

IMPROVING WORLD AGRICULTURAL SUPPLY AND DEMAND ESTIMATES BY INTEGRATING NASA REMOTE SENSING SOIL MOISTURE DATA INTO USDA WORLD AGRICULTURAL OUTLOOK BOARD DECISION MAKING ENVIRONMENT

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ABSTRACT

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 developing monthly World Agricultural Supply and Demand Estimates (WASDE) for the U.S. and major foreign producing countries. Because weather has a significant impact on crop progress, conditions, and production, WAOB prepares frequent agricultural weather assessments, in the GIS-based, Global Agricultural Decision Support Environment (GLADSE). The main objective of this project, thus, is to improve WAOB estimates by integrating NASA remote sensing soil moisture observations and research results into GLADSE. Soil moisture, a primary data gap at WAOB, will be generated by the Land Parameter Retrieval Model (LPRM, developed by NASA GSFC and Vrije Universiteit Amsterdam) and customized to WAOB requirements. LPRM soil moisture will be directly integrated into GLADSE, as well as indirectly by first being assimilated into USDA Agricultural Research Service (ARS) Environmental Policy Integrated Climate (EPIC) crop model. The LPRM-enhanced EPIC will be validated using three major agricultural regions important to WAOB and then integrated into GLADSE. Project benchmarking will be based on retrospective analyses of WAOB analog year comparisons. The latter are between a given year and historical years with similar weather patterns. WAOB is the focal point for economic intelligence within the USDA. Thus, improving WAOB agricultural estimates by integrating satellite observations and model outputs will visibly demonstrate the value of NASA resources and maximize the societal benefits of NASA investments.

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.

Global Agricultural Decision Support Environment (GLADSE)

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). These data, in various digital map, table, and text formats, include daily surface observations (e.g., temperature, precipitation, and wind), radar-derived products (e.g., precipitation), satellite-derived products (e.g., vegetation greenness, snow cover, precipitation), model-derived products (e.g., crop phenology, global weather forecast), press reports, foreign government agricultural census data, and domestic and international crop progress and condition data. The complex and diverse nature of these data requires that the GLADSE be flexible and dynamic. Hence, GLADSE consists of a suite of PC-based analytical tools designed to display, process, and evaluate the data: (1) Visual Basic applications, to compute and display historical rankings of agricultural weather variables during the growing season, which enable inter-annual comparisons; (2) Excel applications, to generate time series analyses of temperature and precipitation, which facilitate weather monitoring during the various stages of crop development; and (3) GIS applications, to overlay and statistically evaluate numerous data sets and to automate data processing, which improve the identification and delineation of crop areas.

Because soil moisture is a primary data gap at WAOB, the overall goal of this project is to improve WAOB forecasts by integrating NASA remote sensing soil moisture observations into GLADSE. Soil moisture data will be generated by the Land Parameter Retrieval Model (LPRM, developed by NASA GSFC and Vrije Universiteit Amsterdam) and customized to WAOB requirements. LPRM soil moisture will be directly integrated into GLADSE, as well as indirectly by first being assimilated into the USDA Agricultural Research Service (ARS) Environmental Policy Integrated Climate (EPIC) crop model.

