A review of the use of remote sensing for crop forecasting in Australia

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Abstract - Operational remote sensing systems are currently being used to monitor crop growth and climate to map impacts on crop production. The linking of these data to traditional crop forecasting systems has the capacity to improve both the spatial and temporal resolution of crop forecasts.

Keywords: crop forecasting, crop growth, yield prediction.

1. INTRODUCTION

Crop forecasting is an essential resource for Australia's agricultural industries. A number of activities are currently carried out in Australia to forecast crop yield and production, including surveys and censuses, crop modelling, weather and climate prediction and mapping using near-real-time remotely-sensed data.

Increasingly, traditional forecasting is being supplemented by information derived from remote sensing data at State and regional-levels. Improvement in the timeliness and accuracy of crop area and yield forecasting through the incorporation of remote sensing will improve our national capacity to respond effectively to the future challenges of climate variability and the impacts of climate change on agriculture.

The aim of this paper is to review Australian experiences in the use of remote sensing for monitoring crop production and forecasting and identify how these may be integrated to improve crop forecasting in the future.

2. AGRICULTURAL CENSUS AND SURVEY

The Australian Bureau of Statistics (ABS) agricultural census is the prime source of agricultural commodities statistics and is conducted every five years. The census is sent to the 170 000 farms with an estimated value of agricultural operations of greater than AUD$5 000. In non-census years the ABS conducts a survey of around 30 000 farms, stratified by industry, size of operation and region. This survey collects a similar data set to the census and estimates are produced at national, state and regional levels. The census and survey are likely to utilise web-based data entry in the future.

While the ABS surveys focus on aggregated production information, ABARES conducts a much smaller annual survey that collects detailed financial information for around 2 000 farms from the broadacre cropping, grazing and dairy industries. These industries account for around 70 per cent of all farms (Lubulwa *et al*., 2010). This survey is also stratified by industry, size and survey region and produces estimates at the regional, state and national levels. The Australian grain industry is covered by 12 of the survey regions. In order to integrate this survey information with other spatial data, a range of data capture methods have been trialled. At a minimum a single point location is recorded for each farm although polygon data capture has also been used for specific projects (e.g. Davidson *et al.,* 2006).

3. MAPPING AGRICULTURAL LAND USE

Operational remote sensing systems are currently being used in assessments of land use, land cover and crop area estimates. Due to the large land area in Australia and with most areas being relatively cloud-free, remote sensing is the most cost-effective option for mapping agricultural land use at a national-scale.

Two sets of data are collected through the Australian Collaborative Land Use and Management Program (ACLUMP) which promotes the development of nationally consistent land use and land management data in Australia:

Catchment-scale mapping is produced by combining Australian State government-held cadastral data (land tenure) with existing land uses and interpretations of satellite imagery. Initial mapping has been carried out using Landsat TM data but more recent updates use SPOT 5, Ikonos and QuickBird data. The data are captured at a range of scales from 1:25 000 in urban, peri-urban and irrigated areas, 1:100 000 in broadacre cropping areas and 1:250 000 in pastoral areas. Data are captured and classified according to hierarchical land use codes and then verified in the field. Independent validation is then carried out to ensure the data have accuracy greater than 85 per cent. These data are updated every 5 to 10 years and are suitable for constructing crop masks.

National-scale mapping is carried out by spatially disaggregating five-yearly ABS agricultural census data using concurrent AVHRR NDVI imagery. The SPREAD II (Barry *et al.,* 2008) model constrains the classification of the NDVI using statistical local area-level ABS census data. The outputs of the model include probability surfaces for each commodity which are then classified into dominant land use and presented at a scale of 1:2 000 000. The most recent map available uses the 2005–06 agricultural census results. These data are useful in determining the variety of crops and agricultural activities in an area and for validation of agricultural production data obtained by remote sensing.

