INTEGRATING NASA SATELLITE DATA INTO USDA WORLD AGRICULTURAL OUTLOOK BOARD DECISION MAKING ENVIRONMENT TO IMPROVE AGRICULTURAL ESTIMATES

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ABSTRACT

The USDA World Agricultural Outlook Board (WAOB) is responsible for monitoring weather and climate impacts on domestic and foreign crop development. One of WAOB's primary goals is to determine the net cumulative effect of weather and climate anomalies on final crop yields. To this end, a broad array of information is consulted. The resulting agricultural weather assessments are published in the Weekly Weather and Crop Bulletin, to keep farmers, policy makers, and commercial agricultural interests informed of weather and climate impacts on agriculture. The goal of the current project is to improve WAOB estimates by integrating NASA satellite precipitation and soil moisture observations into WAOB's decision making environment. Precipitation (Level 3 gridded) is from the TRMM Multi-satellite Precipitation Analysis (TMPA). Soil moisture (Level 2 swath and Level 3 gridded) is generated by the Land Parameter Retrieval Model (LPRM) and operationally produced by the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC). A root zone soil moisture (RZSM) product is also generated, via assimilation of the Level 3 LPRM data by a land surface model (part of a related project). Data services to be available for these products include GeoTIFF, GDS (GrADS Data Server), WMS (Web Map Service), WCS (Web Coverage Service), and NASA Giovanni. Project benchmarking is based on retrospective analyses of WAOB analog year comparisons. The latter are between a given year and historical years with similar weather patterns and estimated crop yields. An analog index (AI) was developed to introduce a more rigorous, statistical approach for identifying analog years. Results thus far show that crop yield estimates derived from TMPA precipitation data are closer to measured yields than are estimates derived from surface-based precipitation measurements. Work is continuing to include LPRM surface soil moisture data and model-assimilated RZSM.

Keywords: Agricultural, crop yield, satellite, precipitation, soil moisture

INTRODUCTION

A primary goal of the U.S. Department of Agriculture (USDA) is to expand markets for U.S. agricultural products and support global economic development. The USDA World Agricultural Outlook Board (WAOB) supports this goal by coordinating the review and approval of the monthly World Agricultural Supply and Demand Estimates (WASDE) report, which summarizes official Departmental forecasts of supply and demand for major U.S. and global crops and U.S. livestock. WAOB ensures that USDA's analysis is accurate, timely, and objective, and that the report is delivered to farmers and ranchers, policy makers, and the public to keep them apprised of potential market opportunities. The WAOB chairs Interagency Commodity Estimates Committees (ICECs), comprising representatives from several key USDA agencies, including the Foreign Agricultural Service (FAS), Economic Research Service (ERS), National Agricultural Statistics Service (NASS), Farm Service Agency (FSA), and the Agricultural Marketing Service (AMS). The ICECs collectively produce the WASDE reports.

The WASDE reports are significantly informed by agricultural weather assessments for major crop producing areas worldwide. Because weather has such a significant impact on crop progress, conditions, and production, the WAOB team of meteorologists prepares these assessments and disseminates them via the Weekly Weather and Crop Bulletin (WWCB), a joint publication of the National Oceanic and Atmospheric Administration (NOAA) and USDA. The WWCB enables the ICECs to critically adjust global supply and demand estimates based on changes in

the weather, as well as keeps senior government officials, commercial entities, and the public informed of weather impacts on global crop development.

The WWCB daily, weekly, monthly, and seasonal assessments are based on a diverse range of data, which drive the WAOB Global Agricultural Decision Support Environment (GLADSE; Figure 1), including maps, charts, and time series of recent weather, climate, and crop observations; numerical output from weather and crop models; and reports from the press, USDA attachés, and foreign governments. The complex and diverse nature of these data requires that the GLADSE be flexible and dynamic.

The overall goal of this project is to improve WAOB forecasts by integrating NASA satellite precipitation and soil moisture observations into GLADSE. Soil moisture data, a primary data gap at WAOB, is generated by the Land Parameter Retrieval Model (LPRM, developed by NASA GSFC and Vrije Universiteit Amsterdam) and customized to WAOB requirements.



Figure 1. Operational flow diagram of GLADSE and other USDA entities and of project components (in blue).

