Special Issue: Global Cropland

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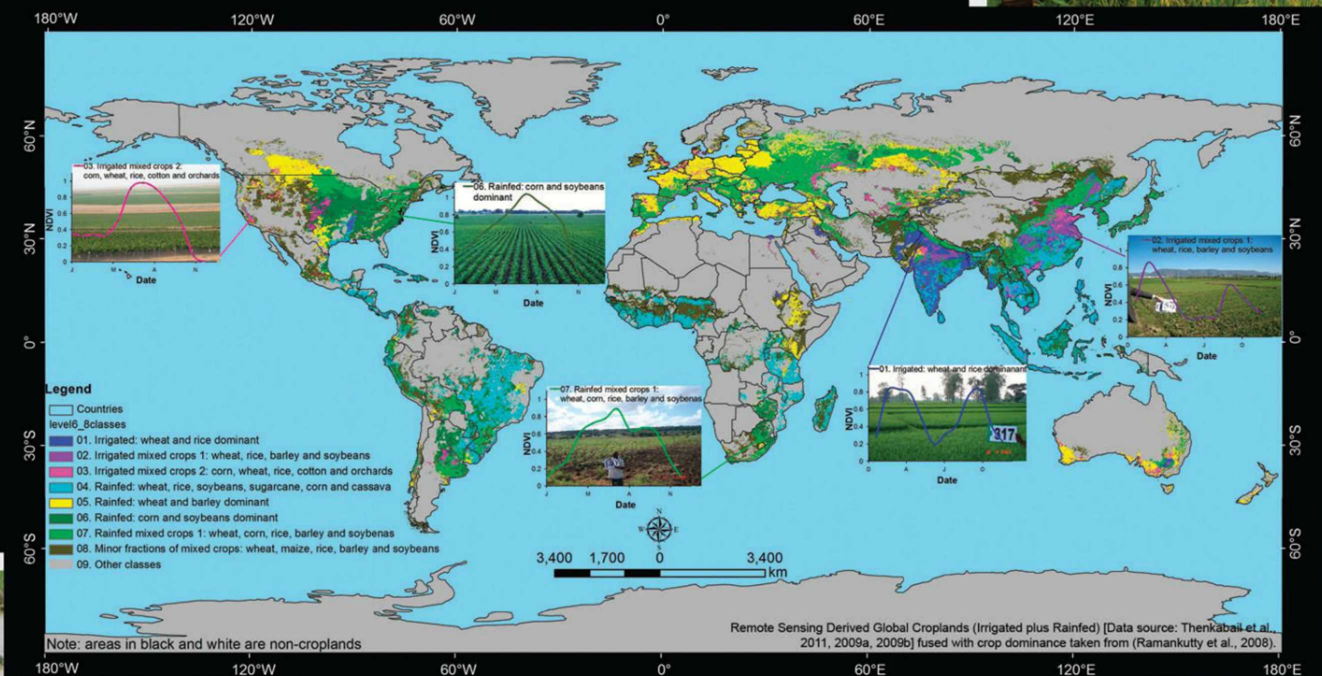

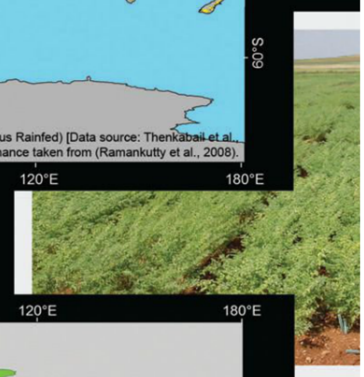

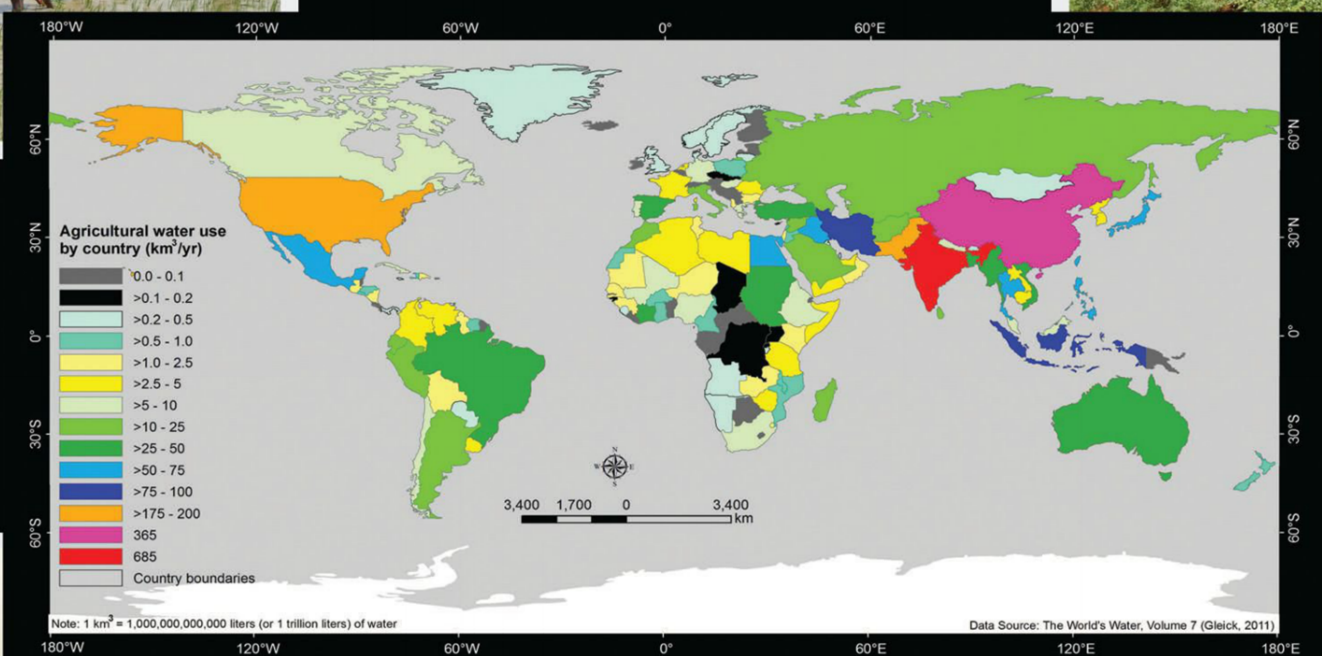

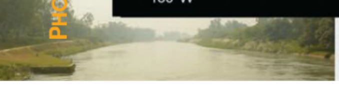

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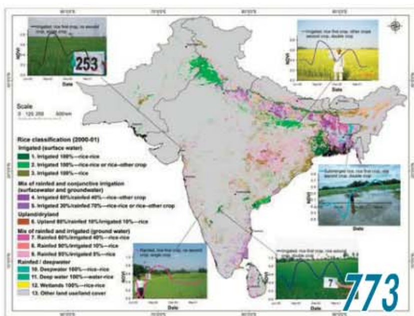
"Global Croplands and Their Water Use" is the theme of this month's special issue. The top image shows spatial distribution of global cropland areas (~1.5 billion hectares) and five dominant crop types (wheat, rice, maize, barley and soybeans). This composite map was produced by Thenkabail and Gumma through spatial modeling involving remote sensing derived global irrigated and rainfed croplands (Thenkabail et al., 2011, 2009a, 2009b) and five dominant global crop types from other sources (Ramankutty *et al.* (2008), Monfreda *et al.* (2008), and Portman *et al.* (2009)).

