Global Drought and Agricultural Water Productivity Monitoring: Transitioning Towards Application Scales

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GEOSS Architecture Implementation Pilot – Phase 3

Global Drought and Agricultural Water Productivity Monitoring: *Transitioning Towards Application Scales*

A Proposal for GEO AIP-3

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1. Background

Drought is likely to increase in a global warming climate (Burke et al., 2006; Sheffield and Wood 2008), and, as such, drought has been listed as one of the Group on Earth Observation (GEO) subtasks for the Water Societal Benefit Area (SBA). The issue of drought and water scarcity or water over-allocation is cross-cutting, having impacts in sustainable agriculture, food security, water quality impacts from fertilizer use and higher stream and lake temperatures, and ecological biodiversity, as well (Figure 1). This pilot project aims to explore the potential for developing regional drought and agricultural productivity monitoring systems that will help quantify our current capability to address these issues.

2. Drought Monitoring at Regional to Global Scales

Drought monitoring compares soil moisture (SM; or other hydrometeorological variables) of a given location (a grid cell), and for that time during the year (that month) against the soil moisture for that location and the same time over a very long period (a climatology from observations or reconstructed by model runs for a 30 year period or longer) (Figure 2). The deficit of the anomalously low soil moisture below climatology determines the drought *magnitude*. When combined with the *area* of such anomalously low soil moisture, and the *duration* of the anomaly, a drought can be characterized as "shallow" or "severe." The drought monitoring system is set up to provide warning to farmers and agricultural managers) and professionals within the food security area, to provide advance warning (particularly, if a seasonal or short-term forecast system is implemented).

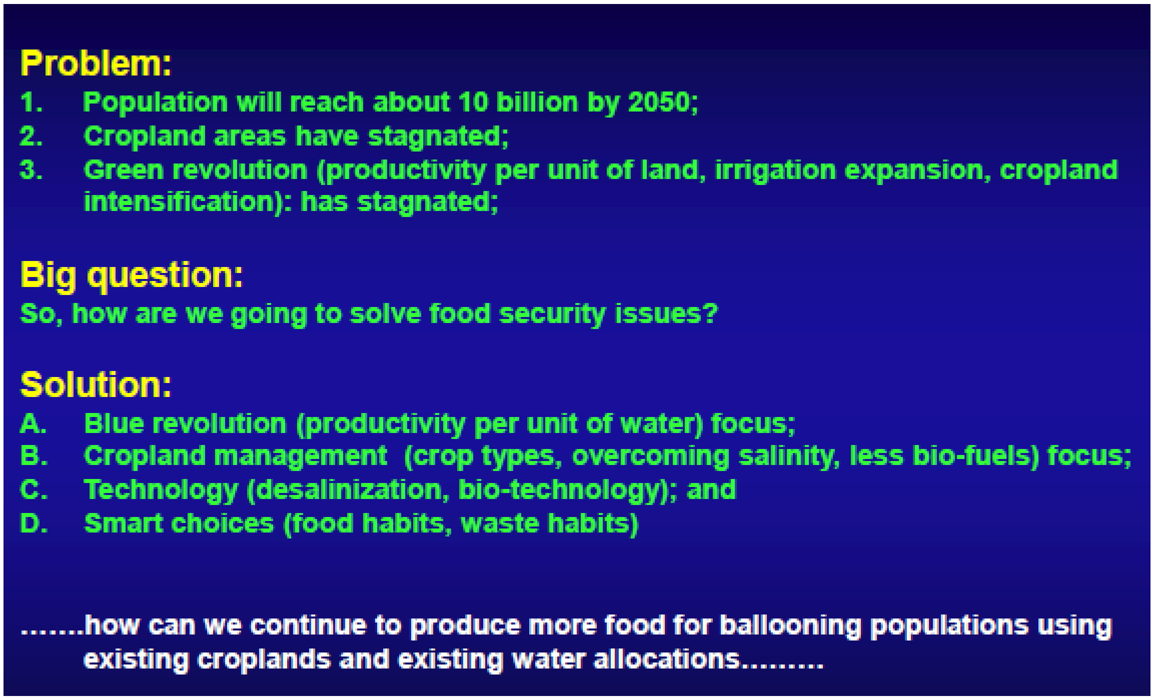

Figure 1. Central question linking global food security to cropland areas, their water use (blue water and green water use , population growth, economic expansion, highlighting the critical need for a drought and soil moisture monitoring system (Thenkabail and Pozzi 2010).