LAND PARAMETER RETRIEVAL MODEL (LPRM) SOIL MOISTURE

LPRM data provide global soil moisture with high temporal (day, night) resolution and 0.25 degree spatial resolution, for the top few cm of the soil column. LRPM is a three-parameter retrieval model for passive microwave data and is based on a microwave radiative transfer model that links surface geophysical variables (i.e., soil moisture, vegetation water content, and soil/canopy temperature) to the observed brightness temperatures (De Jeu et al., 2008; Owe et al., 2008). LPRM uses a nonlinear iterative optimization procedure in a forward modeling approach to partition the natural microwave emission from the Earth's surface into the soil surface and the vegetation canopy. Once convergence between the calculated and observed brightness temperatures is achieved, the model uses a global data base of soil physical properties, together with a soil dielectric model (Wang and Schmugge, 1980) to solve for the surface soil moisture. No field observations of soil moisture, canopy biophysical properties, or other observations are used for calibration purposes. Thus, the model is largely physically-based and applicable at any microwave frequency suitable for soil moisture monitoring.

The migration of the LPRM soil moisture algorithm from Vrije Universiteit Amsterdam (VUA) to GES DISC has been completed, including integration and testing of the algorithm, verification of test outputs with the VUA algorithm developers, and setting up of operational production flow of the LPRM Level 2 (swath) and Level 3

(gridded) data. Both products are available to the general public (via GES DISC's Mirador, http://bit.ly/qcDwy1), in addition to USDA WAOB. Figures 2 and 3 show some example outputs of the LPRM Levels 2 and 3 products, respectively.



Figure 2. Example outputs from LPRM Level 2 product (soil moisture, skin temperature, optical depth, and mask).



Figure 3. Example outputs from LPRM Level 3 product (soil moisture, skin temperature, optical depth, and mask).

LPRM soil moisture has been extensively validated over a large variety of landscapes, using in situ, models, and other satellite soil moisture products, and has an accuracy of about $0.06 \text{ m}^3 \text{ m}^3$ for sparse to moderate vegetated regions (De Jeu et al., 2008). Uncertainties will always exist when satellite-based soil moisture retrievals are compared with point-derived in-situ data, because of differences in sampling depth, temporal differences in acquisition, and spatial extent between satellite and in-situ observations. The LPRM retrieval algorithm has certain known retrieval errors, each identified and labeled in the data by appropriate unique flags, caused by (1) masking effect of vegetation, (2) excessive surface roughness, (3) gross topography, (4) water bodies, (5) ice, snow, and frozen soils, and (6) radio frequency interference (RFI; Njoku et al., 2005).

Work is ongoing to incorporate an uncertainty estimate algorithm into the LPRM Level 2 production (Parinussa et al., 2011) and then to propagate to the Level 3 production. This uncertainty estimate will be included in the reprocessing for the next version, which would result in an important enhancement for LPRM users.

A major event affecting this project was the sudden end of the EOS/Aqua AMSR-E sensor early October 2011. AMSR-E brightness temperatures (Tbs) were the primary input data for LPRM. To mitigate the current gap in forward-processed global soil moisture data, the project is working to use, as replacement for AMSR-E, Tbs from TRMM Microwave Imager (TMI) and Windsat. Fortunately, AMSR2 (follow-on to AMSR-E) from the Japan Aerospace Exploration Agency (JAXA) is scheduled for launch sometime in 2012.

INTEGRATION OF PROJECT OUTPUTS INTO WAOB

Historically, one of the main obstacles to increased use of NASA Earth Science data in operational user environments, such as WAOB's GLADSE, is the data cannot be directly and easily integrated in a form that is usable and effective. Increasingly, this obstacle is being overcome by new Web services technology, so that actual physical locations of data are no longer all important and the traditional massive transfer of all desired data into user archives is largely unnecessary. The GES DISC has been an early adopter of such services-oriented data access and delivery technology (Teng et al., 2005). Services being or to be developed for this project include NASA Giovanni, GrADS Data Server (GDS), Web Map Service (WMS), Web Coverage Service (WCS), and format conversion to GeoTIFF. The general desired service by WAOB is time series of a parameter (e.g., precipitation, soil moisture) for a specified geographical region, in response to a request of a bounding box and time period. A GDS has been configured and successfully tested serving time series of soil moisture data to WAOB. Also successfully tested were the conversion of soil moisture data into GeoTIFF and the importing of the converted files into WAOB's GIS environment.

Giovanni, a Web-based application developed by the GES DISC, provides a simple and intuitive way to visualize, analyze, and access vast amounts of Earth science remote sensing data without having to download the data (Berrick et al., 2009). A prototype Giovanni portal for soil moisture has been developed that includes, for now, EOS/Aqua AMSR-E soil moisture (Njoku et al., 2003), LPRM/AMSR-E soil moisture, LSMEM/TMI soil moisture (Gao et al., 2006), TMPA precipitation (Huffman et al., 2007), and AIRS surface temperature (Aumann et al., 2003). Figure 4 shows the Giovanni portal user interface and example outputs. The portal is planned for public release in spring 2012.