The bottom image, produced using data from World's Water Volume 7 (Gleick, 2011), shows country by country agricultural water use. Globally, humans use about 4000 km³\yr of freshwater of which about 70% goes for agriculture to produce food. Just four countries use 52% of this 70%: India 684 km³\yr, China 364 km³\yr, USA 197 km³\yr, and Pakistan 172 km³\yr.

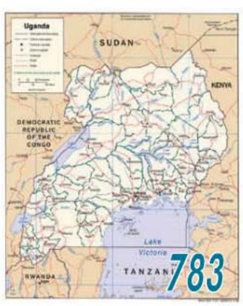
For details see the Highlight article in this issue.

Cover page credits: Dr. Prasad S. Thenkabail, U.S. Geological Survey (USGS) and Dr. Murali Krishna Gumma, International Rice Research Institute (IRRI) with inputs from the USGS Powell Center working group on global croplands (WGGC) team members (http://powellcenter.usgs.gov/current_projects.php#GlobalCroplandMembers). For more information contact: pthenkabail@usgs.gov or thenkabail@gmail.com.

Highlight Article



Special Issue Foreword



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Assessing Future Risks to Agricultural Productivity, Water Resources and Food Security: How Can Remote Sensing Help?

By Prasad S. Thenkabail, Jerry W. Knox, Mutlu Ozdogan, Murali Krishna Gumma, Russell G. Congalton, Zhuoting Wu, Cristina Milesi, Alex Finkral, Mike Marshall, Isabella Mariotto, Songcai You, Chandra Giri, and Pamela Nagler

Introduction

Although global food production has been rising, the world still faces a major food security challenge. Over one billion people are currently undernourished (Wheeler and Kay, 2010). By the 2050s, the human population is projected to grow to 9.1 billion. Over three-quarters of these people will be living in developing countries, in regions that already lack the capacity to feed their populations. Under current agricultural practices, the increased demand for food would require in excess of one billion hectares of new cropland, nearly equivalent to the land area of the United States, and would lead to significant increases in greenhouse gases (Tillman *et al.*, 2011). Since climate is the primary determinant of agricultural productivity, changes to it will influence not only crop yields, but also hydrologic balances and supplies of inputs to managed farming systems, and may lead to a shift in the geographic location of some crops. Therefore, not only must crop productivity (yield per unit of land; kg/m^2) increase, but water productivity (yield per unit of water or "crop per drop"; kg/m^3) must increase as well in order to feed a burgeoning population against a backdrop of changing dietary consumption patterns, a changing climate and the growing scarcity of water and land (Beddington, 2010). The impact from these changes will affect the viability of both dryland subsistence and irrigated commodity food production (Knox, *et al.*, 2010a). Since climate is a primary determinant of agricultural productivity, any changes will influence not only crop yields, but also the hydrologic balances, and supplies of inputs to managed farming systems as well as potentially shifting the geographic location for specific crops. Unless concerted and collective action is taken, society risks worldwide food shortages, scarcity of water resources and insufficient energy. This has the potential to unleash public unrest, cross-border conflicts and migration as people flee the worst-affected regions to seek refuge in "safe havens", a situation that Beddington described as the "perfect storm" (2010).

"Under current agricultural practices, the increased demand for food would require in excess of one billion hectares (~ equivalent to the land area of the United States) of new cropland to feed the 9 billion plus by year 2050."

A step toward solution lies in improving the monitoring of croplands using a means to map them routinely, rapidly, consistently, and with sufficient accuracy (Congalton and Green, 2009). This, in turn, will help determine how croplands are used and how they might be better managed to optimize the use of resources in food production. We must identify regions where there is potential to reduce the "yield gap" by improving water productivity. The yield gap — the difference between potential and actual yield — is a widespread problem that constrains production in both the developed and developing worlds, particularly since croplands account for 80 percent of worldwide freshwater extractions (Licker *et al.*, 2010). Further, we must seek to better understand the links between food production and water scarcity, and the variety of impacts that climate change may have on food supplies (Knox *et al.*, 2010b). In some countries, cropped areas available for food production have begun to decline in response to increased demand for bio-fuel production, encroachment from urbanization, land degradation from mismanagement, and enhanced interest in environmental protection. Emerging insistence on biodiversity conservation and carbon sequestration have also put a cap on possible expansion of cropland into areas such as forests and rangelands.

Given these complexities, together with the need to improve our understanding of the range of options and the global scale of the overarching issues, remote sensing will play an increasingly significant role in supporting both data collection and policy formulation. This will include the creation of a framework of best practices and an advanced global geospatial information system on cropland and water use. Such a system would need to be consistent among nations and regions. It would provide information on issues such as the composition and location of cropping, number of crops per year, rotations, crop health and vigor, irrigation status, flood and drought risk, water demand, and crop and water productivity. Such a global system can be established by fusing advanced remote sensing data from diverse platforms and agencies (e.g., http://wgiss.ceos.org/lsip/satellites_midres1.shtml; http://www.ceos-cove.org/index.php) in combination with national statistics; secondary data, such as elevation, slope, soils, temperature, and precipitation; and, systematic collection of field level observations.

This paper provides a brief overview of the state of the art by which remote sensing technologies can encompass global cropland assessment and the role these technologies can play in the new food security paradigm. We will highlight the main areas of progress and then identify the key challenges that need to be addressed.

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State of the Art in Global Cropland Assessment

There are currently five major global cropland maps: (1) Thenkabail *et al.* (2009a,b, 2011), (2) Ramankutty *et al.* (1998), (3) Goldewijk *et al.* (2011), (4) Portmann *et al.* (2009)\Siebert and Döll (2009), and (5) Pittman *et al.* (2010). These studies have all estimated total worldwide cropland area to be around 1.5 billion hectares, using the year 2000 as a baseline. Throughout the Earth, cropland areas have increased from around 265 Mha in 1700 to around 1,471 Mha in 1990, while pasture area has increased over sixfold, from 524 to 3,451 Mha (Foley *et al.*, 2011). Ramankutty and Foley (1999) estimated cropland and pasture to represent about 36 percent of the world's terrestrial surface (148,940,000 km^2). According to a number of studies, roughly 12 percent of the terrestrial area is cropland and 24 percent pasture. Several studies (Goldewijk, *et al.*, 2011; Portmann, *et al.*, 2008; Ramankutty, *et al.*, 2008) integrated agricultural statistics and census data from national systems using spatial mapping technologies that involved geographic information systems (GIS) to derive global cropland maps. Pittman *et al.* (2010) used the United States Department of Agriculture (USDA) Foreign Agriculture Service (FAS) production, supply, and distribution (PSD) database to produce discrete cropland/non-cropland maps. Thenkabail and others (2009a,b, 2011) produced the first remote sensing-based worldwide irrigated and rainfed cropland maps and statistics for 198 countries through multi-sensor remote sensing data fusion together with secondary and *in-situ* data. They accomplished this (Thenkabail *et al.*, 2009a, 2009b, 2011) by taking advantage of (Thenkabail *et al.*, 2010): (a) free access to well calibrated and guaranteed data such as Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS); (b) frequent temporal coverage of data such as MODIS, backed by high resolution Landsat data; (c) free access to high quality secondary data such as long-term precipitation, evapotranspiration, surface temperature, soils, and the Global Digital Elevation Model (GDEM); (d) global coverage of the data; (e) web-access to data and faster downloading; (f) advances in computer technology; and (g) advances in processing.

