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A review of satellite-based global agricultural monitoring systems available for Africa

Catherine Nakalembe [a,*], Inbal Becker-Reshef [a], Rogerio Bonifacio [b], Guangxiao Hu [a], Michael Laurence Humber [a], Christina Jade Justice [a], John Keniston [a], Kenneth Mwangi [c], Felix Rembold [d], Shraddhanand Shukla [e], Ferdinando Urbano [d], Alyssa Kathleen Whitcraft [a], Yanyun Li [f], Mario Zappacosta [f], Ian Jarvis [g], Antonio Sanchez [a]

[a] *Department of Geographical Science, University of Maryland, College Park, 2181 Lefrak Hall, College Park, 20742, Maryland, USA*
[b] *World Food Programme, United Nations, via Cesare Giulio Viola 68-70, 00148, Italy*
[c] *IGAD Climate Predictions and Applications Center, P.O. BOX 10304 - 00100, Nairobi, 254, Kenya*
[d] *European Commission, Joint Research Centre, Ispra, Italy*
[e] *Climate Hazards Group, University of California, Santa Barbara, USA*
[f] *Food and Agricultural Organization, Viale delle Terme di Caracalla, Rome, 00153, Italy*
[g] *GEOGLAM, 7 bis, avenue de la Paix, Geneva, CH 1211, Switzerland*

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ABSTRACT

The increasing frequency and severity of extreme climatic events and their impacts are being realized in many regions of the world, particularly in smallholder crop and livestock production systems in Sub-Saharan Africa (SSA). These events underscore the need for timely early warning. Satellite Earth Observation (EO) availability, rapid developments in methodology to archive and process them through cloud services and advanced computational capabilities, continue to generate new opportunities for providing accurate, reliable, and timely information for decision-makers across multiple cropping systems and for resource-constrained institutions. Today, systems and tools that leverage these developments to provide open access actionable early warning information exist. Some have already been employed by early adopters and are currently operational in selecting national monitoring programs in Angola, Kenya, Rwanda, Tanzania, and Uganda. Despite these capabilities, many governments in SSA still rely on traditional crop monitoring systems, which mainly rely on sparse and long latency in situ reports with little to no integration of EO-derived crop conditions and yield models. This study reviews open-access operational agricultural monitoring systems available for Africa. These systems provide the best-available open-access EO data that countries can readily take advantage of, adapt, adopt, and leverage to augment national systems and make significant leaps (timeliness, spatial coverage and accuracy) of their monitoring programs. Data accessible (vegetation indices, crop masks) in these systems are described showing typical outputs. Examples are provided including crop conditions maps, and damage assessments and how these have integrated into reporting and decision-making. The discussion compares and contrasts the types of data, assessments and products can expect from using these systems. This paper is intended for individuals and organizations seeking to access and use EO to assess crop conditions who might not have the technical skill or computing facilities to process raw data into informational products.

1. Introduction

In 2019, Eastern and Southern Africa (ESA) lost over 1, 500 lives owing to climate-related disasters, with over 1,300 from cyclone Idai alone (Nakalembe, 2020; Phiri et al., 2020; Devi, 2019). Other events recorded in 2019 included drought, multiple flooding events, landslides, and a one in 25-year desert locust invasion in East Africa (Nakalembe, 2020; Kimathi et al., 2020; Salih et al., 2020). Although poor agricultural production (due to lack of inputs and being largely rain-fed) remains a major driver of food insecurity, the events outlined above directly and indirectly impact crop production and aggravate food insecurity. Political instability exacerbates food insecurity and many countries, such as South Sudan, Mali, Niger, Burkina Faso, and Somalia are unable to produce enough food or gain sufficient access to markets to feed their populations (Sasson, 2012). Political instability

* Corresponding author.
E-mail address: cnakalem@umd.edu (C. Nakalembe).

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also limits traditional approaches to agricultural monitoring including expert scouting estimates (considering weather and historical yield), crop cut information, field assessment and surveys pose extreme danger to field teams, in addition to significant financial costs (Sahajpal et al., 2020). Today, most of these events can be forecast and data and tools exist that can provide early warning and impact assessment which underscores the importance of timely and accurate forecasts of production and near-real-time agricultural monitoring (Nakalembe, 2020; FAO et al., 2020; Becker-Reshef et al., 2019; Rembold et al., 2019).

Satellite Earth observation (EO) data availability and rapid developments in methods and cloud computing infrastructure continue to generate new opportunities to overcome some of the above challenges by providing accurate, reliable, and timely information for agriculture monitoring and provide crop-specific information from parcel to national levels across cropping systems (Kerner et al., 2020b,a; Nakalembe, 2020; Skakun et al., 2019; Rembold et al., 2019; Defourny et al., 2018). EO-data provide critical information for example crop conditions and yield estimates required to stabilize markets, mitigate the food supply crisis, and mobilize humanitarian assistance supporting efforts to evaluate and target productivity-enhancing interventions (Rembold et al., 2019; Becker-Reshef et al., 2019; Fritz et al., 2019).

Remote sensing data are big-data and large volumes are retrieved everyday (Chen et al., 2012; Zhang et al., 2017). These data are from different sources, different sensors, different resolutions and require massive computing capabilities and cloud computing (CC) platforms such as Google Cloud, Amazon Web-services and Microsoft Azure make it possible to process these data into products by providing on-demand cloud infrastructure that provide software as a services and infrastructure as service enabling all the data analysis and product generation to be implement in the cloud instead of the user's desktop (Wang et al., 2015; Chen et al., 2012). CC enables suitable, on-demand access network to distribute band of configured computing assets such as network, storages, servers, services and applications provisioned and released with minimum management effort or interaction with the provider (Diaby and Rad, 2017). CC platforms provide three basic services 1. Infrastructure as a Service (IaaS) that provides flexibility consumer-created software, 2. Platform as a Service (PaaS) that enables the operation of consumer-created software with a convenient operation complexity following resource efficient application architectures and (3) and Software as a Service (SaaS) that hides operation complexity (Kratzke, 2018; Diaby and Rad, 2017). Key characteristics of CC platforms include; broad network access, resource pooling, rapid elasticity, and capability to measure services to control and optimize resources which are critical when processing and making available big datasets such satellite EO. For a detailed review of the history CC platforms including concepts and deployment models see Diaby and Rad (2017): Cloud Computing: A review of the Concepts and Deployment Models and Jonas et al. (2019): Cloud programming simplified: A Berkeley view on serverless computing.