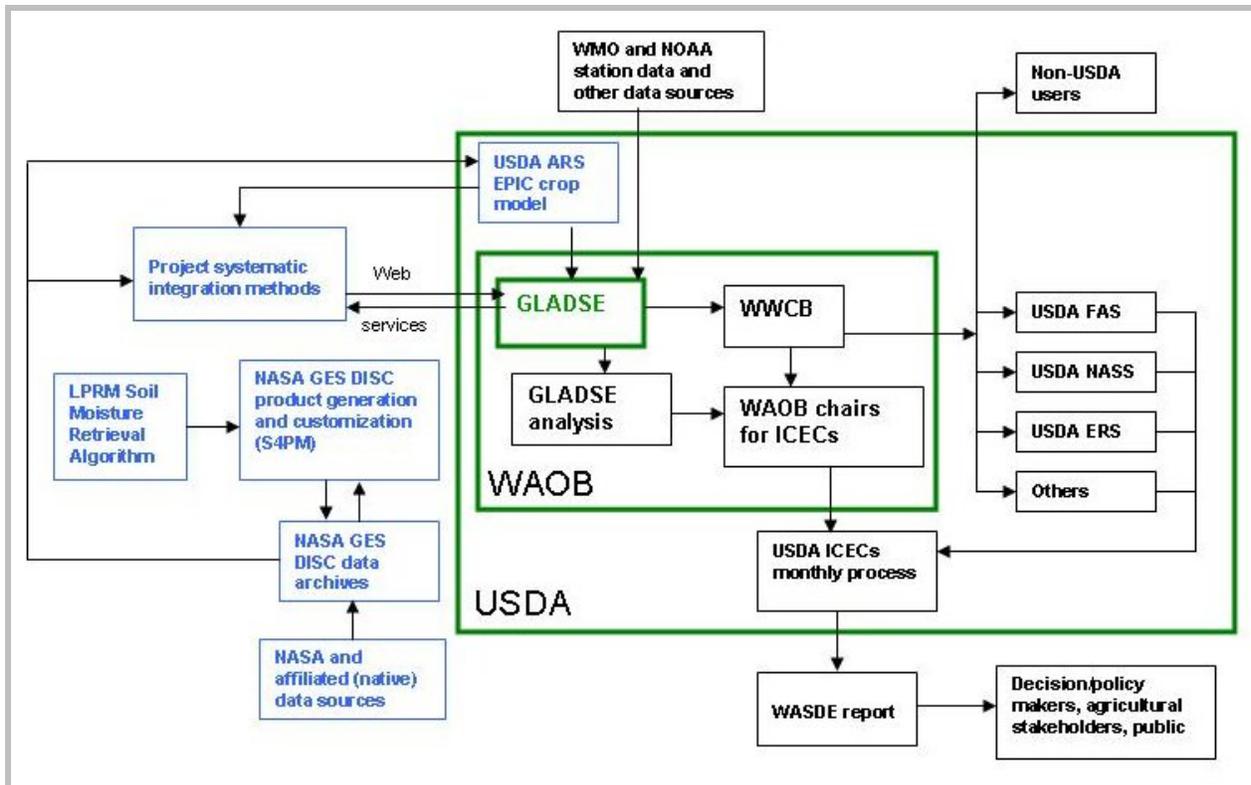


Figure 1. Operational flow diagram of GLADSE and other USDA entities and of project components (in blue).

Key Project Objectives

- To integrate, as seamlessly as possible, WAOB-customized LPRM soil moisture data and the LPRM-enhanced EPIC crop model into the operational WAOB GLADSE.
- To leverage existing Web services at the GES DISC to mediate and facilitate the integration of project outputs into GLADSE.
- To systematically and rigorously evaluate and benchmark the impact of the integration of NASA data and technologies on GLADSE forecasts with three of the major agricultural regions worldwide.

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. LPRM 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 (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, which is especially useful for application to different historical sensors (e.g., SMMR), as well as to currently ongoing (SSM/I, TRMM, AMSR-E, WindSat, SMOS) and future (Aquarius, GPM) sensing systems. Figure 2 shows the timeline of the different microwave satellite sensors used in LPRM. Figure 3 shows some example soil moisture retrievals from the different sensors.

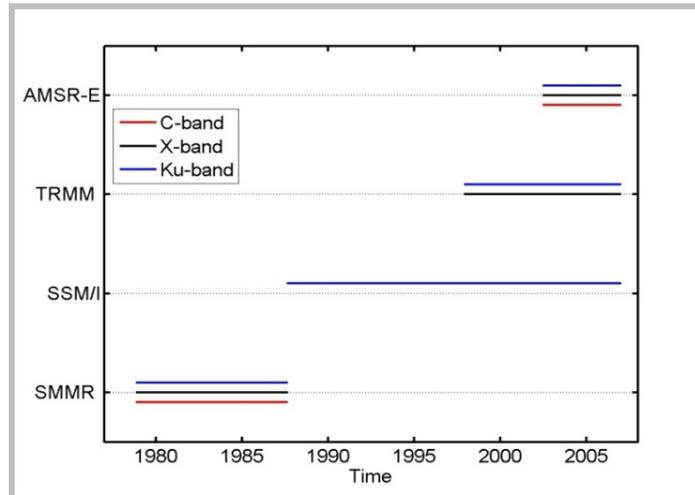


Figure 2. Timeline of the different microwave satellite sensors used in LPRM.