"To feed the World in the 21st Century, not only must crop productivity (yield per unit of land; kg/m^2) increase, but water productivity (yield per unit of water or "crop per drop"; kg/m^3) as well."

Figure 1 shows the spatial distribution of Earth's agricultural cropland areas generated for the five major crops (wheat, rice, corn, barley and soybeans) produced using parcel-based inventory data (Monfreda *et al.*, 2008; Portmann *et al.*, 2008; Ramankutty *et al.*, 2008) overlaid with the global irrigated and rainfed cropland area map produced using remote sensing data by the International Water Management Institute (IWMI) (Thenkabail *et al.*, 2009a,b, 2011). These five crops account for about 60 percent of worldwide cropland areas. Although there is good general agreement, the precise location of these crops is only approximate due to the coarse resolution (approx. 1 to 10 km^2) and fractional representation of the crop data in each grid cell of all maps, since each pixel may contain from 1 to 100 percent of a crop. The IWMI cropland product (Thenkabail *et al.*, 2009a, b, 2011) is at approximately one km^2 resolution. Every pixel has a certain fractional percentage of a crop (typically above 50 percent). The two maps were resampled to one km^2 for seamless spatial analysis.

The existing cropland datasets also differ from one another due to inherent uncertainties in establishing the precise location of croplands, the watering method (whether rainfed, fully irrigated, or with supplemental irrigation), cropping intensities, crop types and/or dominance, and their characteristics (e.g., crop or water productivity measures such as biomass, yield, or water use). Improved knowledge of the uncertainties (see Congalton and Green, 2009) in these estimates will lead to a collection of highly accurate spatial data products to support crop modeling, food security analysis, and decision making.

One important variable affecting global food production is agricultural water use. Figure 2 shows the estimated demand for agricultural water using data by Gleick (2011), at country scale. Worldwide, humans use about 4,000 km^3 per year of fresh water, of which about 80 percent is used by agriculture for food crop production. However, other estimates of Worldwide agricultural cropland water use vary between 6,685 to 7,500 km^3 per year (Siebert and Döll, 2008), of which around 4,586 km^3 per year is by rainfed croplands (green water use) and the rest by irrigated croplands (blue water use) (Thenkabail *et al.*, 2010). Irrigated areas use about 2,099 km^3 yr^{-1} (1,180 km^3 per year of blue water and the rest from rain that falls over irrigated croplands; Siebert and Döll, 2008). Four countries account for the overwhelming proportion of total agricultural water extraction (India 684 km^3 yr^{-1}, China 364 km^3 yr^{-1}, the USA 197 km^3 yr^{-1}, and Pakistan 172 km^3 yr^{-1}; Figure 2). Agricultural water use depends on many factors; these include crop type, cropped area, irrigated area, irrigation efficiency, local agroclimate, geographic location, management practices, and evapotranspiration (ET_{crop}). However, the routine mapping of crop types typically applies an average water consumption value only somewhat modulated by management and geographic context. High resolution mapping sufficient to establish more accurate water use characteristics at global scales is required, and this is quite complex. Hence, initially the predominant focus of Earth's cropland mapping should focus on 18 dominant crop types that collectively account for 85 percent of the global high-resolution cropland area (Table 1). This recommendation was made by the U.S. Geological Survey (USGS) working group on global croplands (https://powellcenter.usgs.gov/globalcrop-landwater/) at the John Wesley Powell Center for Analysis and Synthesis at their 2011 meeting in Fort Collins, Colorado, USA: http://powellcenter.usgs.gov//current_projects.php#GlobalCroplandMembers.

Table 1. Area and relative proportion of the 18 major crop characteristics. [Source: Monfreda *et al.*, 2008].

Crop	Area (1,000 km^2)	Relative Proportion (%)
Wheat	4,028	22
Corn	2,271	13
Rice	1,956	11
Barley	1,580	9
Soybeans	927	5
Pulses	794	4
Cotton	534	3
Potatoes	501	3
Sorghum	501	3
Millet	331	2
Sunflower	290	2
Rye	288	2
Rapeseed/canola	283	2
Sugar cane	265	1
Groundnuts/peanuts	247	1
Cassava	235	1
Sugar beets	154	1
Oil palm fruit	72	<1
Total of major 18 crops	***15,256***	***85***
Others	2,664	15
Total cropland	***17,920***	***100***

Components of Global Cropland Mapping Using Remote Sensing

Remotely sensed data provides the only source of information to make a complex global agricultural monitoring system feasible by being consistent, repeatable, routine, rapid, and scalable. One way forward in cropland mapping will be to use satellite data with a resolution that matches the spatial heterogeneity of the landscape (i.e., 30 meters or better, such as from Landsat) along with more frequent observations (e.g., daily coverage with much coarser spatial resolution from sensors such as the MODIS 250m to 500m data). To these add secondary data (e.g., elevation, precipitation, evapotranspiration (ET), and temperature), national and sub-national statistics, and a large volume of *in-situ* observations that are spatially well distributed. The collection and fusion of these data will allow production of cropland area statistics and crop productivity data ranging from pixel to administrative unit level, both routinely and rapidly, using automated cropland classification algorithms (or ACCAs) as introduced by Thenkabail *et al.* (in review).

and advanced software; and, (h) advances in image processing. Heretofore, most remote sensing work over large areas produced land use/land cover maps (LULC) (Loveland *et al.*, 2000) but not thematic maps that specifically delineate a single category, such as croplands.

Development of a Historical Understanding of Croplands Through a Remote Sensing Pathfinder Dataset

The green revolution era occurred roughly between 1960 and 2000. It is interesting to examine the rapid expansion and intensification of global croplands during this period. Worldwide coverage of remote sensing data for the early years (1960s) of the green revolution is sporadic. Earth observation from satellites began when the Soviet Union launched Sputnik 1 in 1957, followed by NASA's Television Infrared Observation Satellite (TIROS-1), launched on 1 April 1960. Systematic global Earth observation data acquisition began with NOAA's Very High Resolution Radiometer (VHRR) and Advanced VHRR (AVHRR) in 1972, ERTS (Earth Resources Technology Satellites, later Landsat) also in 1972, SPOT (France) in 1986, and IRS (India) in 1988.