Given the very few *in situ* observations, soil moisture is generally estimated using a model or an ensemble of global hydrologic models, which utilize observations of precipitation and meteorological properties of air temperature, solar and terrestrial radiation, wind speed, and snow cover to solve Land Surface Models for resultant soil moisture (generally within the root zone). Some of the models used include the National Center for Atmospheric Research (NCAR) Community Land Model (CLM), the National Oceanic and Atmospheric Administration (NOAA) Noah LSM, the UK JULES model, the Variable Infiltration Capacity (VIC) model, the high resolution version of the NASA/GSFC Global Land Data Assimilation System (GLDAS), and WBM/WTM.

3. Agricultural Productivity Monitoring at Regional to Global Scales

Drought can impact urban and rural domestic water use, but it particularly impacts agriculture, either directly or indirectly via reduction in irrigation water supplies. Agricultural drought monitoring is most useful when it assesses impacts on the actual crops in the area where it strikes, as a slow onset disaster. Agricultural drought monitoring identifies the deficit between crop water demand and available soil moisture. Water usage for agriculture can be added as a term to the surface water budget, which decreases the remaining water available for alternative uses. Water usage for agriculture is determined for each individual crop, since different crops require different amounts of water during their growth stages. For example, winter wheat has a tillering stage before winter, regenerating period, booting stage and a heading stage (which is the period requiring the largest amount of water for the plant to grow). Winter wheat regenerates in early March and tassels in middle April, NDVI increasing continuously, until the peak during the heading stage (at the same time as maximum water demand); subsequently, the leaves and tassels become yellow, causing NDVI to decline due to decrease of greenness; such signatures clearly differentiate winter wheat from forest. Phenology (crop calendar) is hence an important factor in fixing water demand, as are crop type and area planted with each type of crop.

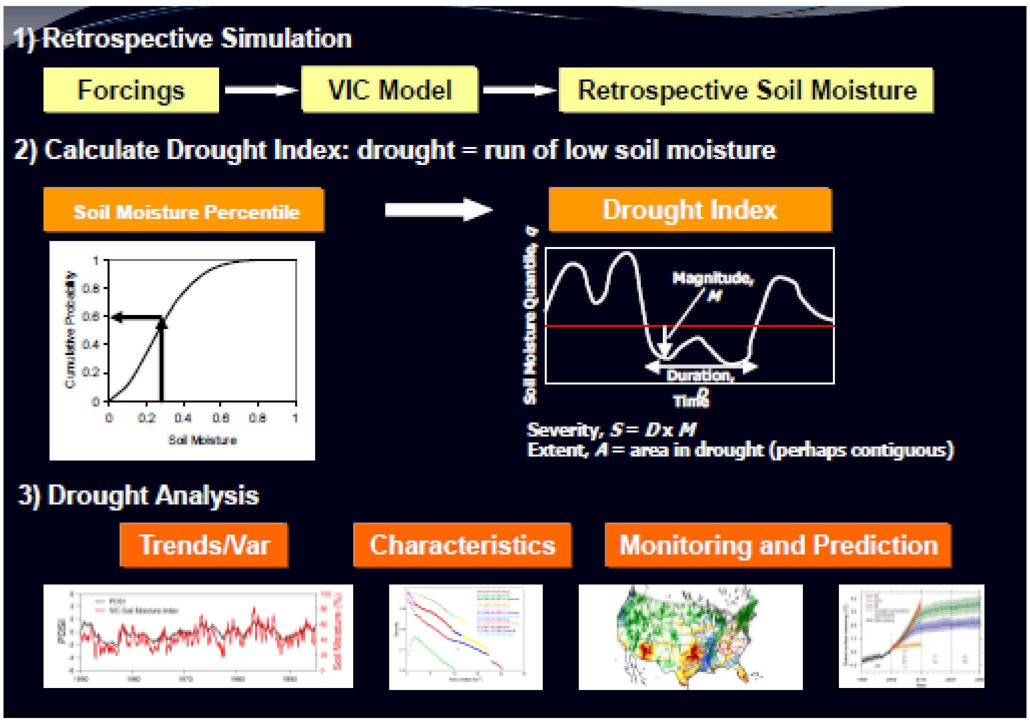

Figure 2. Calculation of a drought index based on observation forced land surface model simulations (Wood 2010)

