

Designing AfriCultuReS services to support food security in Africa

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Abstract

Earth observation (EO) data are increasingly being used to monitor vegetation and detect plant growth anomalies due to water stress, drought, or pests, as well as to monitor water availability, weather conditions, disaster risks, land use/land cover changes and to evaluate soil degradation. Satellite data are provided regularly by worldwide organizations, covering a wide variety of spatial, temporal and spectral characteristics. In addition, weather, climate and crop growth models provide early estimates of the expected weather and climatic patterns and yield, which can be improved by fusion with EO data. The AfriCultuReS project is capitalizing on the above to contribute towards an integrated agricultural monitoring and early warning system

for Africa, supporting decision-making in the field of food security. The aim of this article is to present the design of EO services within the project, and how they will support food security in Africa. The services designed cover the users' requirements related to climate, drought, land, livestock, crops, water, and weather. For each category of services, results from one case study are presented. The services will be distributed to the stakeholders and are expected to provide a continuous monitoring framework for early and accurate assessment of factors affecting food security in Africa.

1 | INTRODUCTION

The World Food Summit determines that a population is food secure “when all people, at all times, have physical, social, and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for active and healthy life” (FAO, 2009). This is hardly the case for Africa, with an estimated 821 million food-insecure people in 2017, which accounts for 31% of the total food-insecure population of the world (CDKN, 2019). In various parts of Africa, climate change has produced lower animal growth rates and productivity in pastoral systems (Nardone, Ronchi, Lacetera, Ranieri, & Bernabucci, 2010; Stige et al., 2006); impacted on agricultural pest patterns (Biber-Freudenberger, Ziemacki, Tonnang, & Borgemeister, 2016); increased desertification (Feng & Fu, 2013), which affects 46 out of 57 African nations; and increased the frequency and intensity of droughts (CDKN, 2019; Intergovernmental Panel on Climate Change, 2020). Droughts and desertification processes impact adversely on water resources, which play a key role in agricultural management practices (Falkenmark & Galaz, 2007) via: withdrawal of water for irrigation; land cover change (e.g. when forests are converted to agricultural land); and alterations in water division due to changes in land use management (Deutsch et al., 2010). In addition, land degradation has decreased agricultural incomes in different countries, with significant consequences for livelihoods; for example, in Ghana, loss of agricultural income due to land degradation was anticipated to cause a 5.4% increase in national poverty rates between 2006 and 2015 (Diao & Sarpong, 2011). It has been argued, though, that many statistics for the African economy lack reliable data, which is an important constraint on decision-making (Jerven, 2013). Thus, there is an urgent need for accurate and widely available multi-source information such as land use, farm statistics, crop models, weather forecasts, and climate projections to contribute to well-informed agricultural risk assessments, decision-making, and governance at multiple levels.

Earth observation (EO) technology has become a common tool to monitor agricultural production systems and food insecurity in industrialized and emerging countries (Rembold et al., 2019; Whitcraft et al., 2019); however, its single use in the context of food security poses challenges related to the estimation of crop areas and production forecasts (Fritz et al., 2019). EO data must be combined or fused with multiple data sources to accurately predict crop production in complex food and farming systems. Consequently, agricultural monitoring systems are often based on rainfall data, sample field measurements, agricultural statistics, agro-meteorological modelling, and EO-based methods. An example of an agricultural monitoring system that covers Africa is CropWatch Cloud (<http://cloud.cropwatch.com.cn/>) which is deployed via Alibaba Cloud and provides users access to EO information layers for crop monitoring. Another example is the Agricultural Market Information System (AMIS; <http://www.amis-outlook.org/>), an inter-agency platform to enhance food market transparency and encourage international policy

coordination in times of crisis. The Crop Monitor tool of GEOGLAM (<https://cropmonitor.org/>) was designed to make available to the public open, timely, science-driven information on crop conditions in support of market transparency for the AMIS. It reflects an international, multi-source, consensus assessment of crop growing conditions, status, and agro-climatic factors likely to impact global production, and focuses on the major producing and trading countries for the four primary crops monitored by AMIS (wheat, maize, rice, and soybeans).