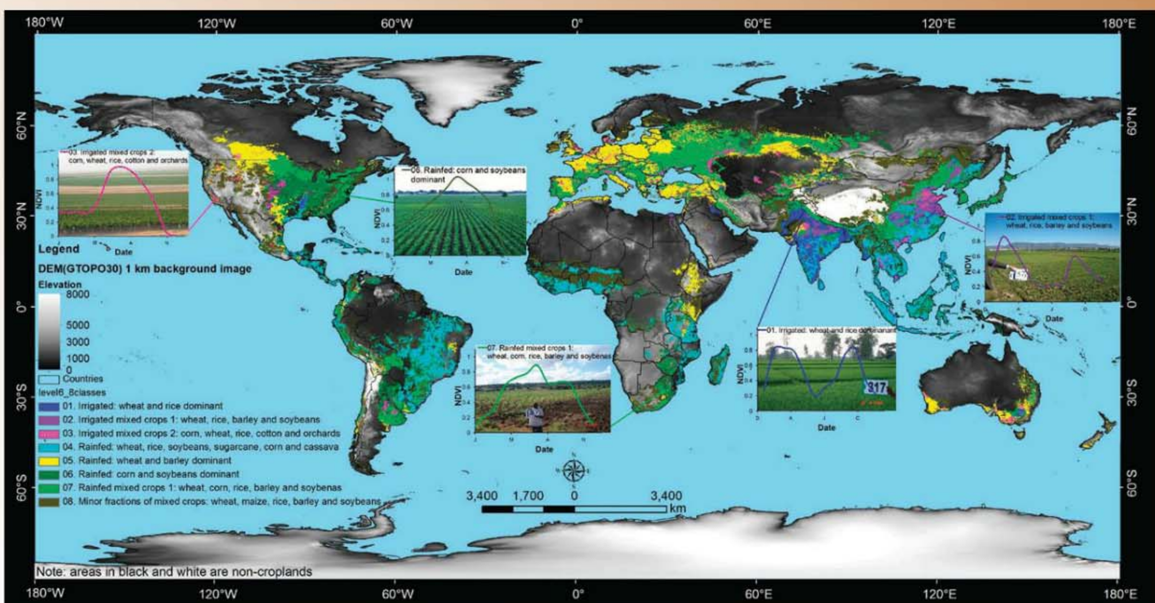

Figure 1. Spatial distribution of the five major global cropland types (wheat, rice, corn, barley and soybeans; which occupy 60% of all global cropland areas). The map is produced by overlying the five dominant crops of the world produced by Ramankutty *et al.* (2008), Monfreda *et al.* (2008), and Portman *et al.* (2009) over the remote sensing derived global irrigated and rainfed cropland area map of the International Water Management Institute (IWMI; Thenkabail *et al.*, 2009a, 2009b, 2011).

The specific remote sensing advances (Thenkabail *et al.*, 2010) that enable global cropland mapping and generation of their statistics include these factors: (a) free access to well calibrated data such as Landsat and MODIS; (b) frequent temporal coverage as provided by MODIS, NPOESS Preparatory Project Visible Infrared Imager Radiometer Suite (NPP VIIRS), and Satellite Pour l'Observation de la Terre (SPOT) Vegetation; (c) frequent sampling of large portions of the world from sensors matching the 30–100 m landscape scale (e.g., Landsat, Indian Remote Sensing Satellites (IRS), SPOT) and very high resolution sensors from the sub-meter to <5m range (e.g., RapidEye, IKONOS, QuickBird, GeoEye) from different space agencies of the world; (d) free access to high quality secondary data such as long-term precipitation, evapotranspiration, surface temperature, soils information, and Global Digital Elevation Model (GDEM) data; (e) global coverage; (f) web-access for immediate data access from anywhere in the world; (g) advances in computer technology, including processing speed

However, the availability of high quality, well calibrated remote sensing pathfinder datasets allows scientists to develop a global inventory of historical cropland information dating back to the 1970s. There are still problems with calibration of data from certain sensors (e.g., Landsat MSS), but work is underway to address them. The sources of these datasets include AVHRR Global Inventory Modeling and Mapping Studies (GIMMS; 1981-2006), MODIS time-series (2000-present), and Landsat Global Land Survey nominal 30 m mosaics for the 1970s, 1980s, 1990s, 2000s, a mid-decadal 2005, and 2010s. These data will help build an inventory of historical agricultural development by providing information on such factors as which areas have switched from rainfed to irrigated production (both full and supplemental), and non-cropped to cropped (and vice versa). A complete history will require systematic analysis of remotely sensed data as well as a compilation of all routinely populated cropland databases from the agricultural departments of all countries throughout the world.

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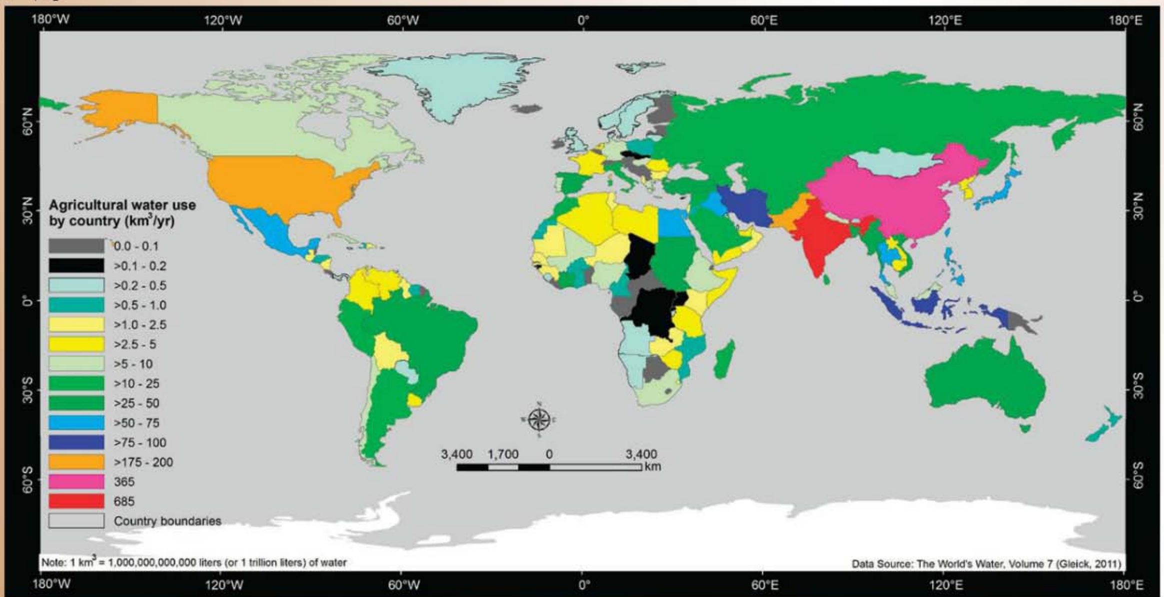

Figure 2. Country-wise agricultural crop water use in km^3/yr. In India, China, and Pakistan as a result of double and triple cropping that are irrigated, the water use is dominated by irrigated croplands (blue water use). In USA, the water use is dominated by rainfed croplands (green water use). Data source: Gleick (2011).

