution (dark grid, a) and selected pixels with fractional area larger than 50% (red cross lattice, b).

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).

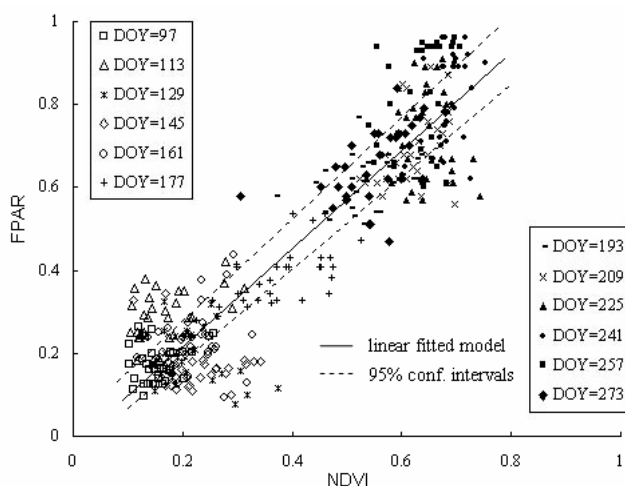


Figure 3. Scattergram of MODIS NDVI and FPAR data for different days of year (DOY) during the cotton growth period in Khorezm, and their linear fitted model and regression 95% confidence intervals.

The scattergram shows a good linear relationship between MODIS NDVI and FPAR data ($N = 384$) with:

$$\text{FPAR} = -0.0187 + 1.1799 * \text{NDVI} \quad (3)$$

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 H_i (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 H_i 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 H_i 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 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).

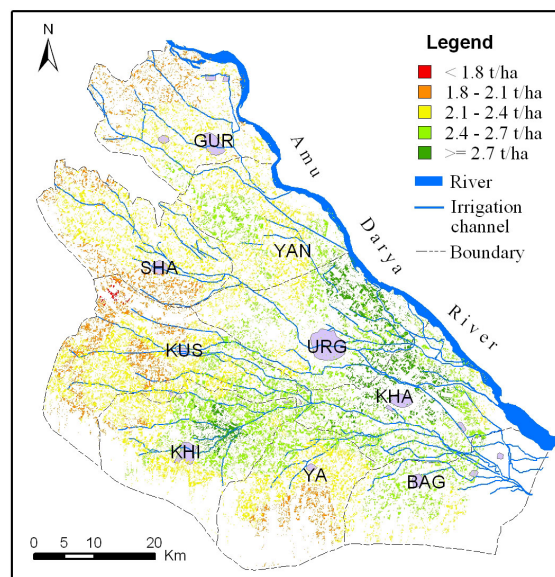


Figure 4. Cotton yield variation across Khorezm in 2002 after block-kriging interpolation from selected MODIS pixels.

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 Gurlan (GUR)) or in areas farther away from the Amu Darya River where no strong primary irrigation water supply exists (e.g. Kushkupyur (KUS), Yangiaryk (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
Kushkupyur (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, Kushkupyur 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, Urganch 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.

5. REFERENCES

- Allen, R.G., L.S. Pereira, D. Raes, M. Smith. 1998. Crop evapotranspiration: guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper, No. 56, FAO, Rome.
- Baez-Gonzalez, A.D., P.Y. Chen, M. Tiscareno-Lopez, and R. Srinivasan. 2002. Using satellite and field data with crop growth modeling to monitor and estimate corn yield in Mexico. *Crop Sci.* 42:1943–1949.
- Bastiaanssen, W.G.M. and S. Ali. 2003. A new crop yield forecasting model based on satellite measurements applied across the Indus Basin, Pakistan. *Agric. Ecosyst. and Environ.* 94: 321-340.
- BISNIS. 2004. Business Information Service for the Newly Independent States, Department of Commerce, USA. http://www.bisnis.doc.gov/bisnis/bisdoc/0405_UZ_News.htm (assessed 05 Feb. 2007).
- Conrad, C., G.R. Ruecker, C. Schweitzer, S. Dech, and M. Hafeez. 2004b. Modeling seasonal actual evapotranspiration with remote sensing and GIS in Khorezm region, Uzbekistan. *In Proc. of the 11th SPIE International Symposium on Remote Sensing, Maspalomas, Gran Canaria / Spain, 13-16 September 2004.*
- Doraiswamy, P.C., J.L. Hatfield, T.J. Jackson, B. Akhmedov, J. Prueger, and A. Stern. 2003. Crop conditions and yield simulations using Landsat and MODIS. *Remote Sens. Environ.* 92: 548-559.