Recent work by Potgieter *et al.* (2010) has investigated the potential of using MODIS 16-day composite EVI time-series across the cropping season to classify crop areas. This work successfully discriminated the winter crops in Queensland's major grain growing areas by applying the Fourier Transform approach to initial EVI profiles and then classified crop types using ground data collected from a range of collaborators. A more recent analysis demonstrated similar success with a parametric curve fitting approach that also shows promise for within-season analyses (Potgieter and Lawson, 2010). Estimates are enhanced by the use of potential crop area masks. This work demonstrates that successful crop discrimination requires accurate ground data and a regional approach.

4. CROP PRODUCTION FORECASTING

Crop forecasting systems in Australia are mostly limited to the major cereal crops. Crop forecasts have been developed to assist decision-making for handling and marketing crop commodities and for the assessment of the impact of extreme climatic events.

Simple agro-climatic models are the preferred models for regional crop forecasts. A comparative study by Hammer *et al.* (1996) found that simpler empirical models and agro-climatic (stress index approaches) had better predictive ability and had less input requirements than some of the more complex simulation approaches (e.g. APSIM).

The stress index models (Oz-Wheat, SSIM and STIN) (derived from Nix and Fitzpatrick,1969) use a weekly simple dynamic tipping bucket water balance model. Climate and crop-specific parameters are integrated to produce a stress index. The model input parameters are selected based on the best fit when calibrated against actual shire or local government area (LGA) yields from ABS. The stress index model outputs are generated at point-scale and then aggregated to create a LGA-scale index. This index value is transformed to yield/unit area through a simple regression model.

The various crop models currently estimate up to 80 per cent of the variation in yield. Estimates of regional yield contend with the use of average inputs for the regional-scale that actually encompasses heterogeneity of those inputs, inaccuracy of climate forecasts and the inability to model pests, disease and erosion.

National commodity forecasts

ABARES produces the national crop production forecast four times per year - in February, June, September and December. Inputs include regional yield forecasts based on a simple stress index model (detailed above) provided by the Agricultural Production Systems Research Unit of the Queensland Department of Employment, Economic Development and Innovation (QDEEDI), information on the seasonal climate outlook from the Australian Government Bureau of Meteorology and estimates of area planted from bulk handlers, traders, agronomists and industry bodies.

Unforseen changes to input factors including seasonal conditions over the forecast period present a risk in forecasting production. As a result, actual production can sometimes differ from the initial point forecasts.

State commodity forecasts

QDEEDI runs seasonal crop outlooks for wheat and sorghum for LGAs within Queensland and north-eastern New South Wales. These outlooks are updated each month during the growing seasons for wheat and sorghum. Both outlooks integrate a simple agro-climatic stress index model (Oz-Wheat or SSIM), which is sensitive to water deficit or excess during the growing season, with actual climate data, up to the forecasting date, and projected climate data, based on the Southern Oscillation Index (SOI) phase system after the forecasting date.

Western Australian Department of Agriculture and Food (DAFWA) produces a seasonal crop outlook for wheat for LGAs for Western Australia. This report is updated each month from April to December. This outlook combines the simple stress index model STIN from actual climate data up to the forecasting date and projected seasonal climate data based on the average for the last 30 years.

5. CROP YIELD MODELLING

Over the past decade, the increased availability of regional yield data, improvements to seasonal forecasts and modelling technology and the integration of remote sensing data have made it possible to advance regional-scale crop modelling. The current and potential advancements in regional-scale crop yield modelling are discussed below.

Improvements to seasonal forecasting

To generate forecasts, models are run using actual climate data up to the forecasting date and then use projected climate data for the rest of the season. The projected climate data can come from statistical systems with median climate and analogue years (such as ENSO, SOI, SAM or IOD phases) as predictors. Outputs from Dynamical General Circulation Models (GCMs) provide predictions of many aspects of the climate system and so their output can be readily adapted for a wide range of applications.

Hansen *et al.* (2004) have studied the use of GCM-predicted seasonal rainfall with a wheat simulation model to forecast regional and state yields in Queensland. The results have shown an improved yield forecast accuracy during the pre-planting period when the SOI phase seems to be less predictable. This encouraging result may substantially increase the role of these forecasts in handling and marketing of the Australian grain crop.