Cropland Monitoring in the 21st Century

The emphasis on global crop-specific monitoring in the 21st century will involve fusion of data collected by a wide array of satellites and sensors from numerous national space agencies. This will allow us to capture phenology along with crop types, growth stages, their source of water (irrigated or rainfed), and their productivity. These satellites can be categorized as follows: (a) coarse spatial resolution sensors (>100m) with frequent, even daily coverage of the world (e.g., AVHRR, MODIS, and Visible Infrared Imager Radiometer Suite VIIRS, NASA); (b) high resolution (30–100m) with less frequent coverage of the world, about once in 8 to 16 days, (e.g., Landsat, RESOURCESAT, SPOT, and China-Brazil Earth Resource Satellite-CBERS); (c) very high resolution (sub-meter to <30 m) with infrequent coverage of the world, that is, based on need, (e.g., IKONOS, QuickBird, GeoEye, RapidEye, WorldView-2); (d) non-optical sensors, such as Radarsat, and Japanese Earth Resource Satellite (JERS) Synthetic Aperture Radar (SAR); and, (e) emerging microsatellites (e.g., UK pioneered satellites by Surrey Space Center for emerging space nations — KITSAT for Korea, PoSAT for Portugal, BADR for Pakistan, TMSAT for South Africa, plus DMC International Imaging (DMCii) disaster monitoring constellation). An excellent catalogue of these satellites and sensors is available at http://wgiss.ceos.org/lsip/satellites_midres1.shtml or http://www.ceos-cove.org/index.php. Cropland monitoring in the 21st century will involve using data fusion or combination (Thenkabail *et al.*, 2011) from these sensors, taking advantage of the advances in components of global cropland mapping using remote sensing (previous section), gaining a historical perspective using pathfinder datasets (previous sub-section), applying data fusion approaches (Thenkabail *et al.*, 2009a, b), and developing automated cropland algorithms (next section).

"A step toward ensuring food security in the 21st Century lies in improving the monitoring of croplands using a means to map them routinely, rapidly, consistently, and with sufficient accuracy."

Automated Methods for Cropland Mapping Globally

There is a growing body of scientific evidence on mapping of both irrigated and rainfed cropland based on classification and analysis of remotely sensed data (Friedl *et al.*, 2002; Hansen *et al.*, 2002; Loveland *et al.*, 2000; Ozdogan and Woodcock, 2006; Thenkabail *et al.*, 2009a,b; Wardlow and Egbert, 2008; Wardlow *et al.*, 2006; Wardlow *et al.*, 2007; Xiao *et al.*, 2006). Some of the methods used include: (a) spectral matching techniques (SMTs); (b) decision tree algorithms; (c) tasseled cap brightness-greenness-wetness transformation; (d) space-time spiral curves; (e) Change Vector Analysis (CVA); (f) phenology; and, (g) fusion of climate data with remotely sensed observations. Coincidentally, these methods also allow sub-pixel calculation of the areas. Most of these approaches rely extensively on human interpretation, making the process resource-intensive, time consuming, and difficult to repeat for both space and frequency.

There is a growing need for improved data on cropland mapping, particularly over large areas —countries or regions such as river basins — in order to address food and water security issues. Effective operational cropland mapping must be automated, accurate, and be able to provide maps, statistics, and crop characteristics quickly, that is, maps should be produced within a few hours or days, repeatedly over space and time.

Fully automated methods do not yet exist, especially over large areas. The best methods are semi-automated, require substantial human intervention, and include major uncertainties when working with independent datasets or when applied to areas away from locations for which they were originally developed. These methods include (Thenkabail *et al.*, in review): (a) Spectral Matching Techniques (SMTs), (b) Ensemble of Machine Learning Algorithms (EMLAs) (e.g., decision trees, neural networks); and, (c) Classification and Regression Trees (CART). The principle of SMTs (Thenkabail *et al.*, 2007) is to match the shape and/or magnitude of the Normalized Difference Vegetation Index (NDVI) or similar index or band reflectivity to an ideal or target spectrum (pure class or "end-member"). Thenkabail *et al.* (2007) advocated four key SMTs: (1) Spectral Correlation Similarity (SCS) – a measure of shape; (2) Spectral Similarity Value (SSV)

– a measure of both shape and magnitude; (3) Euclidian Distance Similarity (EDS) – a distance measurement; and, (4) Modified Spectral Angle Similarity (MSAS) – a hyper angle measurement. EMLAs include decision tree algorithms and neural networks (Chan and Paelinckx, 2008), which are computationally fast to implement. CART is a data mining decision-tree (DT) that takes spectral and ancillary data and recursively splits it until end points or terminal nodes are reached (Zheng *et al.*, 2009).

All these methods are powerful, and have shown potential to be automated. Nevertheless, implementation of these algorithms is limited due to complexity of methods, inability to demonstrate repeatability and the need for substantial expert input to train algorithms to produce accurate cropland mapping over time. Furthermore, it is necessary to create new perspectives and concepts in order to develop simple algorithms that are automated and can generate instant and accurate computations of cropland areas and their characteristics over large areas repeatedly season after season, year after year. A recent advance in automating the cropland classification process has been proposed by Thenkabail *et al.*, (in review), in what they define as an Automated Cropland Classification Algorithm (ACCA).

The process of creating an ACCA involves three steps. First, an accurate cropland truth layer (CTL) is obtained from other reliable sources (e.g., National Systems such as USDA cropland data layer) or generated using a megafile data cube (MFDC) validated by *in-situ* observations. The MFDC fuses data from multiple sources: first, Landsat and MODIS throughout the growing season, monthly composites, for example. Next, the MFDC is linked with secondary data such as Shuttle Radar Topography Mission (SRTM) elevation, slopes, precipitation, temperature, evapotranspiration, and *in-situ* data that can include ground observations as well as very high resolution (sub-meter to 5 meter) image data. This step involves understanding agricultural cropland dynamics and mapping these lands through knowledge-capture techniques such as: (a) identifying croplands versus non-croplands and crop type or dominance based on spectral matching techniques, decision trees, Tasseled Cap bi-spectral plots, and very high resolution imagery; (b) determining irrigation status based on temporal characteristics (e.g. NDVI), water use by crops, secondary data (elevation, precipitation, temperature), and identification of irrigation structure (e.g., canals and wells); (c) establishing which croplands are large scale (contiguous) versus small scale (fragmented); (d) characterizing cropping intensities as single, double, triple, or continuous cropping; (e) interpreting MODIS NDVI temporal bi-spectral plots to identify and label classes; and, (f) using *in-situ* data from very high resolution imagery, field-plot data, and national statistics. The process of generating cropland truth layers (CTL) varies widely and can be found in numerous studies (Ozdogan and Gutman, 2008; Thenkabail *et al.*, 2011; Wardlow and Egbert, 2008). The second step of ACCA involves writing a series of rules\codes (e.g., Figure 3) using the same MFDC as the one used to create CTL. When the ACCA algorithm is run on MFDC, it will produce an ACCA derived cropland layer (ACL) that should replicate (or come very close) to the CTL. This is a complex process of coding, refining, running, revising, re-coding and re-running the ACCA, which is a rule-based algorithm. For a country or a river basin, one may need hundreds of rules\codes like those illustrated in Figure 3. Hence, many iterations are required until the ACL converges perfectly (or nearly so) with CTL. A particular ACCA rule or a set of rules may successfully replicate croplands and/or their