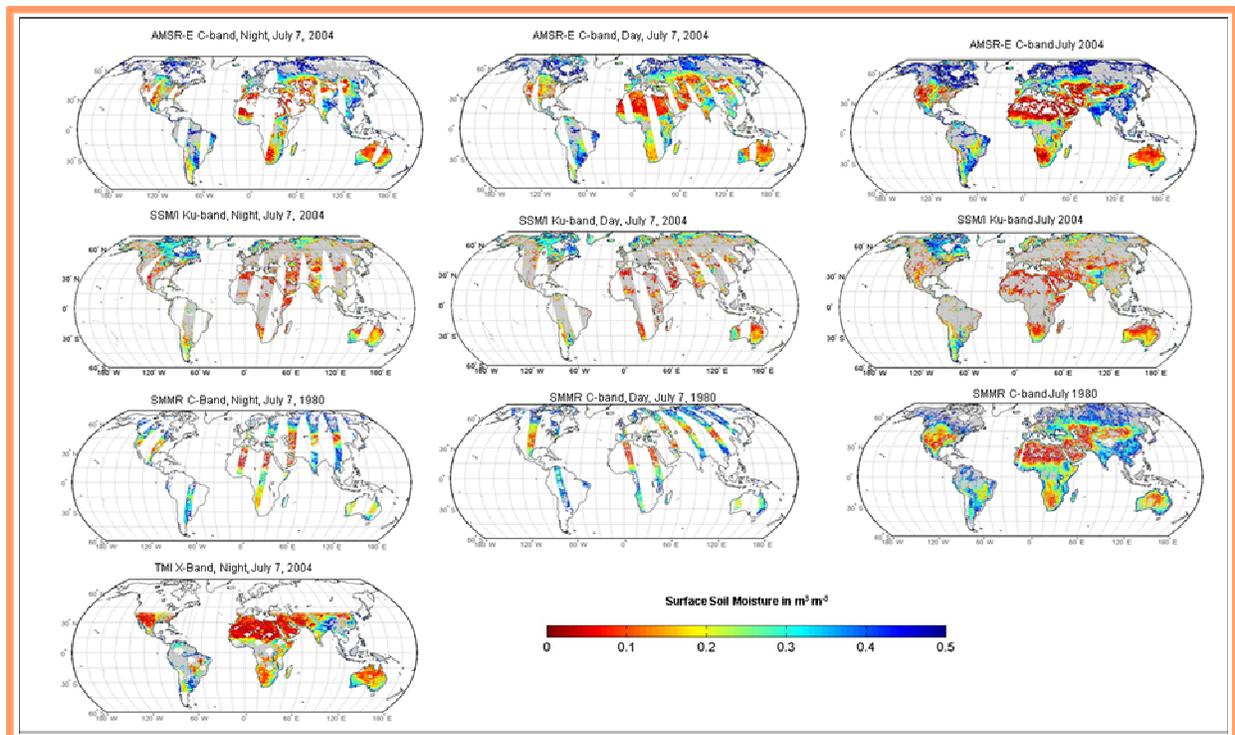


Figure 3. 24-hour (left) and average monthly (right) soil moisture retrievals from the different sensors. Data are flagged and masked out when vegetation cover is too dense to retrieve reliable soil moisture. Differences in frequency bands (i.e., C, X, and Ku bands) significantly affect the retrieval capabilities above vegetated areas.

Validation of LPRM Products

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).