Integration of remote sensing data and forecasting

Integrated crop forecasting approaches are currently experimental. Improvements in crop simulation models can be achieved by integrating variables derived from remote sensing to 'scale-up' crop yield simulations. There are two main approaches: *direct integration of satellite data* into models to calibrate the simulation model parameters and *hybrid models* which combine the outputs of growth simulation models with remotely-sensed crop indices to produce predictive regression models related to yield.

Remote sensing data can be directly incorporated into the simulation model to calibrate the simulation parameters. The method is based on the correlation between the temporal changes in satellite-derived vegetation indices (e.g. NDVI) and primary production (crop yields) based on the absorption of photosynthetically active radiation by the canopy. Remote sensing data can also provide an estimate of biomass. Earlier regional studies found that using NDVI data during the grain-fill period only improved the estimates of potential spring wheat yields (Doraiswamy, 2003).

Some field-scale studies have shown that NDVI data can be integrated in crop growth simulations to calibrate or adjust parameters during the simulation period (run-time calibration) (Jongschaap, 2006). The method is based on replacing simulated values by remotely-sensed values and the hypothesis that those physiological conditions of the crop as expressed by leaf area index and other plant growth parameters can be quantified using remote sensing information that has greater accuracy than the simulations. Remotely-sensed observations may be taken at the canopy level (airborne) or from satellites to cover larger spatial areas. Results show that run-time calibration (using input from remotely-sensed sources) of mechanistic simulation models may improve the accuracy of predicted yields.

Hybrid models

Hybrid models use Partial Least Square (PLS) models to solve multiple combinations of simulated parameters and satellite-derived vegetation indices (e.g. NDVI). This concept allows for the parameters that contribute most to higher model performance to be selected for a given region (Boken *et al.*, 2002 and Schut *et al.*, 2009). Research suggests that these products are more robust than simulation models especially during drought because they better account for impacts of climate on yield.

Recent research has shown that the combination of NDVI and outputs from simulation models improves wheat yield and production forecasts. In a study on improving the current in-season wheat yield and production forecasting system for Western Australia on a LGA basis (Schut *et al.*, 2009), ten predictive PLS models were developed containing various combinations of the variables calculated from STIN and temporal NDVI data series from AVHRR and/or MODIS for the period 1991–2006. The results showed that the multivariate models outperformed the simple models with predictive capability increasing with the number of variables involved in the PLS model. The best model had a mean relative prediction error (RE) per LGA of 10 per cent for yield and 15 per cent for production, compared to RE of 13 per cent for yield and 18 per cent for production for the Stress Index-based model.

The results of another study using a similar hybrid predictive model for wheat yield in Canada showed that for most regions the model including NDVI averaged over the heading phase produced the highest R^2 (up to 0.79) (Boken *et al.*, 2002). It was concluded that the predictive power (accuracy) of hybrid models is significantly greater than that of simulation models without additional variables derived from remote sensing.

6. IMPACTS OF EXTREME EVENTS ON AGRICULTURE

A number of extreme events and natural disasters can influence the reliability of crop forecasts including drought, floods and fire. In most cases the location and spatial extent of these events are mapped or have spatial information whilst their impacts on productions are not necessarily estimated. Linking of these factors to crop production and yield would enhance the accuracy of crop forecasts. Relevant sources of information include:

- Droughts, wind, storms, heat and frost (Bureau of Meteorology)
- Fire (sentinel.ga.gov.au), floods and natural hazards (Geoscience Australia)
- Plague locusts (www.daff.gov.au/animal-plant-health/locusts/current)
- Dust storms (dustwatch.edu.au)
- Seasonal climate outlook (BOM and www.bom.gov.au/silo/SILO2/ website)
- Pasture growth (www.longpaddock.qld.gov.au and www.pasturesfromspace.csiro.au/).

7. INTEGRATED CROP FORECASTING SYSTEM

To improve crop yield forecasts for Australia, an integrated crop forecasting system could be achieved by linking and delivering remotely-sensed and contextual data, historical trends and model outputs at spatial and temporal resolutions appropriate for farming industries.