- Fensholt, R., I. Sandholt, and M.S. Rasmussen. 2004. Evaluation of MODIS LAI, fAPAR and the relation between fAPAR and NDVI in a semi-arid environment using in situ measurements. *Remote Sens. Environ.* 91: 490-507.
- Forkutsa, I. 2006. Modeling water and salt dynamics under irrigated cotton with shallow groundwater in the Khorezm region of Uzbekistan. *Univ. Bonn. ZEF Series in Ecology and Development*, No. 37, 158 pp.
- Goetz, S.J., S.D. Prince, S.N. Goward, M.M. Thawley, and J. Small. 1999. Satellite remote sensing of primary production: an improved production efficiency modeling approach. *Ecol. Model.* 122:239-255.
- Hargreaves, G.L., G.H. Hargreaves, and J.P. Riley. 1985. Irrigation water requirement for Senegal River Basin. *J. Irrig. Drainage Eng-ASCE.* 111:265-275.
- Huete, A., K. Didan, T. Miura, E.P. Rodriguez, X. Gao, and L.G. Ferreira. 2002. Overview of the Radiometric and Biophysical Performance of the MODIS Vegetation Indices. *Remote Sens. Environ.* 83: 195-213.
- Justice, C., J. Townshend, E. Vermote, E. Masouka, R. Wolfe, N. Saleous, D. Roy, and J. Morisette. 2002. An overview of MODIS land data processing and product status. *Remote Sens. Environ.* 83: 3-15.
- Lobell, D.B., G.P. Asner, J.I. Ortiz-Monasterio, and T.L. Benning. 2003. Remote sensing of regional crop production in the Yaqui Valley, Mexico: estimates and uncertainties. *Agric., Ecosyst. Environ.* 94:205-220.
- MODIS Land Team. 2003. User's Guide of GPP and NPP (MOD17A2/A3) Products-NASA MODIS Land Algorithm, Version 1.3. p50.
- Monteith, J.L. 1972. Solar-radiation and productivity in tropical ecosystems. *J. Appl. Ecol.* 9: 747-766.
- Monteith, J.L. 1977. Climate and efficiency of crop production in Britain. *Philos. Trans. R. Soc. B-Biol. Sci.* 281:277-294.
- Moulin, S., A. Bondeau, and R. Delécolle. 1998. Combining agricultural crop models and satellite observations: from field to regional scales. *Int. J. Remote Sens.* 19:1021-1036.
- Myneni, R.B., S. Hoffman, Y. Knyazikhin, J.L. Privette, J. Glassy, Y. Tian, Y. Wang, X. Song, Y. Zhang, G.R. Smith, A. Lotsch, M. Friedl, J.T. Morisette, P. Votava, R.R. Nemani, and S.W. Running. 2002. Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. *Remote Sens. Environ.* 83: 214-231.
- OblStat. 2002. Regional Department of the Ministry of Macro-Economics and Statistics of the Republic of Uzbekistan in Khorezm Oblast; Agricultural Indicators for Khorezm Oblast, 1998-2001, Urgench.
- Prince, S.D., and S.N. Goward. 1995. Global primary production: A remote sensing approach. *J. Biogeogr.* 22: 815-835.
- Quarmby, N.A., M. Milnes, T.L. Hindle, and N. Silleos. 1993. The use of multi-temporal NDVI measurements from AVHRR data for crop yield estimation and prediction. *Int. J. Rem. Sens.* 14: 199-210.
- Ressl, R., S.W. Dech, A. Ptichnikov, N. Novikova, and P. Micklin. 1998. Desertification Monitoring and Land use Optimization in the Aral Sea Area with GIS. *GIS Zeitschrift für Geoinformationssysteme*, 6:25-32.
- Rosenthal, W.D., and T.J. Gerik. 1991. Radiation use efficiency among cotton cultivars. *Agron. J.* 83: 655-658.
- Ruecker, G.R., and C. Conrad. 2003. Exploring Leaf Area Index Development and Land Cover Classification in the Lower Amu-Darya Basin in Uzbekistan Based on Multi-Temporal and Multi-Spatial Remote Sensing Data. *ZEF Work Papers for Sustainable Development*, Series No. 5. Center for Development Research, Bonn, Germany.
- Running, S.W., D. Baldocchi, D. Turner, S.T. Gower, P. Bakwin, and K. Hibbard. 1999. A global terrestrial monitoring network integrating tower fluxes, flask sampling, ecosystem modeling and EOS satellite data. *Remote Sens. Environ.* 70:108-127.
- Schweitzer, C. 2005. Entwicklung eines wissensbasierten Klassifizierungsansatzes zur Kartierung der Landnutzung in Khorezm (Usbekistan) auf der Basis von Expertenwissen, GIS-Daten sowie multi-spektralen/multitemporalen Landsat/MODIS Daten, unpublished Master thesis, University of Göttingen, p. 110.
- Shi, Z., Ruecker, G.R., Mueller, M., Conrad, C., Ibragimov, N., Lamers, J.P.A., Martius, C., Strunz, G., Dech, S., Vlek, P.L.G. 2007 Modeling of Cotton Yields in the Amu Darya River Floodplains of Uzbekistan Integrating Multitemporal Remote Sensing and Minimum Field Data, forthcoming in *Journal of Agronomy*.
- Smith, M., R. Allen, J.L. Monteith, L.A. Pereira, A. Perrier, and A. Segeren. 1991. Report on the expert consultation for the revision of FAO methodology of crop water requirements. FAO/AGL, Rome.
- Sys, I.C., E. Van Ranst, and J. Debaveye. 1991. Land evaluation, Part I: Principles in land evaluation and crop production calculation. *Agricultural Publication-N° 7*, General Administration for Development Cooperation of Belgium, Brussels.
- Varlet-Grancher, C., R. Bonhomme, M. Chartier, and P. Artis. 1982. Efficience de la conversion de l'énergie solaire par un couvert végétal. *Acta Oecologia. Oecol. Plant.*, 3, 3-26.
- Vlek, P.L.G., C. Martius, P. Wehrheim, A. Schoeller-Schletter, and J. Lamers. 2003. Economic Restructuring of Land and Water Use in the Region Khorezm (Uzbekistan) (Project Proposal for Phase I). *ZEF Work Papers for Sustainable Development in Central Asia*, 1, 75 pp. http://www.khorezm.uni-bonn.de/unterseite_publications_work_paper_series.htm. (assessed 3 Jan. 2007).

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CROP YIELD PREDICTION WITH SPOT VGT IN MEDITERRANEAN AND CENTRAL ASIAN COUNTRIES

I. Savin

AGRIFISH unit, Institute for the Protection and Security of the Citizen, Joint Research Centre, European Commission –
igor.savin@jrc.it

Commission VIII, WG VIII/10

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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