As vegetation density increases, the masking effect of vegetation eventually may result in the observed emissivity due entirely to the vegetation (Figure 3). This “total masking” corresponds to some point on the growth curve of a particular crop. As part of the integration of LPRM into GLADSE, the “total masking” point of a crop and, thus, the point during the growing season beyond which LPRM would not be applicable, will be determined. Fortunately, soil moisture is most critical during the green-up phase of the crop season, during which LPRM would be applicable. Furthermore, crops in many arid and semi arid regions are sufficiently sparse that crop maturation may not appreciably affect the retrieval process.

ENVIRONMENTAL POLICY INTEGRATED CLIMATE (EPIC) CROP MODEL

EPIC is a comprehensive crop growth and environmental assessment model developed by the USDA-ARS (Williams et al., 2006, 2008). It provides continuous daily simulation of the growth of many crops, soil moisture profile, hydrology, erosion, sedimentation, and management practices and their impacts on crop growth and environmental sustainability (Figure 4). Several studies have validated the model simulations of soil moisture availability and crop yield/soil moisture responses (Roloff et al., 1998; Costantini et al., 2002; Doraiswamy et al.,

2003). For rain-fed agriculture, rain is a required input for the model, to simulate the critical soil moisture component. Current rain input is from World Meteorological Organization (WMO) station data. However, because of the spatial variability of rain, the WMO station rain input is a source of model uncertainty.

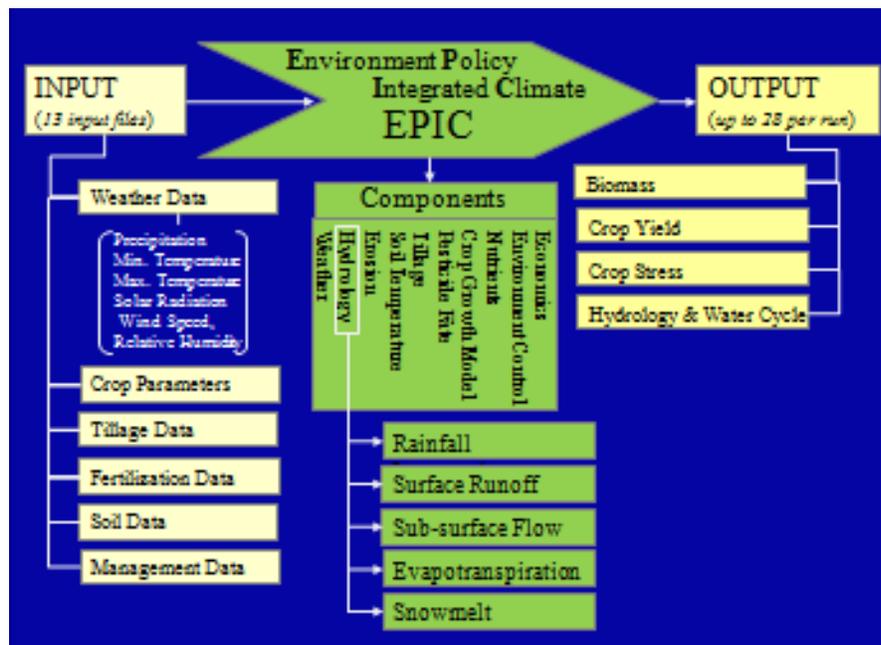


Figure 4. High-level view of data flow through the Environmental Policy Integrated Climate (EPIC) model.

Surface and Root Zone Soil Moisture

Integrating the LPRM soil moisture product into EPIC and replacing the current EPIC surface soil moisture simulated and interpolated from WMO and other local station data could provide better spatial surface soil moisture and reduce model uncertainty. However, because current satellite microwave retrievals are sensitive to only the soil moisture in the top several cm of the soil surface (i.e., “skin depth”), it is critical that EPIC also uses the surface soil moisture to determine the down profile to derived subsurface (root zone) soil moisture. The top layer soil moisture is part of the soil moisture profile water balance that is recalculated in the model on a daily time-step. The subsurface moisture budget is calculated using soil profile characteristics such as water holding capacity and texture. Re-computing the model subsurface soil moisture based on the LPRM surface soil moisture could also reduce model uncertainty.