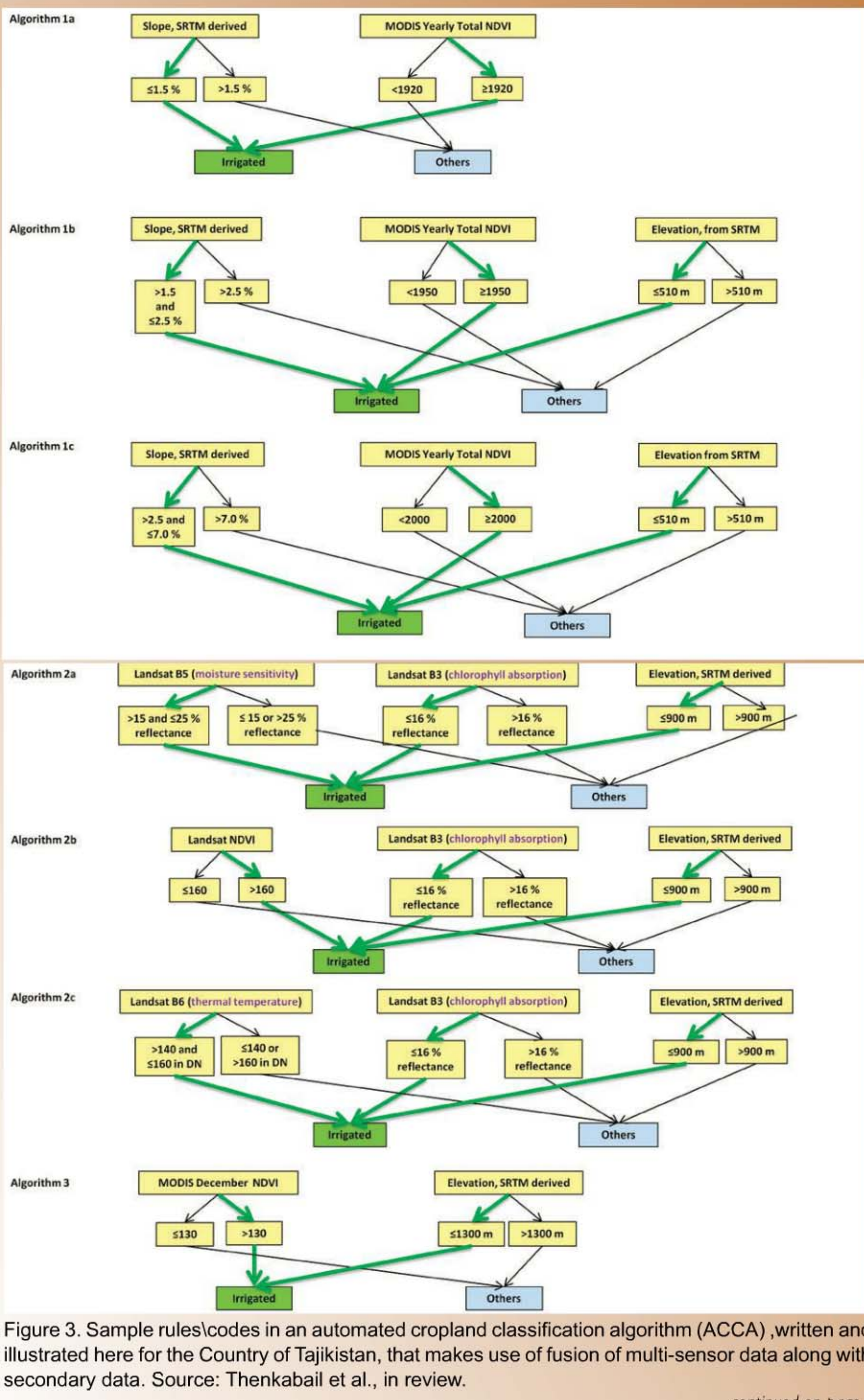

Figure 3. Sample rules\codes in an automated cropland classification algorithm (ACCA) ,written and illustrated here for the Country of Tajikistan, that makes use of fusion of multi-sensor data along with secondary data. Source: Thenkabail et al., in review.

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characteristics (e.g., irrigated versus rainfed) for a portion of the CTL. If the ACCA rule does not perfectly separate cropland areas and/or their characteristics in the CTL, the rules are refined and re-run until we obtain a perfect or near perfect match between the ACL and the CTL. Subsequent ACCA rules will then be directed at replicating the remaining parts of the CTL until such rules, which may be numerous, successfully separate all of the croplands and their characteristics seen in the CTL. Once the ACCA is successfully established, we now run the ACCA on independent MDFCs (e.g., from different years) for the same area. Recent research by Thenkabail *et al.* (in review) and Wu and Thenkabail (in preparation) demonstrated that the ACL successfully mapped croplands of an independent years for Tajikistan and California, typically, with over 90 percent overall accuracy. The ACL, for example, was produced within 30 minutes on a desktop Dell Precision T7400 for the entire country of Tajikistan once the MFDC for a year was composed and ready. Thus the ACCA concept is seamless over the entire country. It is extremely rapid; an ACL can be produced in hours, even minutes, depending on the scope of the area and the computing power available. Moreover, it is repeatable year after year using a consistent set of multiple sensor data fusion organized in a MFDC. ACCA is distinct from all other classification systems because it produces the ACL without user intervention, it works on independent MFDC datasets that are constituted to accurately resemble the MFDC that was used to develop the ACCA algorithm, and it typically provides output within a few minutes or hours. In spite of this hands-off approach, the accuracy of ACL's for independent datasets is very high (Thenkabail *et al.*, in review; and Wu and Thenkabail, in preparation). An ACCA algorithm along with sample datasets are available to the public over the USGS Powell Center web site on global croplands: https://powellcenter.usgs.gov/globalcroplandwater/; http://powellcenter.usgs.gov/current_projects.php#GlobalCroplandsAbstract .

Remote Sensing – Opportunities for Progress and Challenges Ahead

Apart from the advances made in remote sensing of global croplands (previous sections), further advances in the application of remote sensing will require additional components:

- **Develop the temporal history of crops:** Cropland phenology, cropping intensity, and crop calendars are best studied using a time-series of remotely sensed observations. A first example is the one illustrated for South Asia (Figure 4; adopted from Gumma *et al.*, 2011) using MODIS time-series data for rice-dominant cropped areas. This will require a cropland knowledge base from precise locations. The *in-situ* data (as illustrated for several points in Figure 4) need to be collected routinely from large numbers of spatially well-distributed points with precisely known coordinates in order to capture cropland knowledge. Detailed field plot data will help establish cropping patterns, calendars, intensity and types, as well as productivity or yield (Dheeravath *et al.*, 2010). A second example is the month by month dynamics of the NOAA AVHRR NDVI (0.1 degree) of the irrigated areas of the World illustrated for the year 2000 (Figure 5).

  As we progress from one month to other we see the NDVI dynamics of different parts of the world changing based on cropping phenology. For example, in the Ganges river basin crops growing season peaks during August-September (Season 1; Kharif) and February-March (Season 2; Rabi) (Figure 5). In Argentina and Egypt's Nile Basin the crops peak during January through March (Figure 5). In the heavily irrigated Nile Basin a second peak occurs during July and August. This information can then be entered into automated and semi-automated cropland classification algorithms (previous section).

