A Community Research and Development Agenda for GEOGLAM: Operational R&D

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1. Background

The focus of the international GEOGLAM initiative is on increasing and enhancing the use of Earth Observations (EO) for agricultural monitoring (www.geoglam.org). A G20 mandate, along with policy frameworks such as the U.N. Sustainable Development Goals (SDGs) are driving GEOGLAM to move towards enabling quantitative, operational agricultural monitoring over multiple time-scales. High quality, robust, and consistently-validated EO-based datasets and sharable analysis tools are important contributions to organizations with an ongoing, operational mandate. To promote an environment wherein the GEOGLAM Agricultural Monitoring Community of Practice (CoP) can regularly produce high-quality, EO-based datasets relevant to national and global policy mandates, we have identified a priority set of target products and areas for research and development.

As new EO satellite technology, sensing systems, data availability, computing infrastructure and advanced data science methods are developed, there are new opportunities for enhancing agricultural monitoring. Similarly as operational monitoring entities become more familiar with EO capabilities, new applications and observation requirements can be identified. Developing new or improved monitoring methods requires research and development with a view to eventual operational implementation. We call this ‘operational research and development (R&D)’, in contrast to fundamental or exploratory research. Fundamental research often provides the basis for operational R&D, which is driven by the practical needs of the targeted operational communities.

The output of fundamental research is usually in the form of scientific papers. The output of operational R&D is usually in the form of data products and tools to use the products to derive information needed to support decision-making and to be integrated into decision support systems. Operational R&D often involves an iterative accommodation between what is ideally needed and what is currently technically feasible, which in turn helps set the agenda for improvements in Earth observations and future research.

Support for operational R&D comes from those agencies that are promoting the applied use of EO or from the operational agencies, ministries or organizations that are interested in enhancing their decision support systems. It is this R&D component that allows organizations to adopt the newest technologies so that the information generated leverages the latest research while still providing routine, defensible information.

A research component of GEOGLAM was established at the outset of the initiative, built around a series of experiments focused on algorithm and method development and inter-comparison at a number of well-documented agricultural research sites in different cropping systems. This Joint Experiment for Crop Assessment and Monitoring (JECAM) (www.jecam.org) provides a test-bed for algorithms and methods and for testing protocols for data collection and is resulting in a series of 'best-practice' documents aimed at helping the Community of Practice. A well-documented set of long term monitoring sites in different cropping systems, with on-going field-based measurements provides a solid basis for algorithm and method development and can contribute to product accuracy assessment and will continue to be an important part of the GEOGLAM Community Research Agenda going forward.

This document identifies a priority set of topics identified by the GEOGLAM Community for research and development. This initial set of topics grouped and listed below was discussed at the Annual GEOGLAM Meeting in Sanya, China, August 2018 and subsequently at the JECAM Meeting in Taipei, September 2018.

2. Essential Agricultural Variables and Assessments

The Agricultural Monitoring Community of Practice has identified a set of variables that contribute to a standard set of assessments associated with agricultural production forecasting. These are referred to as the GEOGLAM Essential Agricultural Variables (EAVs, Whitcraft et al. 2015, Whitcraft et al. submitted). While some of these measurements are well-established, such as agrometeorological measurements of Rainfall, Humidity, Air Temperature or some fundamental satellite data records, for example, Surface Reflectance, Land Surface Temperature, Microwave Backscatter, other higher-level satellite-based measurements or products are areas for continued research and development. These are as follows:

2.1 Within Season Crop Type Mapping and Area Estimation

Identification of crop type as early as possible in the season provides a critical input into estimation of area planted, a key input in production forecasts and estimations (Wu et al. 2014). Spectral and temporal approaches are being developed along with probabilistic field-based sampling, and it is important to estimate the uncertainties associated with these products (Song et al. 2017, Khan et al. 2018). Satellite-based crop type mapping using single multispectral instruments, such as Landsat, has been undertaken at the local scale since the launch of ERTS-1 in 1972. More recently, with increasing numbers of sensors in space, multi-sensor fusion methods have been adopted (Blaes et al. 2005, Gao et al. 2006, Gao et al. 2017). In a number of cases, operational satellite-based, national level crop type mapping has been established using EO data (e.g. Johnson and Mueller. (2010), Fisette et al. (2014), Griffiths et al. (2018), Defourny et al. 2019). The challenge for the research community is to provide robust methods that can be used to generate field scale products that can be routinely generated on an annual basis at national, continental to global scales. Recent focus has been on major cereal and oilseed crops. Emphasis now needs to include the identification of other crop types (e.g. other small grains, millets, pulses, cash crops, plantation crops, permanent crops, and horticultural crops (vegetables and fruits)) with subnational to regional importance for food security and agricultural markets. Research is also advancing methods to establish reliable planting dates and growing season calendars (Phan et al. 2017, Urban et al. 2018). Research is needed to develop methods appropriate for smallholder agricultural systems, which are characterized by small field sizes, intercropping and variable yield.