Several international projects focus on food security. GCRF-Africap (<https://africap.info>) emphasizes the use of models together with fieldwork. While it has no EO component, it does place great emphasis on the use of models within broader integrated assessment frameworks that make use of a range of expertise across the natural and social sciences. TWIGA (<https://twiga-h2020.eu/index.html>) is a Horizon 2020 project aiming to provide currently unavailable geoinformation on weather, water, and climate for sub-Saharan Africa by enhancing satellite-based geodata with innovative in-situ sensors and developing related information services that answer needs of African stakeholders and the GEOSS community. CONFER is a Horizon 2020 programme starting in September 2020 the aim of which is to co-develop dedicated climate services for the water, energy, and food security sectors with stakeholders and end-users, to enhance their ability to plan for and adapt to seasonal climate fluctuations. The project will use machine learning, remote sensing and modelling within a climate services framework. However, no project so far offers an integrated collection of services that include monitoring, early warning, and future predictions.

The EU-funded Horizon 2020 project AfriCultuReS: Enhancing Food Security in African Agricultural Systems with the Support of Remote Sensing (grant no. 774652) uses EO-based products, meteorological and climate data to develop an integrated agricultural monitoring and early warning system for Africa to support decision-making in the field of food security. The target sectors of the AfriCultuReS project are the public sector, the agribusiness sector, the financial sector, and the academic sector. We have engaged with potential users from eight African countries through several workshops and surveys to collect specific requirements and feedback about data and products useful for monitoring and assessing agricultural production, and to understand capacity-building needs. With the help of user feedback, we developed a service portfolio with seven service categories (climate, drought, livestock, land, crop, weather, and water). In this article, we present how these services have been designed and implemented with several case studies.

2 | MATERIAL AND METHODS

2.1 | Study areas

The focus of AfriCultuReS activities is on the following regions in Africa: Equatorial and Central Africa, East African Highlands, Gulf of Guinea, Great Horn of Africa, North Africa Mediterranean, Sahel, and Southern Africa. More specifically, eight pilot countries were selected in the aforementioned regions (Figure 1)—Tunisia, Niger, Ghana, Ethiopia, Kenya, Rwanda, Mozambique, and South Africa—considered to reflect the diversity of climate, ecosystems, and farming conditions in Africa. Test sites within the pilot countries were selected for testing products at finer spatial scales. Work in each of the eight countries is carried out in close collaboration with a local African partner organization, a full list of which can be found on the AfriCultuReS website (www.africultures.eu).

According to the Köppen–Geiger climate classification, which employs seasonal precipitation and temperature regimes, there are three first-order climate classification divisions in Africa: tropical, dry, and temperate plus. From north to south, climatic conditions transition from warm Mediterranean over the coasts of North Africa to semi-arid and warm desert over the Sahara, switching to tropical savannah and monsoon climate over the equatorial regions and then transitioning again to humid subtropical and warm/temperate oceanic in the south.

The delineation of the major farming systems provides a useful framework within which appropriate agricultural development strategies and interventions can be determined. These have been identified and then mapped,

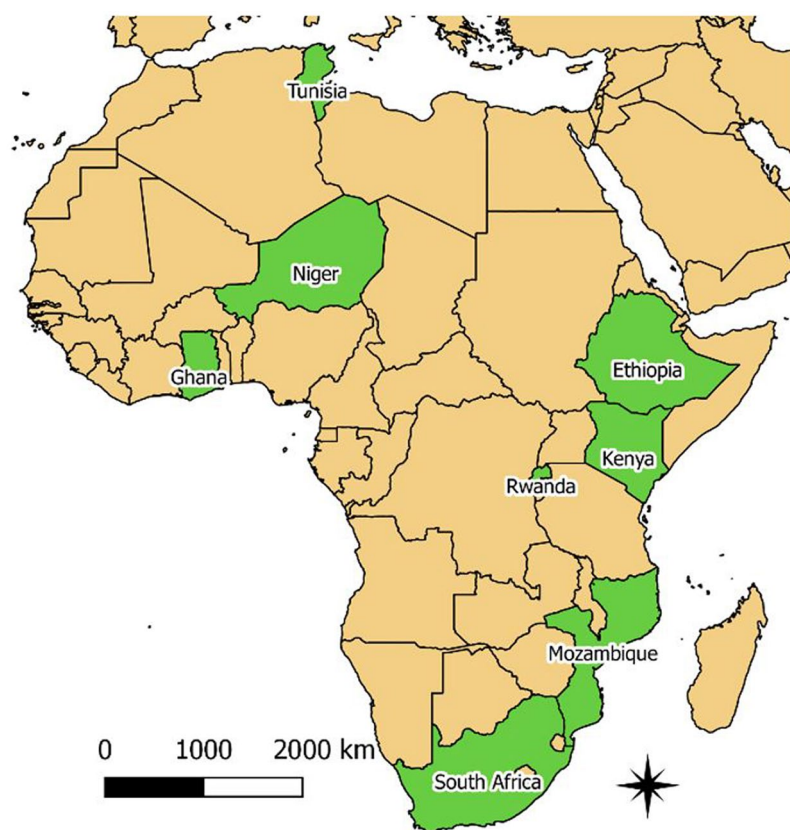


FIGURE 1 Distribution of the AfriCultuReS pilot countries

in order to estimate the magnitudes of their populations and resource bases. Each of these broad systems is characterized by a typical farm type or household livelihood pattern, although significant sub-types are described where appropriate.