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Figure 4. (a) Giovanni Soil Moisture Portal user interface; example outputs (b) global lat-lon map of LPRM-AMSRE Level 3 soil moisture, C-band, for day 12/31/2010; (c) lat-lon map, time-averaged (May 1-31, 2010), Parana, Brazil; and (d) time series (May 1-31, 2010), Parana, Brazil.

MEASURING IMPROVEMENTS TO GLADSE

Because both the amount and timing of precipitation significantly affect crop yields, WAOB often uses precipitation time series to identify growing seasons with similar weather patterns and help estimate crop yields for the current growing season, based on observed yields in analog years. Historically, these analog years are visually identified; however, the qualitative nature of this method sometimes precludes the definitive identification of the best analog year. Thus, one goal of this study is to derive a more rigorous, statistical approach for identifying analog years, based on a modified coefficient of determination, termed the analog index (AI). A second goal is to compare the performance of AI for time series derived from surface-based observations vs. satellite-based measurements (NASA TRMM and other data). Previous work has shown promise towards achieving these goals (Teng and Shannon, 2010).

Figure 5 shows an (obvious) example of analog year comparisons for crop yield forecasts. In 2006, drought in New South Wales, Australia, threatened a reduction in winter wheat yields estimated by WAOB meteorologists to be similar to that of 2002, based on analog analyses of precipitation time series. Indeed, following the harvest, wheat yields were found to be well below the trend. Although the weather was similar in both years, yields differed. This variability can be attributed to a number of factors, including subtle differences in the timing of the rainfall, varieties of wheat planted, and amount of wheat grazed rather than harvested.

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Figure 5. Example of using analog year comparisons to estimate crop yields. 2006 is the target year; 2002 is an analog year.

Figure 6 (of Western Australia) illustrates the importance of timing of precipitation relative to the stages of crop development. Similar amounts of rain fell during the 2002 and 2006 winter wheat growing seasons. In 2002, however, a noticeable drying trend occurred as the season progressed. In contrast, in an otherwise dry 2006 growing season, a period of near-normal rainfall during the middle of the season benefited the crop, as it approached the moisture-sensitive reproductive stages of development in early September. This timely rainfall helped to elevate 2006 winter wheat yields (1.27 t/ha) to above 2002 levels (0.91 t/ha).



Figure 6. Example of importance of timing of precipitation relative to the stages of crop development.

The analog index (AI) is a modified form of the coefficient of determination and is expressed as

$$AI = 1 - \frac{\sum_i (P_i - PA_i)^2}{\sum_i (P_i - coeff * P_i)^2}$$

where P is the precipitation during the target year, PA is the precipitation during the potential analog year, and coeff serves as a threshold that helps evaluate the goodness of fit between P and PA. AI values range from $-\infty$ to 1.0, with values approaching 1.0 indicative of the strongest analog relationships between P and PA. In this study, time series with positive AI values are considered analog years. Values of coeff could range from 0.0 to 1.0 and is derived iteratively for each region. In this study, the 2008 growing season was selected as the target year, and the 2003 to 2007 growing seasons were treated as potential analog years. For all five study areas (Iowa, U.S.; Jalisco, Mexico; Parana, Brazil; central Argentina; and Free State, South Africa), crop yield estimates derived from satellite-based precipitation data are closer to measured yields than are estimates derived from surface-based precipitation



measurements.

Satellite data being at least comparable to weather station data, in identifying analog years, points to the possibility of "calibrating" the analog analysis methodology in station-rich areas, to be then applied in station-poor areas of the world, which would significantly extend the global coverage of WAOB analysts in conducting crop yield forecasts. Work is continuing to include satellite-based surface soil moisture data and model-assimilated root zone soil moisture.

WAOB is the focal point for economic intelligence within the USDA. Thus, improving WAOB's agricultural forecasts by integrating NASA satellite data into WAOB's GLADSE will visibly demonstrate the value of NASA resources and maximize the societal benefits of NASA investments.

ACKNOWLEDGMENT

The reported work is supported by NASA ROSES NNH08ZDA001N-DECISIONS, Goddard Earth Sciences Data and Information Services Center (GES DISC), USDA World Agricultural Outlook Board, and Vrije Universiteit Amsterdam. The authors also acknowledge and are grateful for the contributions by Fan Fang, Guang-Dih Lei, and Hualan Rui (GES DISC/Adnet); Thomas Holmes (USDA ARS); and Robert Parinussa (VUA).

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