The use of models for agricultural and drought monitoring requires these type of data to be specified at each model grid cell, that is the proportion of land cover and the proportion of land use, including crops. Earth Observations can be used to improve the precision with which this information is made available to the model (for example, as a dynamic crop mask). For example, the International Water Management Institute (IWMI) Global Irrigation Area Map (GIAM) has assembled a global map at 10 km; furthermore, additional supplemental studies have been carried out at MODIS scales (500 m to 1 km). Thenkabail et al (2009) and Dheeravath et al (2009) compare GIAM 10km irrigated area versus GIAM 500m irrigated areas for the most heavily irrigated states within India; and the discrepancies can be striking: higher resolution imagery (MODIS over AVHRR) increases the detection of more cropland. A similar trend is to be expected moving from MODIS to Landsat (30 m) (Velpuri et al 2009), which will allow upgrading from crop *dominance* to crop *type* classifications. Higher resolution and multiple satellite images (a time series) are needed to differentiate among vegetation types, including crop types. The overall objective is to reduce uncertainties of estimating actual water demands.

Earth Observations can also be used to monitor evapotranspiration (i.e., estimate crop evapotranspiration and consumption of fresh water through evaporation over the spatial resolution of the grid cell), using energy balance modeling techniques such as METRIC, EPIC, dis-ALEXI, and SEBA.

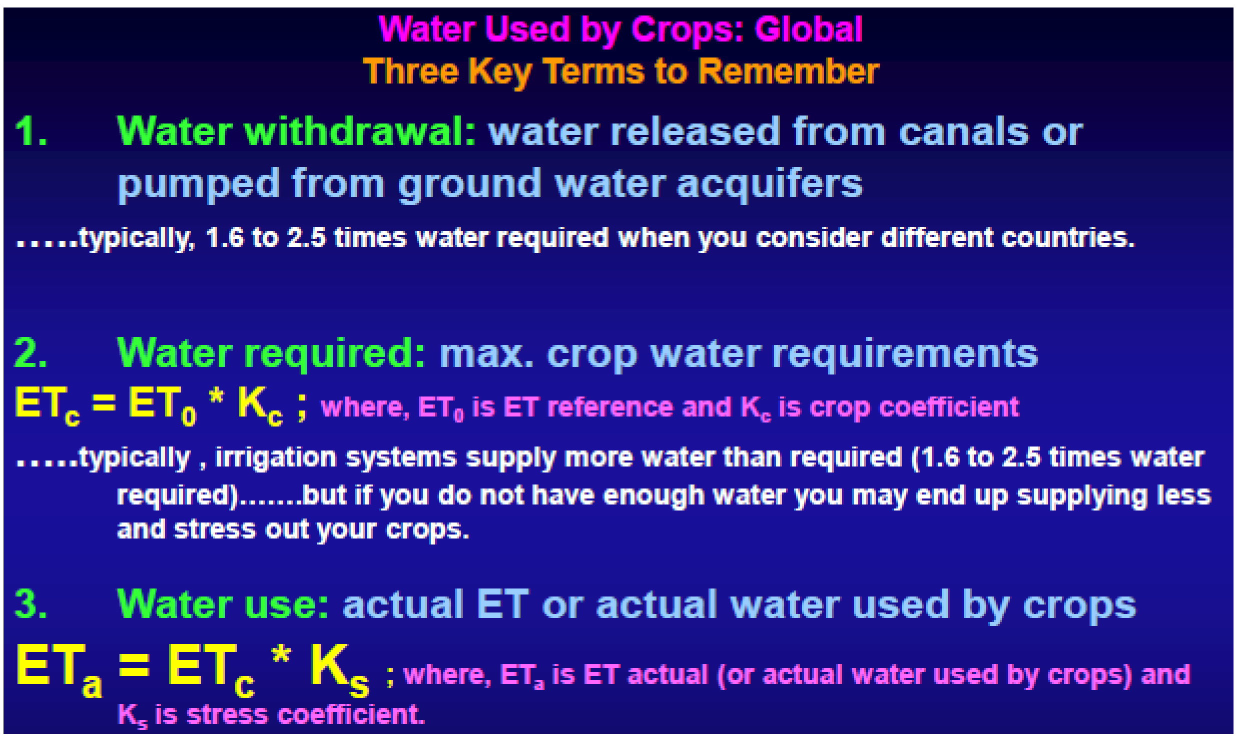

Figure 3. Optimal crop water requirements during best practices to maximize yields compared with actual water use and actual irrigation water supplied (e.g., at head water or through pumping).