Today, Google Earth Engine (GEE) platform for example, combines a multi-petabyte catalog of satellite imagery and geospatial datasets with planetary-scale analysis capabilities needed to detect changes, map trends, and quantify differences on the Earth's surface (Gorelick et al., 2017; Google Earth Engine Team, 0000). Google Earth Engine is a cloud-based platform for planetary-scale geospatial analysis that brings Google's massive computational capabilities and has been used extensively to process EO for tracking deforestation, drought, disaster, disease, food security, water management, climate monitoring and environmental protection. The platform has revolutionized the remote sensing field by providing access CC allowing users to conduct analyses that would otherwise require enormous resources to access (download), store and analyze. The datasets accessible in GEE are listed in Earth Engine Data Catalog. These data and GEE's cloud compute capabilities are available to scientists, researchers, and developers lowering the cost and time of obtaining and pre-precessing and developing products from satellite imagery and building use-case specific applications that ease data analysis and visualization. These data that are updated consistently including Landsat, Sentinel and Moderate Resolution Imaging Spectroradiometer (MODIS) time-series data are often used to derive crop masks and to monitor crop conditions (Google Earth Engine Team, 0000; Lobell et al., 2015). Global scale products such as the Global Food Security-Support Analysis Data at 30 m (GFSAD30) global cropland data (Xiong et al., 2017) and high resolution maps of global forest cover change Hansen et al. (2013) have leveraged GEE's cloud computing platform. GEE also powers ASAP High Resolution Viewer that is reviewed in this paper.

Despite this, many governments in Sub-Saharan Africa (SSA) remain poorly positioned to use readily available EO-data to inform agriculture and food security decisions and programs (Carletto et al., 2015). Government departments lack the requisite technical capacity, computing infrastructure, and investments to realize these and most importantly the policy frameworks to build these capabilities and institutions (Nakalembe, 2020a). This is worsened by gaps and limited access to baseline data sets, including cropland maps, crop calendars, and meteorological data that are often produced within project frameworks, are inconsistent and seldom produced to meet a country's monitoring needs (Fritz et al., 2019; Nakalembe, 2018). As a consequence many ministries of agriculture in Africa still fully rely on resource-intensive traditional surveys or farmer-reported information complemented by *adhoc* monitoring (Lobell et al., 2015; Zhang et al., 2019a; Sahajpal et al., 2020). There is little to no integration of EO information in many government systems that mostly rely on field assessments for monitoring (Becker-Reshef et al., 2010; Burke and Lobell, 2017; Lobell et al., 2018). Government efforts to digitize and to make assessments more efficient are impeded by operating costs that are often not budgeted for Sasson (2012). Fortunately there are avenues to improve agricultural monitoring including leveraging open-access EO-based systems.

This paper provides a synthesis and comparison readily accessible and operational agricultural monitoring systems providing an overview of each system and its datasets, and provide examples of how the systems can be used to conduct crop condition assessments. This review is intended for analysts working in departments in charge of agriculture monitoring (agronomists and food security) officers often in charge of providing food security information and rarely training in the use of EO for this purpose. The study first summarizes the criteria for selecting the systems reviewed, followed by a definitions of ancillary datasets often used in EO-based agricultural monitoring systems. The study describes these datasets to provide non-expert analysts a good overview of the different EO-based datasets relevant for agriculture monitoring. Application-ready monitoring systems are summarized and discussed providing examples of their integrated into global, regional and national monitoring systems in SSA. In the conclusion, we summarize the next steps toward integration, outline capacity-building needs to leverage these systems further, and highlight adoption barriers and system limitations that will need to be addressed for successful uptake and use.

2. Materials and methods

2.1. Criteria for selecting monitoring systems to assess

1. The systems presented in this paper are primarily data archiving systems or data cubes that store a high volume of data (satellite image time-series data) needed to conduct agricultural assessments including conducting crop conditions, yield assessments and impacts of extreme events on cropland. Data cubes allow users to access data arrays that are massively larger than the users' computer main memory and are built to ease access and querying.

Table 1
Summary table of readily accessible cropland masks.

Scale	Product	Resolution	Date	Short description	Source	Reference
Global	MODIS (MOD12V1)	1 km	2000, 2001	Global land cover at 1-km spatial resolution using several classification systems, principally that of the IGBP	Boston University	Friedl et al. (2002)
	Global land cover map (GLC-2000, GLC-2009)	1 km	2000, 2009	A harmonized land cover database over the whole globe.	JRC (Link)	Bartholomé and Belward (2005) and ESA (2010)
	SAGE	0.5 Deg	1700–1992	Center for sustainability and the global environment global historical croplands data set	SAGE (Link)	Ramankutty and Foley (1999)
	MODIS land cover type (MCD12Q1)	500 m, 0.05 Deg-CMG & 1 km	2001–2019	Provides global land cover types at yearly intervals (2001–2019), derived from six different classification schemes	NASA (Link)	Friedl and Sulla-Menashe (2018)
	GFSAD30AFCE	30 m	2015	Global Food Security-support Analysis Data (GFSAD) Cropland Extent 2015 Africa 30 m	NASA (Link)	Congalton et al. (2017)
	SPAM		2000, 2005, 2010	Updated global crop data aid in food policy decisions	MapSPAM (Link)	
	ASAP crop layer	1 km	2018	Combines existing data sets	JRC (Link)	Pérez-Hoyos et al. (2017) and Rembold et al. (2019)
	IIASA-IFPRI global cropland map	1 km	2005	1 km global IIASA-IFPRI cropland percentage map for the baseline year 2005 has	IIASA (Link)	Fritz et al. (2015)
Continental	AFRICOVER	30 m	1999	AFRICOVER Land Cover Database and Map of Africa	FAO (Link)	Gregorio and Jansen (1998)
Regional	The West African Sahel Cropland map (WASC30)	30 m	2015	A new 30-m cropland extent product for the nominal year of 2015.	GEE (Link)	Samasse et al. (2020)
National	Togo	10 m	2019	2019 Togo Cropland	NASA Harvest (Link)	Kerner et al. (2020b)
	Kenya	10 m	2019	2020 Kenya Cropland	NASA Harvest (Link)	Tseng et al. (2020)
	Kenya	30 m	2000, 2015	The Kenya Crop Land layer provides information on the extent of cropland, area specific major crop and other crops being grown in the same location.	RCMRD (Link)	

2. The systems are open access and web-based (online), and thus can be accessed from anywhere with an internet connection. No additional hardware, software, or server space are required to operate the system.
3. Basic system customization and maintenance are primarily met by the original developers. Detailed customization might be possible to meet specific user(s) needs.[1]
4. Manuals and materials for self-paced/guided learning are accessible online.
5. The target end-users are agricultural analysts in ministries of agriculture, or individuals at regional centers supporting regional agriculture monitoring activities who may or may not be remote sensing experts. The presumption is that these analysts continuously assess agriculture using the best-available data, knowledge, and information at their disposal and provide actionable information to the decision-makers (e.g., national governments). This criterion is selected to ensure that systems fit the varied needs, have the potential to address critical gaps, and are directly applicable to national agriculture monitoring frameworks; thereby assisting ministries seeking to make improvements in their work flow, improve data quality, and outputs in a sustainable way.