Several methods of integrating LPRM into EPIC are being evaluated, including direct insertion and assimilation via ensemble Kalman filter. First, however, the existing bias between the satellite-derived LPRM and modeled EPIC soil moisture needs to be accounted for (Boone et al., 2004; Reichle and Koster, 2004). Three techniques were examined to rescale the LPRM AMSR-E retrieval to be consistent with the model climatology: (1) Cumulative Distribution Function (CDF; Reichle and Koster, 2004), (2) Cumulative Distribution Function using a polynomial fitting approach (CDF.P-fit; Drusch et al., 2005), and (3) Regional Statistics Method (RSM; Choi and Jacobs, 2008). The rescaling of the three techniques is done, respectively, by matching the cumulative distribution functions of the two data sets, by determining a 3rd degree polynomial fit between the ranked difference between the model and satellite and the ranked satellite data, and by using the model and satellite statistics (mean and standard deviation).

Results from applying the CDF, CDF.P-fit and RSM techniques are summarized in Figures 5 and 6. Simulations were performed over the entire state of Iowa, for a period of six years (2003-2008) at 0.25°, using only the descending LPRM AMSR-E data. Overall, the original LPRM AMSR-E retrieval was found to have higher values and a larger dynamic range than those of the EPIC surface soil moisture (Figures 5A and 6). The CDF’s of the rescaled data are closer to the model CDF than is the CDF of the original LPRM (Figure 5B). The same trend can be also observed in the time series analysis shown in Figure 6. The best fit between EPIC and the rescaled LPRM AMSR-E was achieved using the CDF technique. In Figure 5B, the deviation of the CDF.P-fit and RSM CDF’s from the EPIC CDF is higher when soil moisture values exceed ~0.3 m³/m³, due to the difference between

EPIC and LPRM behavior during the wetter winter months. Results from this preliminary analysis seem to indicate that the CDF-rescaled LPRM estimates would be best for the subsequent assimilation procedure.

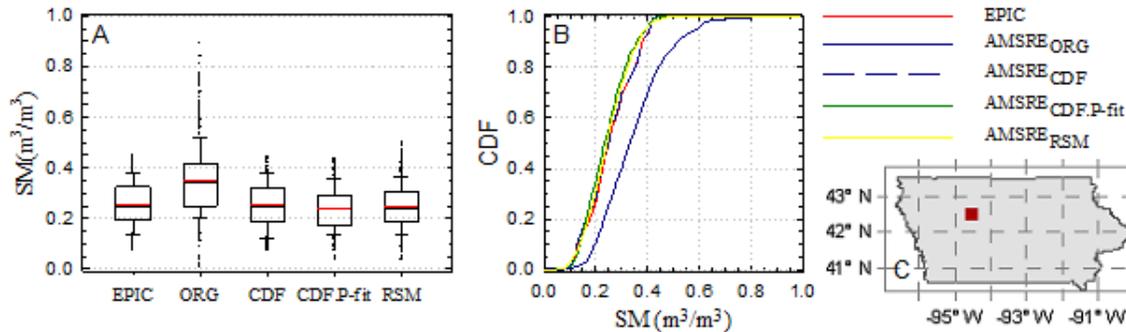


Figure 5. Results from the CDF/RSM-rescaling of LPRM AMSR-E soil moisture for a random 0.25° grid cell located in Iowa, U.S. (42.5N, 94.5W).