Thirdly, agricultural *production* can be linked to the fraction of photosynthetic active radiation (fPAR) or derived from regressions of ground-based crop production measurement with satellite imagery while the satellite overpasses occurs at the same time as the ground-based survey. This third source of information—agricultural production—can be used with the second source of information (the estimated evapotranspiration as identified by satellites) to combine measures of the efficiency or productivity of water use by vegetation. When agricultural production (kg/m^2) is divided by water use (m^3 of water/m^2), the resultant product is agricultural *water productivity* (kg of produce/m^3 of water) (Figure 5). Agricultural water productivity mapping provides the capability of mapping the efficiency of water use over each grid cell and each pixel.

$$\mathbf{WP} = \frac{\textbf{Crop Productivity}}{\textbf{Water use}}$$

Water productivity (WP): is crop water productivity (kg/m^3)/(\$/m^3)

Crop Productivity (CP): in units of Biomass (kg/m^2) or Yield (kg/m^2) or Value (\$/m^2)

Water use (WU): is seasonal actual ET (thousand m^3/m^2)

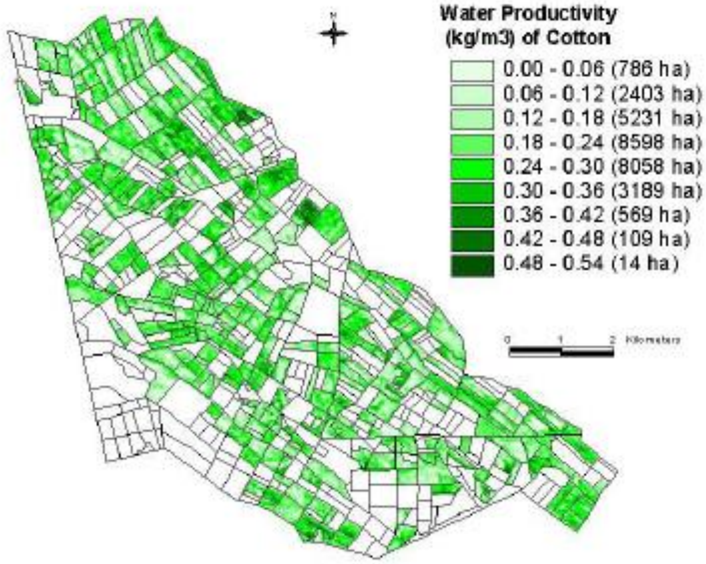

Figure 4 Map of Water Productivity (crop per drop or productivity per unit of water) in cotton fields in Uzbekistan (Platonov et al 2008). Nearly 80% of cotton crops have low water productivity indicating opportunity to increase food production in low water productivity areas using the same allocation of water and existing croplands.

There are two ways to estimate water use by crops, and the two techniques can be compared against each other. The energy balance approach (e.g. using SEBAL, METRIC, SETI, EPIC, dis-ALEXI) is the before-mentioned technique, while the second is the water balance approach (LSMs including routing). Water is lost in the process of making it available for irrigation: during the process of pumping it to the surface or through drainage as water is drawn through a canal system to the crop site. This loss is the reason for the difference between "gross" irrigation requirement and "net" irrigation requirement, as coined by Doell and Siebert (2002). The net irrigation requirement is divided by a "project efficiency" of irrigation, which refers to the volume of water transpired by the crop as a ratio of the volume of water diverted from the river or reservoirs at the inlet to an irrigation project or pumped from groundwater. The water budget equation can be extended to include terms for such loss, so that agricultural production can be divided by the total water consumed in the agricultural operation (both evapotranspiration and water loss), giving a better estimate of agricultural water management being practiced at sites, as revealed by agricultural water productivity mapping using Earth Observations.