2.1.1. Agricultural Land Cover and Land Use Change

Beyond the current season, it is important to understand shifts and trends in agricultural land cover and land use, including agricultural expansion (and associated forest, woodland, or grassland loss), intensification, abandonment or exposure of degraded lands (Song et al. 2018, Zalles et al. 2018). These analyses span broader time scales (decadal) and should capture changes in crop rotations (interannual) and crop type in response to economic development, climate change or shifting market demand. The satellite data record can be used to document the changes combined with statistical or census data or with land change models. The economic and trade implications of such changes are an important area for research. This is a trans-domain research effort that is at the core of understanding competing land use interests and is critical to understanding how policy mandates may intersect or potentially conflict (e.g. Prishchepov et al. 2012).

2.2 Crop Yield Estimation and Forecasting.

Along with area, yield is the other critical component to production forecasting (within season) and estimation (end of season). In addition to informing the markets, and national policies, such information also helps in preparing for acute food shortages as they impact food security (Nakalembe, 2018; Rembold et al., 2018). Three approaches are currently being explored to generate spatially explicit, satellite-based yield products: satellite-based empirical regression against statistical yield data using multi-year data, stratified probabilistic field-based sampling; and, an integration of satellite data, meteorological station data with process-based crop yield models (Becker Reshef et al. 2010, Challinor et al. 2014, Duveiller et al. 2013, Franch et al 2015, Lobell et al. 2015). One of the current constraints to advancing these methods is the lack of availability of sufficient field-based crop yield data to test the models at high spatial resolution, over large areas. A shared data set of field level crop yield collected over a range of cropping systems is an essential element for this community research agenda. Integration of short and medium-term weather forecasts is also a key component for improving current yield forecasting capabilities with promising results in this area (e.g. Peng et al., 2018). In addition to crop yield, there is an interest to develop better estimations of grain quality, which has yet to be explored using satellite data. Most studies have focused on major cereal crops, research needs to include yield estimation for other crops (Dubey et al. 2018) and in particular in regions most vulnerable to food insecurity, where there is often the highest uncertainty in crop assessments (Rembold et al. 2018, Becker-Reshef et al. 2019 submitted, Bonifacio et al. 2019 submitted).

2.3 Crop Condition Assessment

Timely, accurate, and actionable information about crop conditions is invaluable for providing an indication of final crop yield (Wu et al. 2014, Van der Velde et al. 2019). Integrating data from multiple sources (e.g. satellite, weather station, field data) is necessary to develop more quantitative indicators of crop condition, particularly in the context of early detection of potential impacts of yield and undertaking rapid assessments in the context of emerging disasters for countries at risk of food insecurity. For example, integration of rainfall data from multiple sources can provide value-added products for operational crop monitoring (Shukla et al. 2017). The GEOGLAM Crop Monitor Bulletins exemplify the value and utility of crop condition assessment, as well as the societal benefit of research based end-user driven operational products. (https:/cropmonitor.org, Becker-Reshef et al. 2019).

2.4 Drought Risk and Impact Assessment

Drought at critical phenological stages can seriously impact crop yield (Prasad et al. 2008, Nakalembe and Owar 2016). Further research is needed to understand the impacts of different drought durations and severity at different phenological stages of crop growth. Developing indicators of agricultural drought risk which include the use of satellite data, is an area receiving increased attention from national management agencies and the private sector e.g. the insurance industry (Coutu et al., 2017; De Leeuw et al., 2014; Osgood et al., 2018), but requires further research and development.

3. Supporting Variables for Agricultural Monitoring and Agricultural Land Management

With the increase in the number and types of sensors (optical, lidar and microwave), spatial resolution and temporal frequency, it is possible to develop new indicators which support assessment of crop condition or forecasting of yield and to characterize and monitor land management practices which have implications for crop production and sustainability:

3.1 Hydrological variables

Adequate water is essential for crop development. Lack of sufficient water or too much water at specific times during the growing season can negatively impact production and harvest. Sustainable water use for agriculture is also a major concern in many parts of the world where ground water is depleted or winter precipitation (snow accumulation) is decreasing. A number of variables are in development.