2.2. Data products used in EO-based agricultural monitoring

The GEO Global Agricultural Monitoring (GEOGLAM) Initiative aims to produce information on the current state of, and monitoring change in, agricultural land cover and land use and has identified several EO-based, high-priority products required for operational monitoring, including cropland masks, crop type maps, crop conditions, crop yield forecast, soil moisture, rainfall, temperature, and evapotranspiration (Whitcraft et al., 2019; GEOGLAM, 2019). Satellite data products used to achieve these high-priority products are defined as essential agricultural variables (EAV) (GEOGLAM, 2019). EAVs represent information "building blocks" that are rudimentary indicators of state and change in our domain and as such, these low-level indicators can be built up and integrated with other information for monitoring (GEOGLAM, 2019).

This section briefly defines these EAVs that are integral to EO-based agricultural monitoring and their relevance in operational agricultural monitoring summarized in Table 2, while Table 3 summarizes some indices commonly used in agricultural monitoring systems.

Cropland maps, also referred to as crop cover maps or crop masks, are often derived from remote sensing satellite images using image classification techniques combined with ground sampled data. The masks are used to identify and separate pixels that represent croplands from other land cover types and are required in most EO-based monitoring and yield forecasting systems to segment data to exclude other land classes and segments where cropland is sparse or non-existent. These data improve yield models by limiting the model inputs to the target cropped areas (Zhang et al., 2019b). Ideally, a crop mask should be updated annually to provide a relatively reliable estimate of changes in crop distribution to support monitoring activities and provide accurate more input yield and crop condition assessments. Table 1 summarizes recent and easily accessible cropland masks some are detailed in Nakalembe et al. (2017) and Fritz et al. (2010)

Crop type masks identify main crop types or groups and delineate their extent within a region (Zhang et al., 2019b). Crop type masks should ideally be updated within the season to address dynamic area changes and crop rotations (Zhang et al., 2019b).

[1] Fit-for-purpose customization might include developing a dedicated portal, updating ancillary datasets (see Section 2.2), linking with existing systems.

Table 2
EO-based essential agricultural variables for agricultural monitoring.

Dataset	Definition
Cropland masks	Spatial data sets or geographic boundaries which define areas of agriculture for the purposes of visualization or to restrict spatial computations and analysis to a given area where agriculture is prevalent or considered to dominate the landscape.
Annual-Cropland masks	Annual-Crop Mask is defined by all areas of land where at least one crop is sowed/planted and fully harvestable within the 12 months after the sowing or planting date, and refers to a given reference period (typically a growing season corresponding to targeted crops). The annual crop produces a herbaceous cover and is sometimes combined with trees, woody vegetation or perennial crops.
Crop-type mask	Crop masks differentiated by specific crop types are referred to as crop type maps.
Eo-based crop-yield models and forecasts	Based on predictive models using observable indicators of crops progress using meteorological and remotely sensed vegetation indices.

Table 3
Satellite derived indices commonly used for agricultural monitoring.

	Indices	Definition
Crop conditions indicators	NDVI	Normalized Difference Vegetation Index is a ratio between the red (R) and near infrared (NIR) values in traditional fashion: (NIR − R)/(NIR + R), which is used to quantify vegetation greenness.
	EVI	Enhanced Vegetation Index is also a ratio between the R and NIR values (similar to NDVI), while reducing the background noise, atmospheric noise, and saturation in most cases.
	VCI	Vegetation Condition Index compares the current NDVI to the range of values observed in the same period in previous years.
Drought indicators	NDWI	The Normalized Difference Water Index is a ratio between the NIR and short-wave near-infrared (SWIR): (NIR - SWIR)/ (NIR + SWIR), which reflects the moisture content in plants and soil.
	WSI	Water Satisfaction Index is an indicator of crop (or rangeland) performance based on the availability of water to the crop during the growing season.
	SPI	Standardized precipitation Index is used for estimating wet or dry conditions based on precipitation variables.
	LST	Land Surface Temperature is how hot the “surface” of the Earth would feel to the touch in a particular location.
	RFE	Rainfall Estimates is the estimated precipitation.

Crop Condition Crop condition indicators like the Normalized Difference Vegetation Index (NDVI) serve as the basis for crop condition monitoring, providing information on crop development and vigor. These indicators typically provide information, through time, related to crop status and biomass, weather (e.g. temperature, rainfall), or water availability (e.g. soil moisture, water stress) which are all factors impacting crop growth (Zhang et al., 2019b; Becker-Reshef et al., 2019; Sahajpal et al., 2020; Lobell et al., 2015).

Crop yield estimates are traditionally made through surveys, sample crop-cuts, farmer interviews, or self-reporting by farmers (Zhang et al., 2019b; Becker-Reshef et al., 2019; Sahajpal et al., 2020; Lobell et al., 2015). These approaches, particularly for season monitoring and yield forecasting, can be significantly enhanced by integrating time-series of satellite and meteorological indices that provide field specific indicators related to crop conditions and yields.

Time-series data enable temporal profiling of a pixel or a region showing a distinct annual seasonality over the years and can be used to compare condition across seasons and across years (Rembold et al., 2015). For example NDVI time-series data from MODIS provide timely, repeated and synoptic indicator of the impact of these factors on potential yields and various studies have demonstrated the utility of NDVI and similar indicators (see Table 3) in capturing yield variations at field scales (Zhang et al., 2019b; Becker-Reshef et al., 2019; Sahajpal et al., 2020; Lobell et al., 2015). A range of satellite based crop condition alerts and yield forecasting models have been developed and demonstrated (Burke and Lobell, 2017; Skakun et al., 2016; Lobell et al., 2015). For example, Lobell et al. (2015) developed the scalable satellite-based crop yield mapper (SCYM) approach that provides per pixel yield predictions by applying regression to satellite observations and gridded weather. However, their applicability in operational monitoring is still limited, especially in smallholder agricultural systems due to limitations in the spatial resolution and temporal frequency of satellite images (particularly in cloudy regions) and lack of ground data (within season) and reliable statistical time-series required to train yield models and to develop in season crop type maps (Kerner et al., 2020b,a). Yield estimates require satellite images, gridded monthly weather data, and crop type maps and well-tested crop models (Lobell et al., 2015).

3. Application-ready satellite-based agricultural monitoring systems

This section provides an overview of the application-ready satellite-based agriculture monitoring systems that meet the selection criteria discussed above. Table 4 summarizes the goals, target audience, data, data sources, operating costs, functions, and features of the monitoring systems.