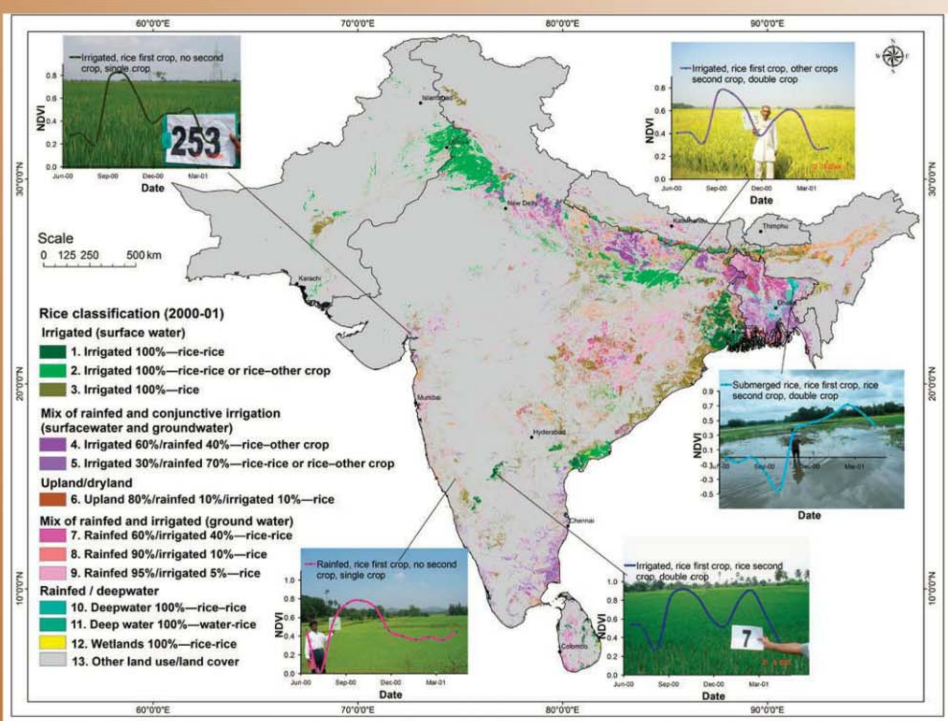

Figure 4. Crop phenologies and intensities studied using time-series remotely sensed data illustrated for rice crop in South Asia. A clear and deep understanding of phenologies and intensities will require us to develop a temporal (e.g., this figure) and spectral (e.g., Figure 5) knowledge base of each crop in different agro-ecosystems of the world leading to mapping distinct classes within a crop, which in turn will lead to accurate assessments of green water use (rainfed croplands) and blue water use (irrigated croplands). [adopted from Gumma *et al.*, 2011].

- **Capture spectral signatures:** Progress in remote sensing of agricultural croplands will require that we model biophysical and biochemical properties of crops and their productivities with much greater accuracy than that achieved to date. This will require construction of a hyperspectral crop library as seen in Figure 6. It must document detailed spectral characterization of crops throughout the growing season in agricultural systems worldwide. Hyperspectral narrow bands (HNBs) and hyperspectral vegetation indices (HVIs), that are computed based on specific portions of the spectrum (Thenkabail and Gumma, 2012. Thenkabail *et al.*, 2002) will help us model various crop biophysical and biochemical parameters with increasing confidence. These parameters may include biomass, leaf area index, yield, nitrogen, carotenoid, anthocyanins, and plant water content (a detailed discussion of these is in Thenkabail *et al.*,

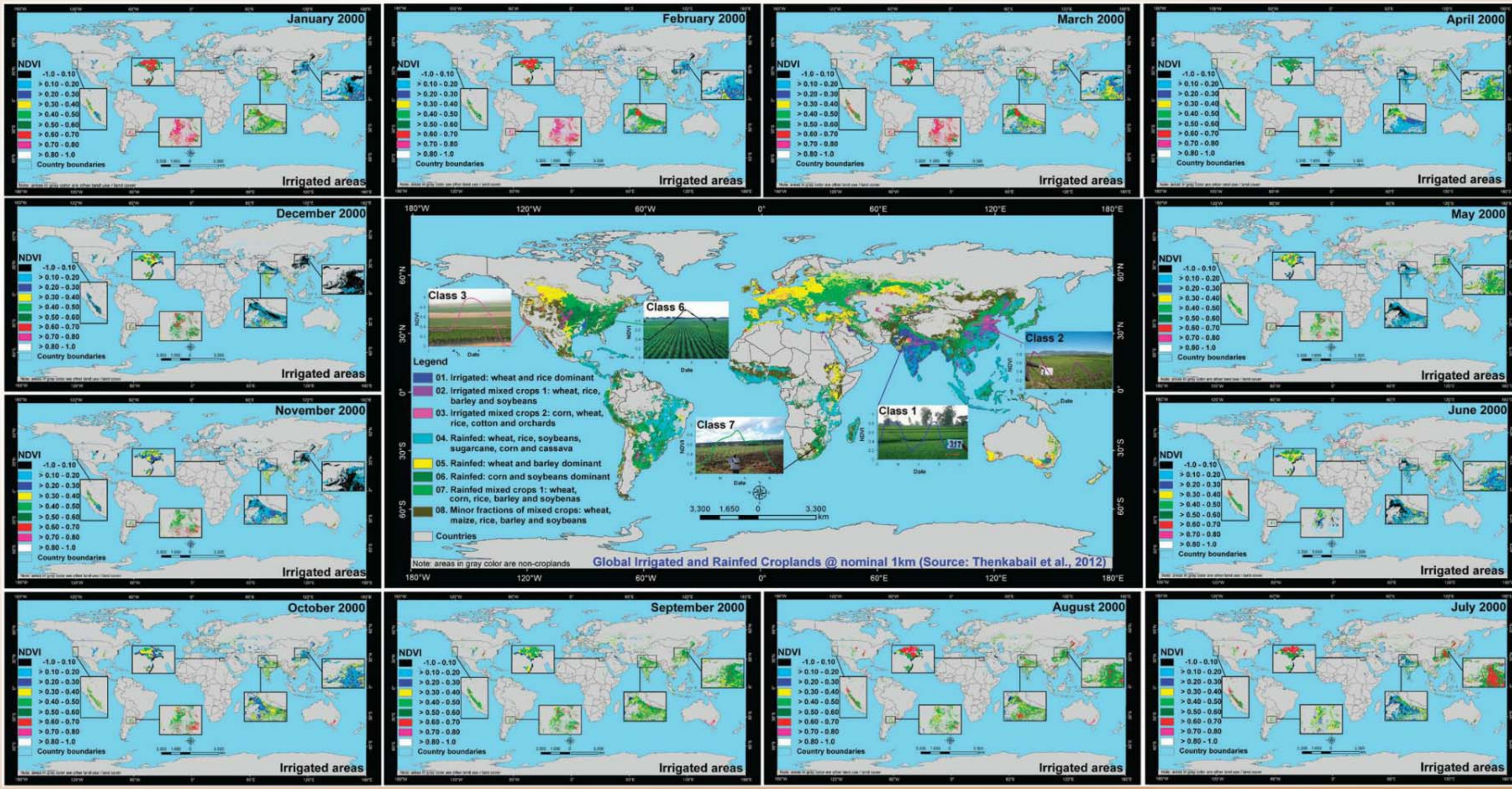

Figure 5. Center image: Irrigated and rainfed cropland areas of the world (same as Figure 1). **Surrounding 12 images:** The NOAA AVHRR 0.1 degree resolution normalized difference vegetation index (NDVI) dynamics of the irrigated areas of the World (Thenkabail *et al*., 2009a, b, this paper) for the year 2000.