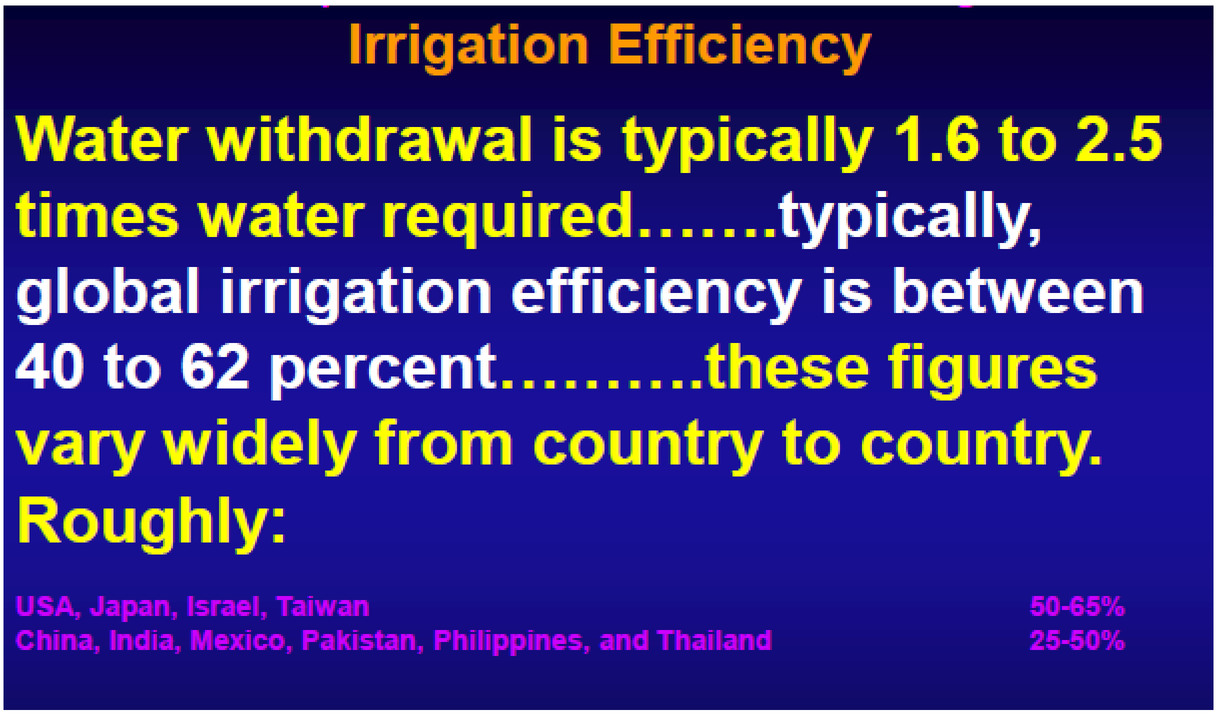

Figure 5 Practical Application of drought monitoring system to save water and produce more food

Some Land Surface Models simulate irrigation by employing irrigation "triggers": during a LSM model run, if soil moisture falls below a specified soil moisture threshold (the trigger), then irrigation water is applied for surface sources within the model. Then the irrigation water used in the model can be compared against evapotranspiration estimated using an energy balance technique, such as EPIC or dis-ALEXI. Root zone soil moisture may be defined as the numerator of the difference between estimated soil moisture and the soil moisture content that exists at the wilting point of the vegetation divided by the denominator of the difference between soil moisture content at field capacity and the soil moisture content at the wilting point.

Farmers not using soil moisture sensors at 30 to 40 cm depth (in the developed world) currently may base soil dryness on soil color, wilting, or irrigate by a set schedule during periods without rainfall. The agricultural drought monitor would provide a capability to reduce water wastage by improving the knowledge of soil moisture conditions, a situation that will hopefully improve when the NASA Soil Moisture Active and Passive (SMAP) mission comes on-line.

4. Advanced Methodologies of Global Cropland Monitoring

Global classification of agricultural area (agricultural land use), agricultural crop type, and crop phenology provides the information necessary to identify agricultural crop fractional coverage on a grid cell, the water demand of a crop during a calendar month during its growth cycle, and crop type (e.g. cotton versus wheat). Two major methodologies have been proposed and utilized in the semi-automated process of sorting through images in order to identify irrigated areas. The two techniques are the GIAM approach (Thenkabail et al 2009) and Ozdogan and Gutman (2008). The basis for Ozdogan and Gutman (2008) is the following procedure:

1. A climatological moisture index (the Budkyko (1974) Radiative Dryness Index) uses mean annual net radiation and mean measured annual precipitation from the WorldClim 1 km spatial resolution database to sort through the Ramankutty and Foley (XXXX) static distribution of croplands, in order to locate areas of *effective irrigation potential*;
2. NDVI time series identifies a mismatch between the greenness cycle of rain-fed crops and the greenness cycle of irrigated crops, particularly in arid and semi-arid environments, which separates areas of rain-fed from areas of irrigated crops.
3. If the same crop type is grown in the same growing season, some crops with irrigation and some without irrigation, or having some crops irrigated and some not within the same area is very difficult to identify, because the irrigated crops display only a slightly larger NDVI in such a situations; Odogan and Gutman (2008) propose a supplemental technique, that of using the (Gitelson et. al 2003) Green Index (GI) which may have a higher sensitivity of chlorophyll to moisture than NDVI.
4. These effective irrigation potential identified areas and remotely sensed indices are utilized within a supervised classification algorithm (decision tree) in order to identify areas where irrigation is practiced;
5. Sub-pixel proportion of irrigation is estimated.