The classification of the farming systems in the Global South has been based on the following criteria (Dixon, Gibbon, & Gulliver, 2001): the availability of natural resources (water, land, grazing areas and forest), climatic conditions, landscape, farm size, tenure, and organization; the dominant pattern of farm activities and household livelihoods (such as type of crops, livestock, trees, aquaculture, hunting and gathering, processing and off-farm activities); and the main technologies used, which determine the level of intensity of production and integration of farming activities.

Based on these criteria, the following eight broad categories of farming system have been distinguished:

- irrigated farming systems, embracing a broad range of food and cash crop production;
- wetland rice-based farming systems, dependent upon monsoon rains supplemented by irrigation;
- rainfed farming systems in humid areas of high resource potential, characterized by a crop activity (notably root crops, cereals, industrial tree crops—both small scale and plantation—and commercial horticulture) or mixed crop-livestock systems;
- rainfed farming systems in steep and highland areas, which are often mixed crop-livestock systems;
- rainfed farming systems in dry or cold low potential areas, with mixed crop, livestock and pastoral systems merging into sparse and often dispersed systems with very low current productivity or potential, because of extreme aridity or cold;

- dualistic (mixed large commercial and smallholder) farming systems, across a variety of ecologies and with diverse production patterns;
- coastal artisanal fishing, often mixed farming systems; and
- urban-based farming systems, typically focused on horticultural and livestock production.

2.2 | User requirements and EO data identification

Gaining an understanding of user needs necessitated addressing three main issues: the crops most important to food security in the eight focus countries; the most important agricultural risks in each country; and the kinds of EO-based products which could best contribute to ameliorating these risks. Secondary data sources used to understand these issues included the EarthStat (Monfreda, Ramankutty, & Foley, 2008) and FAOSTAT databases in the case of key crops, and an in-depth review of academic literature in the case of agricultural risks.

Secondary data were complemented by engagements with potential users through surveys, as well as through rounds of in-country stakeholder workshops organized in collaboration with local African partner organizations in 2018 and 2019. Representatives from the four identified user sectors (public sector, academia, finance and agribusiness) were invited to workshops, although representation of different sectors varied between countries. Further rounds of workshops are planned for 2020 and 2021, during which potential users will be able to interact with the AfriCultuReS platform and provide further input into design and functionality.

These various data sources were combined, analysed and translated into users' requirements following the Group on Earth Observation (GEO) User Requirements Registry approach (<http://www.geo-tasks.org/urr-tutorials>) and linking this information to the GEO Societal Benefit Areas (SBAs; <https://www.earthobservations.org/sbas.php>). Requirements mainly cover the SBAs of Food Security and Sustainable Agriculture and Water Resources Management. Finally, users' requirements have been stored in a database. Similar review processes will follow in order to adjust and consolidate the database.

Questionnaires and surveys were also sent to local African partners to identify EO, meteorological, and in-situ data available for the regions of interest. In order to satisfy users' needs and to produce food-security-related estimates and warnings, a broad range of EO raw and processed data were investigated. The EO products that were considered are either already available from third parties or being produced by the project. For the selection of the relevant EO-based geodata the following key characteristics were taken into account: the spatial, temporal, and spectral resolutions; the radiometric resolution; the timeliness of data; the accuracy of data; the swath width; the launch date, availability of archive data and continuity of data provision; the simplicity and easiness of access; interoperability; the automation.

2.3 | Development of AfriCultuReS services

In order to provide the information identified through the analysis of the users' requirements, several services have been proposed at various temporal and spatial scales. As a general rule, after extensively analysing the project's needs, in particular in terms of EO products to be developed, several guidelines were followed for the implementation of AfriCultuReS services. The same guidelines have been taken into consideration for the selection, processing, and management of the EO data. These guidelines are:

- to deliver space-based agricultural production services that will be aligned with the African Space Policy and Strategy and AfriGEOSS, the African segment of the GEO in the domain of food security; and
- to rely upon the data and services provided by Copernicus and the GEO initiatives, as well as other third-party EO data and value-added services, such as the European Space Agency (ESA) Food Security Thematic Exploitation Platform, or the Landsat archive on Amazon Web Services.