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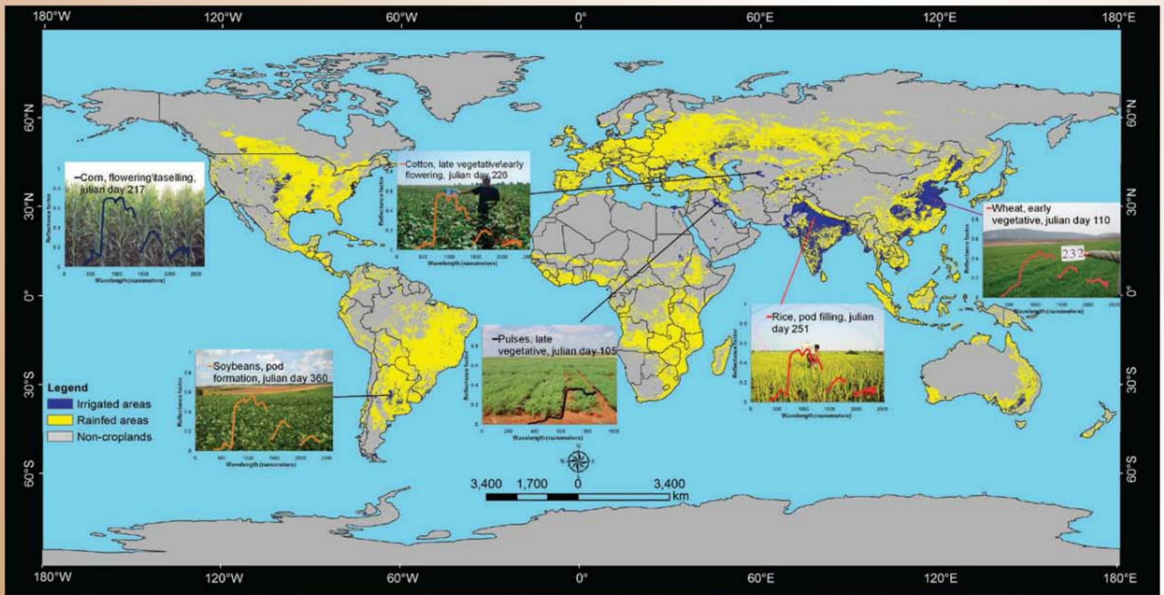

Figure 6. Hyperspectral signature bank of world crops. The initial goal of a global cropland monitoring system should consist of developing hyperspectral signature bank of major world crops (e.g., this figure) along with crop phenologies (e.g., Figure 4) in order to: (a) establish improved models of crop biophysical and biochemical quantities, (b) increase crop classification accuracies, and (c) produce accurate crop and water productivity models. The six leading world crops (Table 1) cover 64% of the global cropland areas. Sample hyperspectral signatures of these six world crops are illustrated in the figure. The background image is irrigated and rainfed croplands of the world (Thenkabail *et al.*, 2011, 2009a, 2009b).

2011 , and Thenkabail and Gumma, 2012). The HNBs and HVIs will also advance crop classification accuracies and improve crop and water productivity models. Further, the collection of spectra will act as a signature bank that can be used for future identification and labeling of crops and their characteristics at local, regional, national, and global levels. Acquisition of hyperspectral crop signature data (e.g., Figure 6) will become more routine with the launch of the Hyperspectral Infrared Imager (HyspIRI), which will provide imaging spectroscopy data covering the entire world and acquired every 19 days.

Importance of Accurate and Routine Cropland Mapping in Crop Water use Assessments

There are significant advances in the last two decades in crop water use assessments from actual evapotranspiration (ET_{actual}) modeling using remote sensing data and methods (Zwart, 2010). By helping to monitor agricultural water removal (evapotranspiration), these assessments can help reduce the waste of water from agricultural activities, reduce over-exploitation of aquifers, and optimize the scheduling of irrigation. In any case, the accuracy of crop water use assessments relies on accurate cropland mapping including types, growth stages, and crop health. Therefore, the advances in cropland mapping discussed in this paper would also lead to improved estimates of water use on croplands and help develop policies to grow crops where it is most efficient in terms of water availability. This will be of great importance given that nearly 70 to 80 percent of all human water use on Earth is in the agriculture sector (Thenkabail *et al.*, 2010). Detailed assessments of current and future changes in cropland will help us determine the water "footprint" of agricultural production and its dependence on "blue" and "green" sources. Blue water is associated with crop production under irrigation with water obtained from lakes, reservoirs, rivers and from the groundwater (saturated zone). Green water is associated with crop production from rainfall and constitutes 70 percent of the water consumed by croplands. These definitions have received widespread attention, particularly in policy discussions regarding water scarcity and food security. However, the real challenge lies in reconciling the spatial and temporal distributions of consumptive water use for agriculture with the availability of local water resources, and then identifying opportunities to reduce the environmental impact of agricultural demand.

Cropland Web Resources

There is an increasing volume of literature (published and gray), data and information on global cropland mapping. A list of important sources is as follows:

- **https://powellcenter.usgs.gov/globalcroplandwater/**
- **http://www.iwmigiam.org**
- **http://www.geog.mcgill.ca/~nramankutty/Datasets/Datasets.html**
- **http://www.sage.wisc.edu/mapsdatamodels.html**
- **http://www.fao.org/nr/water/aquastat/irrigationmap/index.stm**
- **http://www.fao.org/nr/water/aquastat/main/index.stm**
- **http://www.nass.usda.gov/research/Cropland/SARS1a.htm**
- **http://www.pecad.fas.usda.gov/cropexplorer/datasources.cfm**
- **http://www.geo.uni-frankfurt.de/ipg/ag/dl/forschung/MIRCA/index.html**
- **http://www.geo.uni-frankfurt.de/ipg/ag/dl/forschung/GCWM/index.html**
- **http://gcmd.nasa.gov/records/GCMD_SAGE_MAJORCROPS.html**
- **http://www.mdpi.com/journal/remotesensing/special_issues/croplands/**
- **http://www.earthobservations.org/cop_ag_gams.shtml**
- **http://powellcenter.usgs.gov/current_projects.php#GlobalCroplandsAbstract**
- **http://www.earthobservations.org/cop_ag_gams.shtml**
- **http://www.ceos.org/**
- **http://sharaku.eorc.jaxa.jp/GSMaP/index.htm**
- **http://kuroshio.eorc.jaxa.jp/JASMES/index.html**

Summary

This paper emphasizes the importance of remote sensing and continued research about ways to use its assets in global agricultural cropland mapping and water use evaluation. Current cropland map products are derived from coarse resolution remotely sensed data and traditional classification methods that require substantial human involvement. We have discussed the advances and developmental needs of semi-automated and automated classification algorithms in routine, rapid, and accurate mapping of global croplands and their characteristics. Advances in global cropland mapping will require data fusion and\or combination techniques from multiple satellite sensors, secondary data sources, and a large and systematic collection of *in-situ* information, including temporal phenologies and hyper-

"Remotely sensed data provide the only source of information to make a complex global agricultural monitoring system feasible by being consistent, repeatable, routine, rapid, and scalable."

spectral signatures. As Beddington (2010) stresses, the fundamental issues for policy makers and scientists are whether by the year 2050 over nine billion people can be fed equitably, healthily, and sustainably and how sound management can make water use more sustainable as a growing population moves up from poverty. In this context, the role of remote sensing is clear. There is an unequivocal need to provide a more systematic and integrated approach to global cropland mapping to support a range of initiatives, including assessments of crop productivity, helping to identify food security "hotspots" of vulnerability and resiliency, assessing the agricultural risks due to climate change and quantifying agricultural water demand.

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