3.1.1 Soil Moisture and Evapotranspiration (ET)

These are important indicators of crop growing condition. To-date, global satellite data products for these products have been derived from coarse resolution sensors (greater or much greater than 1 km) (Champagne 2016, Bolten et al. 2010, Champagne et al. 2010), yet recent research has demonstrated that quantifying field-scale surface soil moisture is feasible (Mohanty et al. 2017, Hosseini and McNairn 2017). The use of thermal geostationary sensors provides characterization of the diurnal cycle to determine ET (Anderson et al. 2011) and as these data become available at higher spatial resolutions they will become more relevant for agricultural applications (Yang et al. 2017). The use of microwave sensors for ET estimation is also being explored (Holmes et al. 2018). Downscaling coarse resolution methodologies (Peng et al. 2017), assessing the accuracy of the different products, and evaluating new sensors capable of measuring soil moisture and ET are areas for research. Assimilation of various sources of soil moisture data can be used to generate products ready for decision support (McNally et al. 2017).

3.1.2 Irrigated Area

Identification and annual mapping of active irrigated area (Dienes et al. 2017) has large implications for crop yield, especially when irrigation is undertaken by smallholder farmers (Bastiaanssen et al. 2000) and can help quantify competition for freshwater resources, which is projected to increase under a changing climate. Remote sensing methods are also being developed to assist in developing irrigation management (Melton et al. 2012, Shen et al. 2018).

3.1.3 Water Productivity

Water productivity (crop yield per unit of water depleted) provides an important indicator of the efficiency of water management (Howell 2001, IAEG-SDGs 2018, Wu et al. 2015). This is particularly relevant in the context of the increasing water use efficiency.

3.2 Agricultural Practices and Land Management

Satellite data provide a means to monitor the extent of agriculture and identify some aspects of land management (Begue et al. 2018) . Spatially explicit monitoring of management practices over-time also enables identification of yield gaps (Lobell 2013) and an assessment of their effectiveness in terms of resilience to extreme climate events and long term climate change.

3.2.1 Nitrogen content estimation

This is important in terms of monitoring sustainable production practices and as it impacts crop yield and is critical for improving efficiency of agriculture while reducing air and water pollution. Evaluating EO-based spectral methods to identify total nitrogen is a topic for research (Thenkabail & Lyon, 2016).

3.2.2 Till/No Till agriculture

Tillage practices as part of soil conservation are receiving more attention from the policy community at state and local levels. Methods for monitoring tillage practices using moderate to fine EO data are in demand and being developed (Daughtry et al. 2006, Zheng et al. 2014, Azzari et al. 2016). This has particular relevance to monitoring of sustainable agricultural practices and quantifying soil health indicators.

3.2.3 Crop intensification

Implementing double and triple cropping, changes in crop rotation (length of fallow period), increased multi-cropping and irrigation are ways of intensifying production. Methods for monitoring multi-cropping systems is an area for continued research. Identification of areas of potential intensification can help land management (Gumma et al., 2018) although some research has been done (Biradar & Xiao, 2011), there remains much room for method development and transition to operational implementation.

3.2.4 Crop Disease Identification

Disease identification was one of the first agricultural applications of remote sensing and continues today operationally at the local field level, for example using drone technology. Extensive disease outbreaks can devastate crop production. Early identification of disease outbreaks and mapping of area impacted using a combination of earth observations and drone/in-situ measurements are needed for management purposes and can feed into crop forecasting. Early identification of large area crop diseases is an area for continued research and integration of earth observation with other geospatial data are producing promising results. We anticipate that the increased availability of high spatial, hyperspectral satellite data will facilitate the development of operational capabilities for early identification of crop diseases.

3.2.5 Fallow and Pasturelands Mapping

Most cropping systems have a fallow period which is part of the crop rotation, which needs to be factored into estimation of crop area. Identifying fallow lands (Wu et al. 2014) and distinguishing them from pasture and hay fields can be aided by multi-annual time-series analysis (Alcantra et al. 2012, Wallace et al. 2017).