Secondly, the GIAM methodology consists of the following steps:

1) Create a Master File Data Collection (MFDC);
2) Image segmentation (dividing into various climate and elevation zones, by analogy with the first step in the Ozdogan and Gutman (2008) procedure;
3) Production of an Ideal Spectra Data Base (ISDB);
4) Generate class spectra through classification;

5) Quantitative matching of class spectra with ISDB through spectral matching techniques (SMTs);
6) Resolve mixed classes;
7) Standardize class identification;
8) Estimation of Sub-pixel proportion of irrigation

GIAM was accompanied by an extensive ground truth program that created precise ground truth data from 6000+ spatially well distributed points in the cropland areas of the World. The GIAM Ground Truth program was based upon stratified random sampling by road network and randomized by stopping at different land cover types along the road, collecting data for different locations at intervals of 5 to 10 km over India, that included: a) GPS coordinates; b) watering method (irrigated, rain-fed, supplemental); c) irrigation type, such as "major" irrigation project surface water source, "medium" irrigation project surface water source, groundwater, small reservoirs, and tanks. A second source of field data was provided by the Degree Confluence Project, a network of volunteers who gathered precise geographic locations for every one-degree latitude and longitude and recorded land use and digital photos (Thenkabail et al 2009b).

Given the two approaches, one outcome of the Ozdogan and Gutman (2008) methodology, that was carried out over the USA, was revealed by comparing MODIS selected sites of irrigation, as identified within their classification methodology, with the extensive ground-based surveys of farm production carried out as part of the US Department of Agriculture (USDA) Census of Agriculture (http://www.nass.usda.gov/Census_of_Agriculture/). Although the Ozdogen and Gutman (2008) classification system seemed to perform generally well in semi-arid areas, as revealed with similarity with the USDA surveys, considerable discrepancies were found in the Eastern USA, suggesting either "false positives" (Ozdogan and Gutman 2007) or that a static *climatological* classification may be adequate for a relatively stationary semi arid terrain, but is poorly suited for the humid, dynamic conditions found over the eastern USA (where the discrepancies are greatest) (Figure 6). The greatest consumption of water for US agriculture occurs in the semi-arid Western USA where the agreement between MODIS and ground-based USDA Census data are commensurate. However, the lower panel of figure 6, representing the USDA county-level ground-based irrigation reporting displays irrigation use occurring in southeastern coastal US states, for which there is no corresponding detection using the classification system with MODIS data. There are, at least, two possibilities for this. First, the mean climatological data may be creating a wet "bias" so that the areas are dropped from consideration by the classification system as not being dry enough (by climatological standards). Another possibility is that the USDA census data were collected during a dry year (with more irrigation in the East), whereas the MODIS images represent a different, wetter year. An alternative technique will deploy a dynamic land surface model, to compare with the current GIAM30m methodology, to see if it improves identification of irrigation in more humid conditions. Selection of a case study region, within the eastern USA, may be appropriate to test whether the use of static climatology as first steps in image classification is amiss.