3.1. *Anomaly Hot-spots of Agricultural Production (ASAP)*

ASAP is a web-based decision support system for the early warning of hotspots of agricultural production anomalies (crop and rangeland) developed by the Joint Research Centre (JRC) of the European Commission for food security crisis prevention and response planning anticipation (Rembold et al., 2019). ASAP consists of three interactive online platforms based on weather and EO products that target a wide range of potential users: the Hotspot Assessment tool, the Warning Explorer, and the High Resolution Viewer. Hotspot assessment provides a monthly identification of countries with agricultural production hotspots providing summary narratives that synthesize, in non-technical terms, the analysis of the weather and EO data at the national level. The Warning Explorer is an advanced web-GIS with a console for visualization of statistics. Agriculture monitoring experts, with knowledge of geo-spatial science, can use the Warning Explorer to directly explore EO-based maps and graphs at the sub-national level for further analysis. The High Resolution Viewer is a user-friendly interface linked to the Google Earth Engine (GEE). High spatial and temporal resolution satellite images (Copernicus Sentinel-1 and Sentinel-2, and Landsat −8) with global coverage can be visualized and processed to provide real time information at the local (i.e., field) level.

3.2. *The Early Warning eXplore (EWX)*

EWX is a web-based single-page application for exploration of geospatial data mainly related to agricultural drought monitoring providing early warning information. The EWX provides easy and routine access to critical EO with the primary goal of enhancing their application for disaster mitigation and supporting long-term resilience. These

Table 4
Summary of application ready satellite-based agricultural monitoring systems.

System		ASAP	EWX	GADAS	GLAM	ASIS	VAM Seasonal Explorer
Developer		JRC	USGS, FEWSNET, CHG	USDA	UMD, NASA, USDA	UN FAO	UN WFP
Main goal		An online decision support system for early warning about hotspots of agricultural production anomaly for food security crises prevention and response planning anticipation.	A web-based single-page application for exploration of geospatial data related to climate extremes to support the assessment of agricultural drought and famine early warning.	A global, web-based agricultural assessment application for monitoring global agricultural conditions and assessing the impact of natural disasters on agriculture	First global MODIS based crop condition monitoring systems supporting near-real time crop assessment at multiple scales	A system operated by FAO for monitoring agricultural areas with a high likelihood of water stress/drought at global, regional, and country levels	A platform for monitoring the performance of agricultural seasons
Primary target users		Agricultural & Food security analysts, policy makers	Scientists & climate, agricultural & food analysts	Agricultural analysts	Agricultural & Food security analysts, policy makers	Agricultural & Food security analysts, policy makers	Agricultural analysts
Data sources	MODIS	✓	✓	✓	✓		✓
	VIIRS				✓		
	Landsat	✓			✓		
	Sentinel 1	✓					
	Sentinel 2	✓			✓		
	METOP- AVHRR					✓	
Rainfall		CHIRPS, ECMWF	CHIRPS, CHIRPS Prelim, RFE2, GEFS-CHIRPS	USAF 557th WW11, CHIRPS, CMORPH, GPM IMERG, WMO	CHIRPS	NOAA/FEWSNet, ECMWF	CHIRPS
Temperature		✓	LST	USAF 557th WW, WMO	(MERRA-2)	TCI	
Ancillary Data	Crop masks	✓	✓	✓	✓	✓	
	Crop type masks				✓		
	Rangeland mask	✓					✓
	Water masks	✓	✓	✓	✓	✓	
	Topography		✓	✓	✓		
	Population		✓				
	Land cover			✓			
	Infrastructure			✓			
EO data	Vegetation indices	NDVI, NDVI anomalies cumulated over the growing season	NDVI + ANDVI	NDVI	NDVI, NDWI, (Soil Water Index)	NDVI, NDVI Anomaly, VCI, VHI	NDVI, ANDVI, LST
	Drought indicators	WSI, SPI	NDVI, Zscore	SPI, Drought Severity, Evaporative Stress Index (ESI)	NDVI Anomaly, ESI, (Temperature, Precipitation, Soil Moisture Index)	ASI, Drought Intensity, Mean VHI	
	Hazards			Floods, Earthquakes, Cyclones and Volcanoes			
Download options	Reports	✓		✓		✓	✓
	Geotiffs	✓	✓	✓	✓	✓	✓
	CSVs	✓	✓		✓	✓	✓
	Graphics	✓	✓	✓	✓	✓	✓
Example applications		Used in CM4EW, World Bank Agricultural Observatory, ICPAC, Inamet Angola, LANDMATRIX	GEOGLAM Crop Monitors, Kenya, Tanzania		GEOGLAM Crop Monitors, CM4EW, EACM, National Crop Monitors (Kenya, Tanzania, Uganda, Mali and Rwanda	Feeds into FAO GIEWS and FAO Hand in Hand Geo-spatial Platform. Nicaragua, Bolivia, Peru, the Philippines, Paraguay, Vietnam, d Pakista, and others	Migrate to Amazon Web Services
Future developments		Cloud migration; user interface upgrades	Add new EOs including forecasts, manual development, EWX viewer improvements		GLAM 2.0 a cloud based with new datasets (rainfall, temperature, and integrated moderate-resolution data sets, for example, Landsat, Sentinel, and the Hybrid Landsat–Sentinel products	ASIS dataset published on geo-spatial portals (GEE, ArcGIS Cloud, etc.); set-up country level systems	A wider range of outputs and country specific visualizations

EO are best suited to monitor meteorological and agricultural drought conditions, and examine long-term changes and trends. The EWX allows users to access maps and time-series graphs, aggregated over pre-defined polygons. The EWX allows for quick access to maps of climate and vegetation. Typically, maps of all the datasets are available as absolute values, additive anomaly, and standardized anomaly (additive anomaly divided by standard deviations). While maps provided by EWX allow for a quick overview of drought conditions at a regional scale, for in-depth, targeted, local-scale analysis, the EWX also provides spatially aggregated time-series graphs of EO. Like the maps, time-series graphs are of absolute value, additive anomaly, and standardized anomaly. EWX can be used to access and download EO in a form that is compatible with widely used open-source GIS tools such as QGIS, and programming languages such as Python, to support further analyses. Data accessible in EWX include CHIRPS, CHIPRS Prelim, GEFS-CHIRPS (a bias-corrected and downscaled version of NCEP Global Ensemble Forecast System precipitation forecasts made to be spatially compatible with various CHIRPS products).

3.3. Global Agricultural and Disaster Assessment System (GADAS)

GADAS is a global, web-based agricultural assessment application used to monitor global agricultural conditions and assess the agricultural impact of natural disasters. GADAS is a powerful visualization tool based on an ArcGIS platform that enables Foreign Agriculture Service-International Production Assessment (FAS-IPAD) analysts, and other users, to rapidly assess real-time crop conditions using a wide variety of data layers from a multitude of sources. GADAS integrates a vast array of highly detailed data streams to include daily precipitation data, vegetation index, crop masks, land cover data, irrigation and water data, elevation and infrastructure. In addition, FAS-IPAD has partnered with the Pacific Disaster Center (PDC) in Hawaii to incorporate real-time data streams into the GADAS for worldwide monitoring, tracking, and pre- and post-disaster agricultural assessments resulting natural hazards.