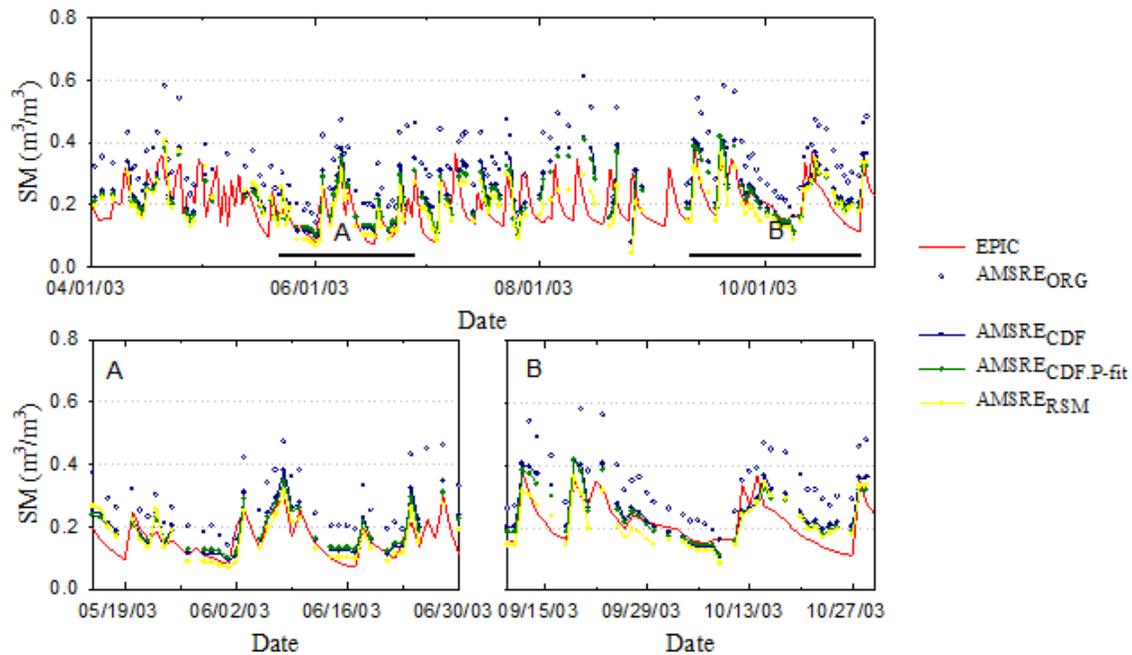


Figure 6. Time series of surface soil moisture from EPIC, original LPRM, and rescaled LPRM data, for grid cell shown in Figure 4C (42.5N, 94.5W) and the 2003 growing season.

Validation of LPRM-Enhanced EPIC Model Outputs

Validation of model outputs will be carried out at sites in the U.S. Midwest, where ample field data exist, as well as with selected sites in Brazil (a current WAOB focus region, especially regarding soybeans) and Australia (a major wheat exporter) (Figure 7). Field validation will leverage ongoing research (e.g., Doraiswamy et al., 2007). Field validation in the three regions will enable the benchmarking of the improvements to the EPIC model (e.g., yield forecasts) by the enhancement of LPRM. Once validated, the LPRM-enhanced EPIC model will be integrated into GLADSE and applied to other major agricultural regions worldwide for which WAOB has responsibility.



Figure 7. Three major agricultural regions worldwide to be used for validation of project results.

INTEGRATION OF PROJECT OUTPUTS INTO WAOB

Science Data Processing and Archiving

The LPRM algorithm will be integrated into the Goddard Earth Sciences Data and Information Services Center (GES DISC) production environment, specifically the Simple, Scalable, Script-based Science Processor for Measurements (S4PM), a system for highly automated processing of science data and the main processing engine at the GES DISC (Lynnes, 2006). It is scalable up to large processing systems (e.g., those at the GES DISC) and down to small, special-purpose processing strings. It is built on top of the Simple, Scalable, Script-based Science Processor (S4P) kernel, an engine, toolkit and graphical monitor for automating script-based, data-driven processing. Figure 8 provides a high-level view of data flow through S4PM. The Simple, Scalable, Script-Based, Science Product Archive (S4PA), based on the same S4P kernel, is a radically simplified data archive architecture that provides users with operational online access to data.

The integration of LPRM into S4PM will follow GES DISC's standard rigorous Science Software Integration and Testing (SSI&T) procedures. Test swath and gridded outputs generated with the integrated LPRM will be carefully compared with the original LPRM development archives to ensure both are identical, before the LPRM algorithm is run operationally.