This inputs and outputs of such a system would include:

- Crop masks delineating areas where crops and pastures could be grown.
- Crop and pasture area estimates, based on the detection of green response using remote sensing data.
- Weather and climate forecasts for the upcoming season.
- Yield prediction based on climate and crop modelling and the use of ancillary data.
- Validation including surveys and ground-truthing.

It is conceivable that a prototype system could be developed linking NDVI or EVI imagery, agricultural commodity statistics and crop calendars to provide estimates of cropping area; and climate data and NDVI or EVI data could be incorporated into simulation models to provide estimates of crop yield. Estimates of crop production could be derived through the combination of yield and area estimates. Ideally crop forecasting would be run every 3 months and be validated against ABS commodity statistics.

In the long-term such a system could be automated and incorporate improved seasonal forecasting data from GCM models, remotely-sensed climate data to replace ground observations) and include impacts of pests, disease and other external factors on crop production.

The following data requirements have been identified to improve crop forecasting:

- High temporal resolution NDVI data - Current satellite data includes the MODIS sensors (Terra and Aqua) (NASA), AVHRR (NOAA), MERIS (Envisat) and SPOT Vegetation (SPOT Image).

- Remote sensing of ground observations used for crop modelling. This will potentially improve the robustness and accuracy of forecasts due to improvements in crop masks and validation and calibration of model parameters. Other biophysical variables derived from remote sensing could also be used to more accurately calibrate crop and pasture growth prediction including wind fields, solar radiation and evapotranspiration.

- Seasonal climate forecasting could be improved by adopting outputs from the dynamical fully-coupled climate models which can predict future climate and associated uncertainty without relying on history. There is the potential for improvements in accuracy and lead - time of seasonal predictions in Australia. The results of a collaborative effort called the Australian Community Climate and Earth System Simulator (ACCESS) will provide the framework for dynamical prediction across all time scales. To improve the seasonal forecasting more research will be carried out on processes such as the Madden-Julian Oscillation, which is the dominant mode of intra-seasonal variability and better assimilation of ocean and climate data into coupled dynamical models.

- The accuracy of wheat yield and production forecasting is likely to be improved if other crops and pastures are effectively masked out using satellite imagery. An accurate method is still required to discriminate between the signatures of annual crops and pastures. One technique that requires further investigation uses the date of green-up to discriminate crops from pastures.

Research conducted by LandGate in Western Australia constrained the classification of MODIS EVI data using latitudinal zones to account for day-length and other crop growth parameters (M Adams, LandGate, *pers. comm.*)

- An accurate near real-time production forecast requires a real-time estimate of the area planted in targeted agricultural systems. The use of satellite imagery for more objective, timely and accurate crop information during entire season is still relatively novel. The results from the study by Potgieter *et al.* (2005), using digital imagery from MODIS platforms to estimate winter crop area planted in Queensland showed a significant potential to capture total regional crop area and a good capability (>95% correct classification) in discriminating between winter crops.

8. CONCLUSIONS

This paper reviews the use of satellite–based remote sensing for mapping and estimating crop production in Australia, identifies the components of a more integrated crop forecasting system and proposes a way forward.

Operational remote sensing systems in Australia have the potential to monitor crop growth and climate inputs and to map impacts on crop production. The linking of these data to traditional crop forecasting systems has the capacity to improve both the spatial and temporal resolution of current crop forecasts and provide lines of evidence to support traditional surveys.

Ancillary datasets and techniques will continue to be relied upon to improve mapping particularly of growth stage and crop yield. These include crop models, crop calendars as well as calibration and validation data.

To improve crop forecasting, an integrated system could be achieved by linking remotely-sensed and contextual data with historical trends and model outputs at spatial and temporal resolution appropriate for farming industries.

The next steps in developing this type of system include building a prototype system and demonstrating the improvements to the existing crop forecasting system in terms of mapping extent and location of crop area, discrimination of crop and pasture land uses, and end-of-season estimates of crop production.

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