3.4. The FAO Agricultural Stress Index System (ASIS)

The Agricultural Stress Index System (ASIS) is a global agricultural drought information system developed and operated by FAO. ASIS simulates the analysis that remote sensing experts and agronomists would undertake and simplifies the usage and interpretation of the data for a broader audience of end-users. The system provides quick-look indicators, such as the Agricultural Stress Index (ASI) and the Drought Intensity, Index to facilitate the early identification of cropland/grassland areas with a high likelihood drought. ASIS has Global and country-level platforms. Global ASIS is operated at the FAO headquarters by the GIEWS, which can support its staple food supply and demand monitoring work.

The country-level platforms were developed as standalone tools to assist countries in strengthening their agricultural drought monitoring and early warning system. The tool is calibrated with local information, including local land use maps, sowing dates, length of the crop cycle, crop coefficients, etc. Both global and country indicators include seasonal indicators, such as the ASI, to detect conditions of severe drought, and the drought intensity, to classify the severity of the drought. They also include non-seasonal indicators, such as NDVI anomaly, VCI, temperature condition index (TCI), and vegetation health index (VHI).

3.5. GLAM (the Global Agricultural Monitoring System)

GLAM is a global agricultural monitoring system that provides timely, easily accessible, scientifically validated, remotely sensed data, and derived products and doubles as data analysis tools for crop condition monitoring and production assessment (Becker-Reshef et al., 2010). The web-based system was originally developed in 2005 by UMD, NASA GSFC and USDA in support of the USDA Foreign Agricultural Service (FAS) crop analysts, enabling utilization of MODIS data for global agricultural monitoring. It was the first system of its kind and provided crop analysts the ability to analyze and query on the fly temporal composites of vegetation index data, and dynamic crop masks to inform their global crop assessments. Since then the original GLAM system has evolved with NASA GSFC operating the USDA GLAM system (GIMMS GLAM), UMD supporting the original system (referred to as GLAM in this paper) and an enhanced, serverless cloud-based system, with a broader suite of EO products, referred to as GLAM 2.0 released in 2019. All systems support crop and pasture condition analysis by allowing users to monitor crop conditions throughout the growing season and track factors impacting agricultural productivity through a range of time vegetation indices and agrometeorological time series data sets as well as cropland, crop type masks . GLAM enables inter-annual comparisons of seasonal dynamics and production of customized crop and pasture condition maps. The system has been adapted and integrated into a range of national monitoring systems and continues to be adapted and enhanced according to end user needs.

3.6. The WFP-VAM (World Food Programme Vulnerability Analysis and Monitoring)

The VAM Data Visualization platform provides rainfall and vegetation seasonal profiles for monitoring the performance of agricultural seasons. Users can assess rainfall and NDVI seasonal profiles (both current and long-term averages) and the progression of rainfall with monthly and three-monthly anomalies. The data can be subset to various administrative boundaries (Fritz et al., 2019). Users can focus their analysis on the whole administrative unit or only on areas that are under cropland or pasture.

4. EO-based monitoring and reporting initiatives

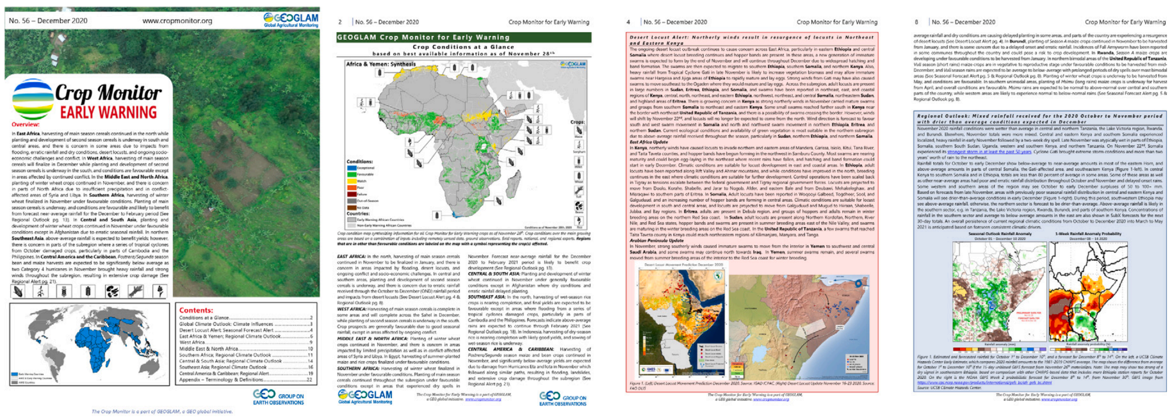
The aforementioned systems are a prerequisite for many operational global, regional, and national agricultural monitoring initiatives and programs. This section describes some of these systems that rely on and/or leverage parts of the systems above to support regular assessments with a focus on Africa.

4.1. Global analysis

4.1.1. GEOGLAM Crop Monitors

The GEOGLAM Crop Monitor for Early Warning (CM4EW) is a partnership with the main international food security monitoring agencies. Following the development of the Crop Monitor for the G20 Agricultural Market Information System (AMIS), which focuses on major commodity/export crops, the CM4EW was established in 2016 to address the pressing need for enhanced reliable and vetted information over countries at risk of shortfalls in production (Becker-Reshef et al., 2020, 2019). CM4EW was formed as a response for enhanced early warning of crop shortfalls in regions at risk to food insecurity (Becker-Reshef et al., 2020)

The CM4EW builds on existing multi-scale monitoring systems available (such as those described in this paper) to provide monthly, transparent, multi-sourced, consensus assessments of the crop growing conditions, status, and agro-climatic conditions that are likely to impact production in countries vulnerable to food insecurity. This information is used to strengthen agricultural humanitarian intervention, food security decision-making, and policy implementation. Through the use of shared definitions and classifications for crop monitoring, experts from across the community are able to come together to share data, information, and experience in a deliberative evidence-building process to reach an agreement on monthly crop conditions (Becker-Reshef et al., 2020).



(a) (b) (c) (d)

Fig. 1. Pages 1, 2, 15 and 25 of the Crop Monitor for Early Warning Bulletin No. 56: Published 3 December, 2020.

CM4EW brings together international experts from national, regional, and global monitoring systems to build consensus on crop conditions presenting the best-available multi-source assessment of current crop conditions. The overlap and agreement between monitoring systems, in addition to supplemental evidence from field observations and ground reports, form the basis of the monthly consensus. This consensus-building process of the CM4EW, comparing and contrasting systems and their outputs, and the resulting information provided in monthly reports fill information gaps related to food security on a global scale. Partner organizations include USAID FEWS NET, UN FAO GIEWS, UN WFP VAM, EC JRC, and IGAD ICPAC which use the aforementioned operational monitoring systems to convey their analysis along with agro-meteorological information and forecasts, field observations, and ground reports. In addition to current cropping conditions, regional and global climate outlooks are included in the CM4EW reporting to draw attention to the observed and forecast abnormal rainfall and temperature conditions that may impact food production or pose other risks to society. These outlooks are based on weather and seasonal climate forecasts from a variety of international and national sources, some of which are compiled on the EWX system. Given the importance of meteorological forecasts in predicting crop outcomes, the CM4EW is expanding its current forecast coverage in partnership with CHC (see Fig. 1).