3.3 Rangeland Productivity and Quality

The rangeland component of GEOGLAM, RAPP is concerned with estimation of rangeland productivity. Research is underway to develop robust methods for estimation of productivity using earth observation in combination with process models (Guerschman et al., 2015).

4. New Technologies and Methods

New sensor technologies, information technology and computing capabilities are fueling a revolution in agricultural remote sensing and data collection the associated in-situ networks. Research and development is needed to develop and evaluate methods to improve operational monitoring.

4.1 Big Data and Cloud Computing.

Although big data have always been a characteristic of satellite remote sensing, the increase in data from multiple moderate resolution, optical and microwave sensors has led to a significant increase in data volumes. The access to these data through cloud computing technology is facilitating remote processing and analysis of high volume (big) data.

4.2 Machine Learning and Artificial Intelligence.

Machine Learning and Artificial Intelligence methods are starting to be applied to ‘big data’ in the context of crop forecasting and crop mapping (Cai et al. 2017). Methods are being explored to include non-traditional data sources in the analysis, for example by using social media or crowd-sourced data. These are all areas for research and development, with a view to developing robust, operational methods.

4.3 Sensor Data Fusion for establishing data records

Traditionally, applications have been built around the use of one sensing system. The development of long-time series for monitoring change requires the use of similar sensors on different satellites to provide dynamic data continuity (Skakun et al. 2018). Use of multiple sensors requires special attention to calibration. With the increase in the number of satellite sensors, the opportunity to use multi-source and multi-scale data for agricultural monitoring has expanded (Torbick et al. 2011, Zhang et al. 2018) and new harmonized data sets are in development (Claverie et al. 2018). Approaches for co-registration, spectral adjustment, cross calibration are being developed. Consistent atmospheric correction is needed or multi-instrument time series. Multi-sensor integration and multi-scale analysis are areas for research and development, holding considerable promise for agricultural applications.

4.4. Data Integration

Although agrometeorological data, weather forecasts and crop models have been used for crop forecasting at the site level, their integration with satellite observations to provide spatially explicit large area forecasts remains an area for research and development. The development and deployment of low-cost, automated ground-based sensors raises the possibility of integrating ground and satellite data in analysis and forecast systems. Modelled weather data that leverages assimilation of satellite observations is critical for developing indicators and driving spatially explicit crop growth models

4.5 Product Accuracy Assessment.

With easier access to both data and computing resources, the ability to develop regional to global data products is more widely available. For products to be useful, the bias and uncertainty (validation) of the products need to be quantified, and for mapping products should be done on a per-pixel basis. To do this in a representative way requires considerable investment. Development of methods for uncertainty assessment is an area for research and development, which often requires scaling-up from field observations to satellite resolutions.

4.6 Object or Event Detection.

The increased availability of fine spatial resolution data opens the door to greater use of contextual information. The development of geographic object-based image analysis methods (e.g. segmentation, classification) is an area of research that could enhance agricultural monitoring (Mrinal et al. 2017, Singha et al. 2016), for example identifying field boundaries or land parcels (Yan and Roy 2016). Similarly, analysis of time-series data can include the automated identification of events.

4.7 New Sensors.

Traditionally, agricultural remote sensing has involved the use of multi-spectral optical, NIR and SWIR data, largely due to the open data policies for those sensors. With the move to more open data, there has been an increase in the development of applications using time-series data from new microwave sensors (Sentinel-1 series). New data are available from the Copernicus instruments and new tools are being developed for operational agricultural monitoring (Defourny et al. 2018). A number of new sensors are planned which will have direct relevance to agricultural monitoring (e.g. NISAR, BIOMASS, RADARSAT Constellation). Other experimental sensors provide an opportunity to explore new potential applications (e.g. VENUS, ECOSTRESS, GEDI). As new sensors come on-line and as the space agencies adopt more open data policies, there is an interest to explore new application opportunities afforded by thermal sensors, multi-frequency/multi-polarization microwave sensors, lidar, hyperspectral and fluorescence sensors for agriculture. A high spatial resolution (50m optical) geostationary system is being developed by the Indian Space Agency (ISRO), which will increase the opportunity for cloud free observations. New smallsat sensor constellations are being developed to provide high spatial resolution, high temporal frequency coverage of interest for agricultural monitoring. These fine spatial resolution data are in the commercial sector and their use for agricultural monitoring is currently being developed and evaluated (e.g. Mascaro 2017, Kross et al. 2015). The evaluation and development of monitoring methods from new sensing system is an area for continued research and development.

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