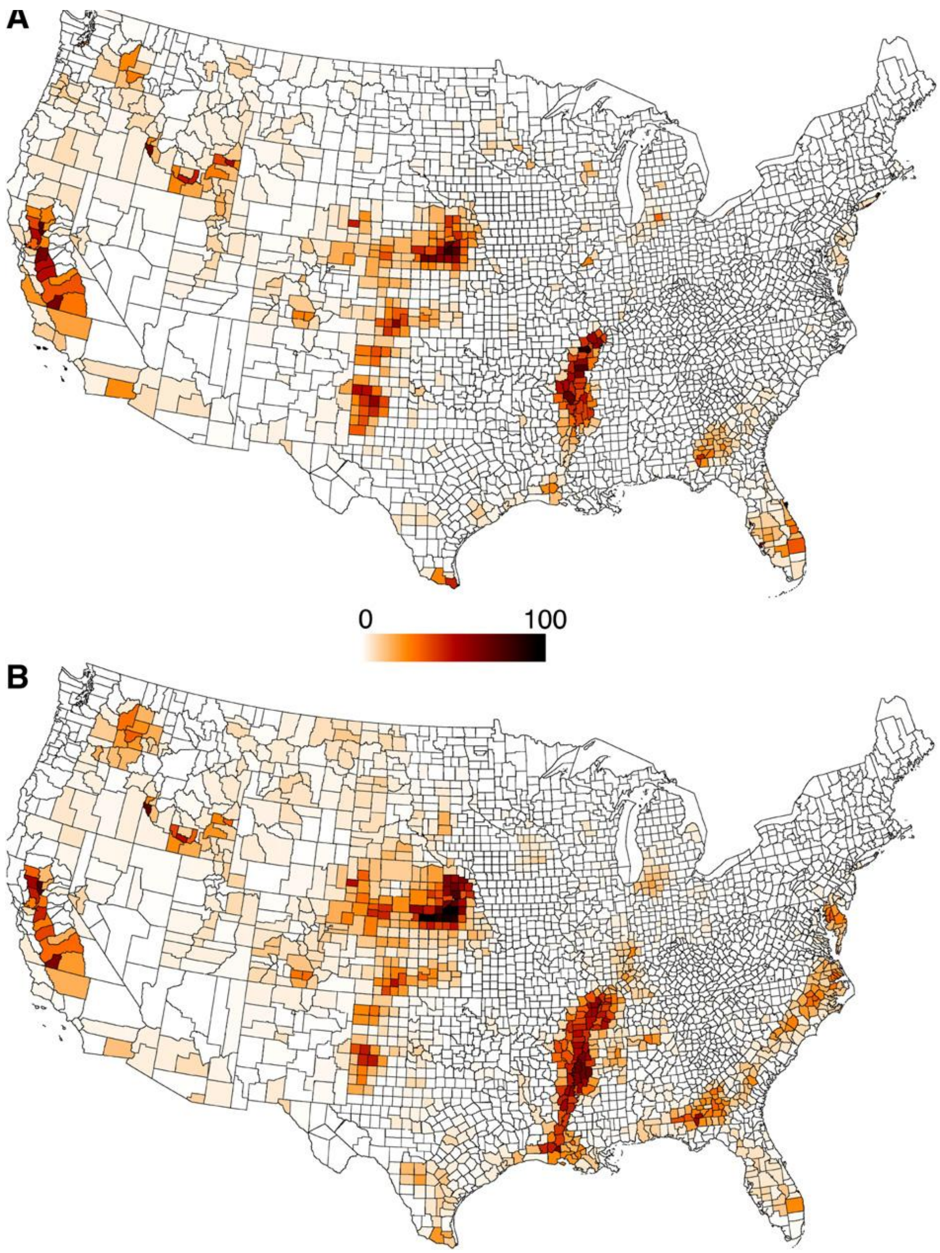

Figure 6 Census-reported irrigation (bottom panel) not showing up in MODIS-classified irrigation (top panel)(Ozdogan and Gutman 2008)

Both the extensive ground-based USDA surveys, including surveys by the California Department of Water Resources, and the extensive GIAM prior work carried out in India suggest both locations as possible regional sites in carrying out pilot projects or case studies of agricultural water use linked to drought monitoring. While the National Integrated Drought Information System (NIDIS) is carrying out extensive work within the US, a complementary project can be carried out, testing the veracity of large scale agricultural water productivity mapping, with accessible field sites (in the USA) and accessible networks (in India). In addition, MODIS scale work has been carried out in both areas with work to be undertaken at higher resolution Landsat (30 m) scales.

5. Deploying global drought monitoring system for global food security

The overall program will be based on merging existing drought, water use and land use monitoring technologies into regional drought and agricultural productivity monitoring systems focus on the U.S.A and India.