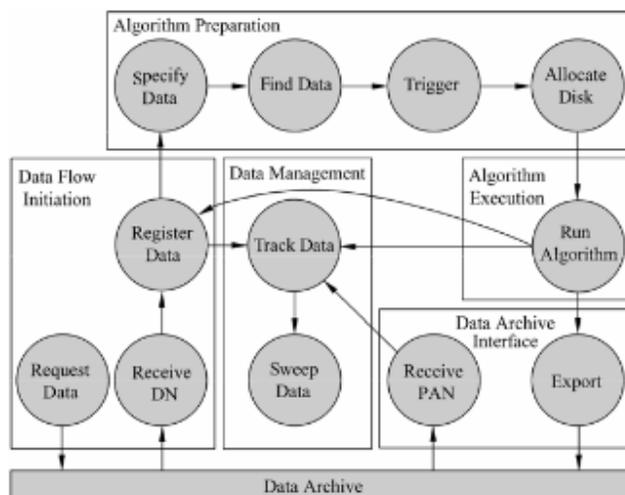


Figure 8. High level view of data flow through the Simple, Scalable, Script-Based Science Processor for Missions (S4PM), which provides highly automated processing of science data at the GES DISC.

Data Services

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), and its existing operational Web services will be leveraged by this project. These Web services (e.g., Web Map Service (WMS), Web Coverage Service (WCS)) will enable the seamless access to project data by WAOB.

For remote, online visualization and analysis options, project outputs will be GrADS Data Server (GDS)-enabled. GDS, the core of which is Open-source Project for a Network Data Access Protocol (OPeNDAP), provides subsetting and analysis services across the internet. GrADS, Grid Analysis and Display System, is an interactive tool that is used for easy access, manipulation, and visualization of earth science data.

The LPRM soil moisture product will be customized according to WAOB requirements (e.g., subsetting, gridding of swath outputs, and conversion to GIS-compatible formats). Customization ensures the data can be directly and easily integrated into GLADSE, in a form that is usable and effective. Once operational, the LPRM soil moisture product will be integrated into WAOB GLADSE directly as well as via EPIC.

Giovanni, Online Visualization and Analysis

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 instance for soil moisture has been developed that includes, for now, the standard soil moisture AMSR-E product from the EOS/Aqua mission. Once the LPRM products are in production, they will be added to the instance. Figure 9 shows the user interface and an example output plot. In addition to the user interface, Giovanni outputs will also be accessible to the WAOB via Web services (e.g., WMS). How the service(s) will be integrated into GLADSE is under discussion.

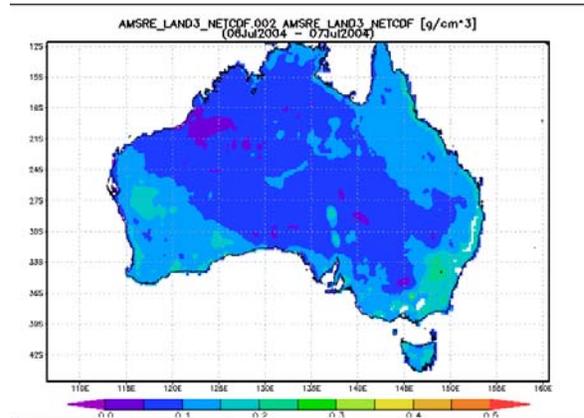
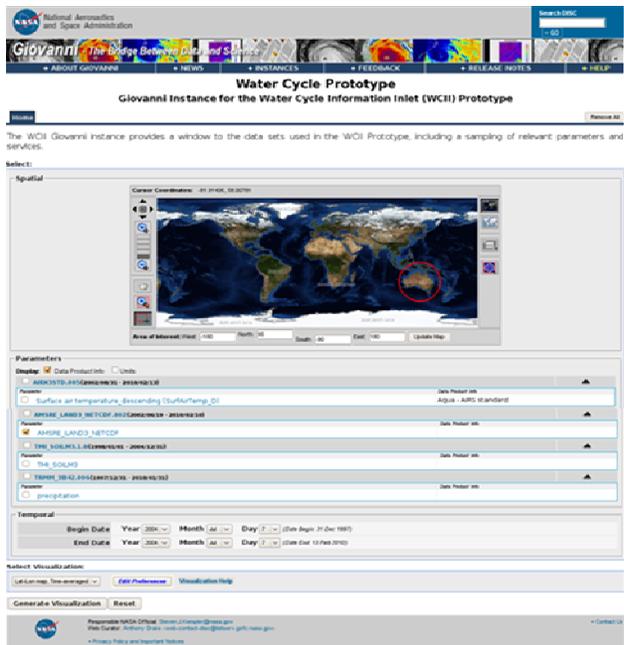