4.1.2. Global Information and Early Warning System on Food and Agriculture (GIEWS)

Established after the food crises of the early the 1970s, the FAO's Global Information and Early Warning System on Food and Agriculture (GIEWS) continuously monitors and reports on food supply and demand worldwide. GIEWS is a leading source of information on food production and food security at national, regional, and global levels. It assesses the impact on agriculture and food security of a multitude of factors, including weather conditions, disease and pest outbreaks, conflict, price of inputs, and implementation of policies. Through assessments and reports, GIEWS alerts national and international decision-makers on impending food crises, thereby guiding their intervention. GIEWS provides comprehensive market intelligence on agricultural commodities and supports national and regional initiatives to establish and enhance early warning systems. GIEWS monitors the growing conditions of major food crops worldwide to assess production prospects. To support analysis and supplement ground-based information, GIEWS utilizes remote sensing data that provide valuable insights into water availability and vegetation health during cropping seasons. In 2014, GIEWS developed the Agricultural Stress Index System (ASIS) (summarized in Section 3.4) for the early identification of cropland and grassland areas affected by water deficits or, in extreme cases, by drought conditions. The ASIS won the 2016 Geospatial World Excellence Award.

4.1.3. Crop Watch

CropWatch, whose research team is part of the Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, has served as China's leading crop monitoring system since 1998. CropWatch can provide assessments of crop production at different spatial levels, as well as other information. CropWatch analyses are based on remote sensing, ground-based indicators and a combination of well-established and innovative methodologies. CropWatch's hierarchical crop monitoring approach involves the use of specific environmental and agricultural indicators at different scales. These include global, regional and national indicators, and – for large countries – sub-national indicators. Inputs at the global level include CropWatch Agroclimatic Indicators (CWAIs) for rainfall, air temperature, photosynthetically active radiation, and potential biomass. The outputs at this level are crop production system zones. At the regional level, in addition to CWAIs, the inputs include the Vegetation Health Index, uncropped arable land, cropping intensity, and Maximum Vegetation Condition Index. The outputs are major production zones. In addition to indicators already mentioned, national-level inputs include crop cultivated area and time profile clustering. The 31 selected countries for global agricultural monitoring represent more than 80% of global production and exports of maize, rice, wheat, and soybean (Wu et al., 2015). For large countries (Argentina, Australia, Brazil, Canada, China, India, Kazakhstan, Russia, and the United States), analysis is performed at the sub-national level. Sub-national level outputs are similar to those at the national levels but with more detail. These include information on cropland use intensity, crop condition, yield, and production.

4.1.4. FEWSNET (the Famine Early Warning Systems Network)

FEWS NET was established in 1985 by the United States Agency for International Development (USAID) to provide unbiased and evidence-based analysis to governments and relief agencies who plan for and respond to humanitarian crises. The network monitors food security in more than 28 countries that experience significant variability in inter-annual rainfall and food production and are at high risk of food insecurity. These countries are spread across Central America and the Caribbean, Central Asia, East Africa, Southern Africa, and West Africa (Verdin et al., 2005). FEWS NET analysts work with scientists, government ministries, and international agencies to track conditions and bring the world timely, comprehensive insights into global food insecurity. FEWS NET analysts work with scientists, government ministries, and international agencies to track conditions and bring timely and comprehensive insights into global food insecurity. FEWS NET provides regular reporting on current and projected acute food insecurity, alerts on crises, reports on factors that impact food insecurity, and data and analysis on food insecurity. FEWS NET uses advanced tools and forecasting to predict acute food insecurity to inform humanitarian responses and share learning and data. FEWS NET analyzes the dynamics of food, nutrition, and livelihood security. Using remote sensing, agroclimatology data, modeling, and field observation, it seeks to obtain a good understanding of the climate system to inform its food security analysis. EWX is a key information source for FEWS NET's agroclimatology analysis. It enables time series analyses to evaluate the climatology of an area, assessing, monitoring and reporting on seasonal progress, which informs scenario development (summarized in Section 3.2) In the future, the FEWS NET will provide advanced innovations and analytical tools to increase its efficiency and services.

4.1.5. The World Food Program Seasonal Monitor

The World Food Program (WFP) Seasonal Monitor is a near-global system that can monitor seasonal growing conditions for all its areas of operation. The Seasonal Monitor uses real time satellite data streams and seasonal forecasts to highlight changes in the progression of the agricultural season. This informs WFP operations and other stakeholders in this field. The seasonal monitor regularly produces a number of agro-meteorological outputs that are used by WFP analysts and officers in the field to identify conditions detrimental to the food security of poor and vulnerable populations. The type of analysis depends on the context of the country and the requirements of the field officers. The analysis may range from short advocacy-oriented pieces to complex multi-dimensional analysis that draw on additional elements, such as market prices and regional cereal stocks. In the future, a wider range of outputs will be produced, including a number of standard drought indices. A visualization platform is also being developed, which will provide country-specific visualizations of outputs and will link them to vulnerability information, providing an in-depth analysis of the impacts of drought and flood hazards.

4.2. Regional

4.2.1. Eastern Africa Crop Monitor

The Eastern Africa region has experienced climatic extremes almost in a cyclic chronology in the last decade. With most livelihoods supported by rain-fed agriculture, droughts and floods have impacted economies and food security. As a response to this, the IGAD Climate Prediction and Applications Center (ICPAC), a specialized institution of the Intergovernmental Authority on Development (IGAD), has developed tools for monitoring, early warning, and assessment, as well as various interventions for agriculture and rangeland. These are aimed at filling information gaps and supporting and improving decision-making at various levels within the food security chain; policy level, distribution, extension services, and even the final user (farmers). In doing so, it aims to effectively contribute to addressing the region's pertinent issue of food security.

The Eastern Africa Crop Monitor (EACM) bulletin (see Fig. 2) has been critical in the development of timely early warning and growing season information. By assessing the season, it can provide a regional and national analysis of the food situation in that region. It was launched in April 2018 and comprises a regional network of key informants on crop condition and drivers. An online portal customizable to regional crop areas was developed for ease of reporting. Several capacity-building campaigns were conducted to train national and regional analysts on EO-based assessments. The EACM has been integrated into the Global Monitoring for Environment and Security-GMES & Africa project and the Greater Horn of Africa Climate Outlook Forum (GHACOF). This is to improve the information provided in agricultural sector advisories for planners and decision-makers. The forums are held at the start of every rainfall season, with the participation of representatives from 11 countries, mostly comprising officials from government authorities, regional partners, and private sector agriculture and food security companies.