1. Deploy the existing coarse scale Princeton experimental global drought monitor (Sheffield et al., 2008), which is based on the VIC land surface model, and compare its nowcasts with existing regional drought monitors (Figure 7);

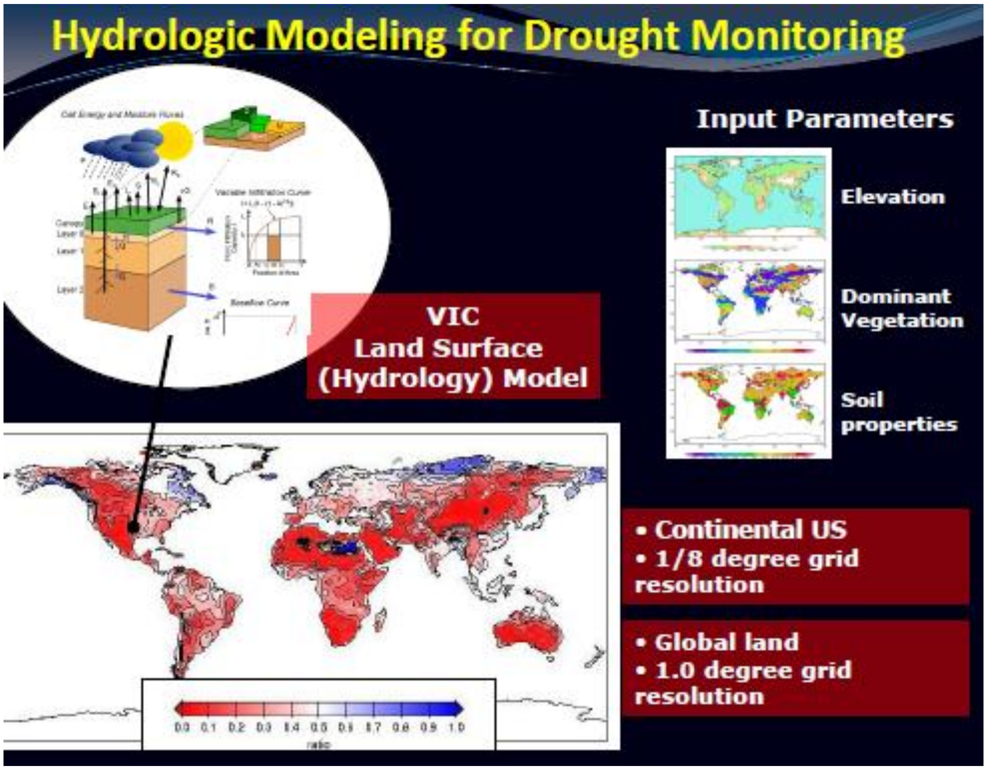

Figure 7. Coarse-scale Global Drought Monitoring (Wood 2010)

2. Increase the resolution of the drought monitor for the regional study areas (likely 1km) that is more useful at application scales for decision support. At the same time, a higher resolution drought monitoring system will be able to more accurately delineate the spatial domains and area of drought. Such a higher resolution system will require correspondingly higher spatial resolution ancillary data such as agricultural crop acreage, crop type, and phenology (crop calendar) distributions. To accomplish this, the project will scale down from MODIS scale to Landsat scales in several regional case studies.

3. Within the regional case studies, Earth Observations will be used for estimating actual agricultural water use with the EPIC and dis-ALEXI methodologies. These results will be compared to the water budget approach using the land surface model;
4. Within some regional areas, a parallel data processing track will be created in which dynamic land surface models will be used to provide the first segmentation and identification of potential irrigation areas, and compare these results with the existing methodological approach based upon static climatology as a first step; this will be undertaken in a more humid, as opposed to semi-arid area (possibly eastern USA);
5. The regional case studies will—by utilizing local ground truth networks—assemble agricultural production data. Dividing the agricultural production for the area by the water use recorded for the area will enable agricultural water productivity to be mapped over a region. The variability expressed within the maps will be linked to local resident conditions in order to test the veracity of agricultural water productivity as a water management tool;
6. Having case studies in USA vs. India will allow comparison of large monoculture agricultural fields (perhaps with standardized irrigation) in the case of the USA versus small agricultural plots with multiple water practices (in the case of India) to ensure that a test of agricultural water productivity will not fail due to homogeneous irrigation and terrain conditions;
7. Datasets will be required to run all models; multiple data collections and data centers will likely have its own schema so that considerable semantic heterogeneity may exist among the multiple data centers. Ontology-enabled semantic data integration will be employed, using water and agricultural ontologies, which will be registered with the GEOSS vocabularies. Web services will also be investigated for transmitting data;
8. The Drought Monitor will be integrated within the GEO Common Infrastructure to be accessible within the GEO portal.
9. Although Soil Moisture nowcasts will be available on the GEO portal, an alternative delivery system may be desired for poorer areas such as India.

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