Figure 9. Prototype Giovanni instance for soil moisture: user interface and example output plot.

METRICS AND CURRENT STATUS

Measuring Improvements to GLADSE

Although the amount of precipitation can have a significant impact on crop production, the timing of the precipitation is often equally as important. For this reason, WAOB frequently examines precipitation time series to estimate crop productivity. An effective method for assessing crop production is the use of analog year comparisons. WAOB applies this technique by comparing the precipitation time series from several historical years with one from the current year. Through visual inspection, the meteorologist attempts to identify those time series, and hence years, that had similar precipitation patterns (i.e., timing and amounts). When analog years are identified, the meteorologist is often able to estimate crop yields for the current season based on the observed yields from the analog years, because of the similarities in the precipitation patterns.

In this project, the value of the NASA-provided soil moisture will be assessed by generating time series of these data, and then using the soil moisture time series and precipitation time series to identify analog years. Given that soil moisture often has a more direct impact than precipitation does on crop water availability, the time series of soil moisture could be more effective than the time series of precipitation in identifying those years with similar crop yields. Retrospective analysis of analogs will be conducted to determine any reduction in the level of uncertainty in identifying analog years, and any reduction in false negatives or false positives.

Figure 10 shows an example from New South Wales, Australia. In 2006, drought in New South Wales threatened to reduce winter wheat yields, a reduction estimated by WAOB meteorologists to be similar to those 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.

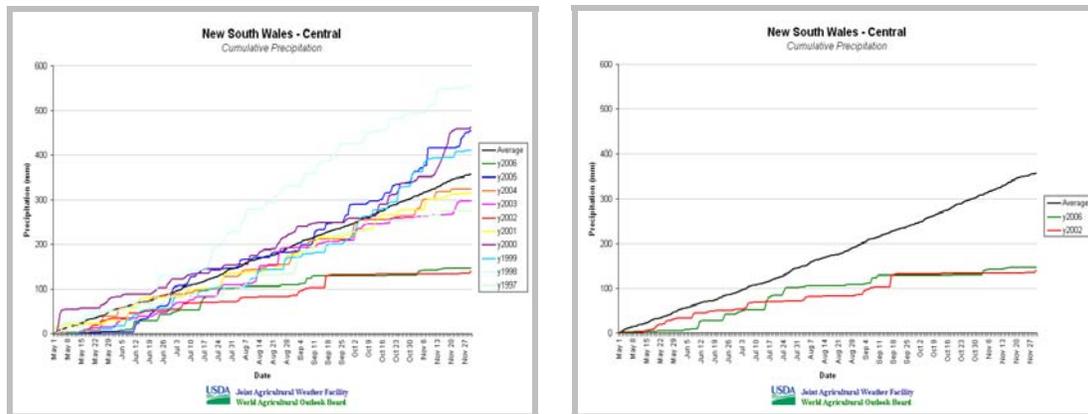


Figure 10. Example of using analog year comparisons to estimate crop yields. 2006 is the target year; 2002 is an analog year.

The comparison of analog years could potentially be improved by quantifying the selection of analogs, instead of the current visual inspection method. Various approaches to quantifying are currently being evaluated.

Current Status

This project has just begun. Current status includes (1) start of integration of LPRM into S4PM, (2) investigation of different methods of integrating LPRM into EPIC, (3) prototyping of Giovanni instance for soil moisture, and (4) start of benchmarking of GLADSE and establishing project metrics.

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

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