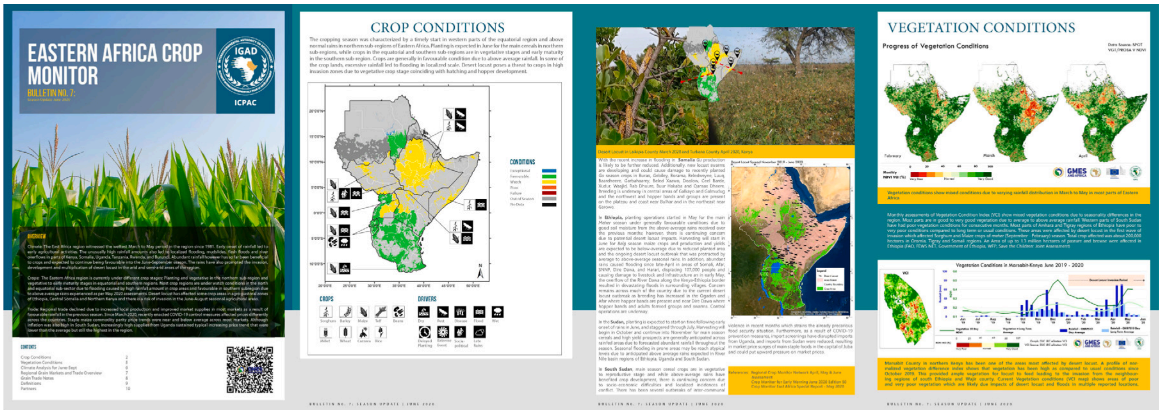
To generate reliable and value-added information on crop monitoring, ICPAC has leveraged collaborations and partnerships with government authorities and other non-governmental authorities. This has yielded rich actionable information that has been used by different actors in planning and decision-making. The EACM has been used in food security analysis both within ICPAC and by our climate services users. For example, in April 2019, owing to a potential drought, there was a critical call for action for regional analysts from various organizations to share information about the previous season's harvest as well as the current availability of commonly traded and consumed food. This was to develop an advisory for governments. The Tanzanian, Kenyan, and Ugandan governments implemented emergency actions while referencing the advisories issued by IGAD through ICPAC. The Eastern Africa Crop Monitor has now turned into a demand service for a wide range of users who seek seasonal and even monthly agriculture-related information.

4.3. National analysis

Recognizing the evident application of regular science-based assessments toward national monitoring activities, the Crop Monitor process has been developed and adopted by national ministries in Eastern Africa and Mali. Through various GEOGLAM contributing programs and projects, the methods and tools have been adapted further and have been co-developed with end-user organizations. National crop monitoring systems are managed by government agencies, and the information produced is integrated into the CM4EW (see Section 4.1.1). Tanzania, Kenya, and Uganda have fully operational systems. Remote sensing-based analysis and products provided by GLAM and EWX have been integrated within agency workflows using the same standardized approach. Comparable national reports are now being produced on a regular basis across these countries, combining remote sensing analysis with other data. GEOGLAM aims to support national crop monitors in collaboration with international donors and partners. The recently launched COPERNICUS4GEOGLAM project, for example, will provide agricultural baseline products aimed at improving the national monitors. Initially, from 2020 to 2021, the project will produce crop-type maps for key food production areas in Western Kenya, Northern Uganda, and North East Tanzania.

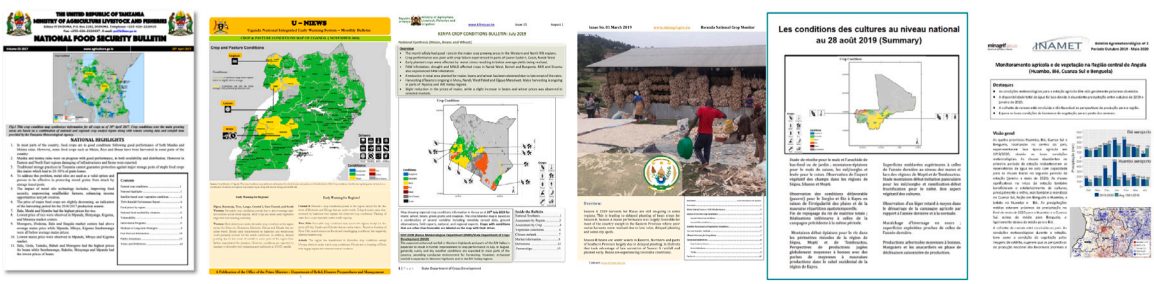
The first National Crop Monitor was developed in partnership with the **Tanzania Ministry of Agriculture (MoA) National Food Security Division (NFSD)**. NFSD is mandated to monitor and report on the country's food security status (see Fig. 3(a)). Through joint needs assessments and training events NFSD decided to include remote sensing-based inputs a enhance their national food security bulletin using the Tanzania Crop Monitor system and GLAM. The team trained on the use of remote sensing information from GLAM that complemented the ministry's existing data collection systems and, since 2015, has integrated this into regular reports from NFSD. Tanzania began including EWX analysis in their national bulletin March 2019.

The Office of the Prime Minister (OPM) adopted the crop monitor for **Uganda National Integrated Early Warning Bulletin (U-NIEWS)** in November 2016 (Fig. 3(b)). The report includes information on: the condition of crops and pasture assessed using the GLAM system, food insecurity status using the Integrated Phase Classification (IPC) assessments, weather, climate, and seasonal rainfall forecast from the Uganda National Meteorological Authority. The bulletin also provides information about disasters that may occur while providing disaster and humanitarian response status updates based on monthly statistics shared by different stakeholders. The report is disseminated to over 7000 users via email and print copies are sent out district offices. It is also accessible via the National Emergency Coordination and Operations Centre website. The OPM also adopted and uses NDVI



(a) (b) (c) (d)

Fig. 2. Pages 1, 2, 4 and 5 of the Crop Monitor for Eastern Africa Crop Monitor Bulletin N0. 7: Season Update June 2020.



(a) Tanzania (b) Uganda (c) Kenya (d) Rwanda (e) Mali (f) Angola

Fig. 3. Cover pages of National Bulletins from Tanzania, Uganda, Kenya, Rwanda, Mali and Angola.

data from the GLAM to assess drought severity in the Karamoja region and to trigger the disaster-risk financing program. This is a safety net program that scales up public works under the Third Northern Uganda Social Action Fund (NUSAF 3) Project.

Kenya: The first Keny National Crop Monitor bulletin for Kenya was released in May 2018 (Fig. 3(c)). The team in the State Department of Crop Development analyzes crop conditions using information from GLAM and EWX combined with field reports from county extension officers and the reports are published on The Ministry of Agriculture, Livestock, Fisheries and Irrigation website.

Other crop monitors in development. Rwanda (Fig. 3(d) and Mali (Fig. 3(e)) are in the process of developing and integrating data from GLAM and EWX into their national bulletins. In Rwanda, the process is being led by the Ministry of Agriculture-MINAGRI, while in Mali, it is being led by the Systeme Alerte Précoce (S.A.P) team in the Food Security Commission. S.A.P already integrates GLAM and EWX analyses to complement their regular monitoring.

Angola. The Angolan National Institute of Meteorology and Geophysics (INAMET) uses ASAP to analyze agricultural conditions at the national level using EO, coupled with meteorological data and models developed in the country to produce Boletim Agrometeorológico (Fig. 3(f)) in partnership with the Angolan Ministry of Agriculture and Rural Development.

5. Discussion

Across all the systems presented in this review the main target audience are agricultural analysts and these same analyst should ideally form the basis of the national, regional and global monitoring initiative such as the CM4EW described in Section 4.1.1. This section compares and contrasts key features about the systems presented in Section 3 and what users can expect in terms of the data accessible, the types of assessment, and products.

Data

MODIS NDVI time-series data form the core of all systems due in part to the consistent over 20 year record of data required for assessing conditions anomalies. Users can plot and visually assess vegetation anomalies in ASAP, EWX, GADAS and GLAM. Plots can be derived for specific administrative regions using preloaded shapefiles in ASAP and EWX but can also upload and/or draw specific areas of interest in GADAS and GLAM to derive area specific statistics.

The GLAM provides a MODIS near real-time product (NRT). NRT imagery are generally available 3–5 h after observation, similarity users can access CHIRPS prelim data in GLAM and EWX. CHIRPS Prelim, a preliminary version of CHIRPS, for monitoring the most current conditions. Soil moisture, soil moisture prelim and CHIRPS GEFS are only accessible in EWX. Prelim and GEFS-CHIRPS products are short-range pendatal rainfall forecasts that enable analysts to gain an idea of how current conditions are likely to evolve toward the end of the current dekad and the following dekad. Seasonal forecasts are also used to provide a longer-term perspective on how the season is likely to evolve. Users can also access ECMWF, and RFE2 data

Crop specific masks are accessible only in GADAS (multiple crops) and GLAM that provides a select few. These allow users to focus their analysis of conditions to specific crops (see Section 2.2). Crop mask should be used with caution since crops grown can change from year to year. The GLAM system also provides multiple cropland masks including SPAM, CCM, GlobeCover, and ASAP

Cropland. ASAP is the only system to include a rangeland mask. Recent and readily accessible masks are summarized in Table 1
The ASAP system provides a unique high resolution viewer that allows users to explore Sentinel-1 radar data and near-real time, crop conditions at field level. This is in addition to allowing users do trend analysis of yield statistics leveraging the stand-alone tool CGMS Statistical Tool (CST). This supports development and selection of crop yield forecast models to facilitate national and sub-national crop yield forecasting.

Assessments

Within ASAP, EWX, GLAM users are able to plot time-series data at various spatial and temporal scales for all regions with the capability to drop custom boundaries in ASAP. GADAS and GLAM.
Using the crop-type masks accessible in GADAS and GLAM users can assess crop-specific conditions although as indicator earlier the validity of crop masks can vary by season
Within both GADAS and ASAP users are able to assess the impacts of extreme events such as flooding using the Global Flood Risk from UNEP for GADAS and using the high resolution viewer in ASAP

Products

ASAP, EWX, GLAM, GADAS and WFP-VAM users are able to conduct their own analysis. Users can also download GeoTIFFs and comma-separated values (CSVs) files from EWX, ASAP and GLAM to conduct own analysis using GIS software and produce custom maps or conduct further spatial analyses. Users interested in creating own products for specific regions are encouraged to use these.
ASAP also provides quick summary reports by country that include spatial statistics of conditions for cropland and rangelands. ASAP is the only system to include automatic alert system providing ten-day automatic warnings about low or delayed vegetation performance. The ASAP system also includes an automated alert system that points users to regions with potential food insecurity risk.
ASIS and WFP's Seasonal Explorer users are able to readily download ready products that are pre-calculated. The products in these 2 system are automated analysis of a remote sensing expert and agronomist would perform for example ASIS provides maps of ASI that is expressed as the percent of the area affected by drought within a region. There for users interested in pre-created products are encouraged to use these two to download ready maps.
In the GLAM and GADAS system users can upload custom geometries (e.g., shp, kml, geojson) to retrieve dataset statistics and visualizations of dataset anomalies in order to provide users with an indication of the relative performance of a crop over time.

Combining custom analysis of NDVI anomalies using ASAP, EWX, GADAS, GLAM, WFP-VAM users can track crop conditions and assess the severity of impacts of events such as drought and flooding. Products such as anomaly maps and time-series plots can be directly integrated into global, regional and national reporting initiatives such as those described in Section 4. Users can also use warnings provided to fast-track response programs. ASIS and the WFP Seasonal Explorer maps can directly be used to highlight emerging food security and humanitarian situations globally therefore making a direct clear source of global data not requiring remote sensing expertise to generate and apply.

While a lot can be achieved by leveraging these systems there are still many adoption barriers, including the lack of investments toward using and applying EO-data in the agricultural sector. While users can quickly pick-up and derive products, they lack clear workflows for including the products in their reporting mechanisms. In organizations where capacity exists, other barriers such as poor internet connectivity and/or associated high costs that are often out-of pocket can limit analysts from accessing these systems. This is compounded by limited availability of high resolution cropland masks and crop masks that can help improve assessments. The GEOGLAM initiative is coordinating and facilitating capacity development programs in order to overcome some of these adoption barriers, as well as aid capacity-building. There are efforts from GEOGLAM partners to coordinate and open training opportunities for more countries and transferring lessons learned to other countries while working to improve the methods and availability of essential products such as crop masks.

However, without intentional development and investments in the local requisite human resources, computational infrastructure (IT systems and internet), research, models and requite data, communication strategies and polices that can truly operationalize and institutionalize data to decisions as described in Nakalembe (2020), the resources the systems described in this paper will never be put to full use.

6. Conclusion

With increasing weather variability, more frequent and extreme events, and the increasing impacts of climate change, food security is projected to further deteriorate in many developing countries. Hence, there is a dire need for accurate and timely information. Data on the situation of food production is even more critical. Earth observations form a strong, reliable, and strategic basis for informing programs and policies that can guide planning, implementation, and program management. This can directly lead to better outcomes for farmers. However, gaps still remain in accessing data and computing facilities, as well as in the capacity of government institutions (Nakalembe, 2020). In light of addressing some of these gaps, we have reviewed satellite-based EO that support early warning of food insecurity and that have been optimized for open access for national agencies. These systems form a clear, strategic approach to accessing information that has been demonstrated to improve decision-making processes and outcomes for farmers (Nakalembe et al., 2021; Becker-Reshef et al., 2020).

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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