TABLE 1 Spatial scales for AfriCultuReS products

Spatial scale	Description and relevance
Coarse: 1:1,000,000–1:4,000,000	Useful at a continental and regional level especially for applications such as drought monitoring or extreme weather risk assessment. This scale is relevant to address the needs of decision- and policy-makers from regional institutions in agribusiness, finance, security, etc.
Medium: 1:250,000–1:1,000,000	Useful for monitoring vegetation status, flood risk assessment, or water resources assessment at a national to provincial scale. This scale is appropriate to address the information needs of national and provincial government ministries
High: 1:10,000–1:250,000	Useful for crop yield prediction, crop health and anomaly detection at a landscape to field level. This scale can address the information needs of farmers and land managers

AfriCultuReS services rely on the users' exploitation of information products that alone, or in combination with other information products, satisfy the users' requirements. In addition, in order to address the diversity of users (i.e., from decision- and policy-makers to farmers and land managers) and needs, the products within the AfriCultuReS project were developed following a multi-scale approach. As a result, three spatial scales were considered, as indicated in Table 1.

The definition of the project's service portfolio in support of enhanced food security decision-making was mostly based on the exploitation of EO data. The analysis of users' needs and the technological capacity of project partners have gone a step further into the detailed definition of the services' components, leading to the seven general categories of services described below.

2.3.1 | Climate services

As has been reflected by the World Meteorological Organization (WMO, 2019), climate services should provide the scientific basis to enable policy- and decision-makers at different temporal (e.g., weather, season, decades) and spatial (e.g., country or local) scales to establish the proper actions (e.g., when to plant or irrigate) and adaptation plans (e.g., investing in drought-resilient crops and livestock). In this sense, AfriCultuReS climate services have a twofold purpose. On the one hand, they provide the necessary climatic information (e.g., rainfall, temperatures, radiation) to other services (e.g., crop and drought services) to be used as input (Kim, Shin, Lee, & Jeong, 2019). On the other hand, they provide information about mid-term climate variability (seasonal forecasts) and long-term climate change scenarios. With this in mind, the current state-of-the-art climatic information was considered. In particular, at seasonal scale, the multi-model seasonal forecast system provided by the Copernicus Programme (<https://www.copernicus.eu/>) through the Copernicus Climate Data Store (<https://climate.copernicus.eu/climate-data-store>) was used, while at decadal scale and for climate change projections, Phase 6 of the Coupled Model Intercomparison Project (CMIP6) and CORDEX-Africa (Hewitson, Lennard, Nikulin, & Jones, 2012) were considered, respectively; both of them distributed through the Earth System Grid Federation (Carenton-Madiec, Denvil, & Greenslade, 2015). All this climatic information was downloaded and post-processed to make it remotely available through the Santander User Data Gateway (<http://www.meteo.unican.es/udg-wiki>; Cofiño et al., 2018) in order to obtain the final products defined or requested by users by applying the tools included in the climate4R framework (Iturbide et al., 2019) and to be seamlessly included by the remainder of the AfriCultuReS services.

2.3.2 | Crop services

Crop services provide manifold information for decision-making on crop production. AfriCultuReS crop services include crop and calendar yearly mapping, frequent crop phenology and condition monitoring, as well as forecasts on expected yield for main crops, based on crop growth models. These multi-scale crop services, including the crop early warning service, provide the basis for evidence-based decision-making on food security. Current and seasonal maps on crop land use and main crops grown allow the precise identification, location, and measurement of production areas. These inputs are a corner stone of planning and prioritization of zonal interventions to improve crop cultivation conditions or to cope with food production shortages.

In the case of crop condition assessment, this is done directly through the use of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI), or using the Vegetation Condition Index (VCI) which compares the current NDVI to the range of values observed in the same period in previous years. The NDVI has been selected as the vegetation index most commonly adopted to represent the amount of live biomass present in a pixel, while the LAI is recognized by international organizations such as the Global Climate Observing System and Global Terrestrial Observing System as one of the essential climate variables. The VCI is widely used to monitor vegetation and drought conditions (Quiring & Ganesh, 2010). The VCI was designed to evaluate vegetation health, while separating the weather-related component of the NDVI from the ecological element. VCI data are characterized using the vegetation condition classes previously proposed: 0.7–1, normal vegetation condition; 0.5–0.7, moderate vegetation condition; 0.3–0.5, poor vegetation growth; less than 0.3 extremely poor growth condition (Qian et al., 2016). The service at high resolution is based on NDVI and LAI historical values retrieved from Sentinel-2 images (Figure 2).

2.3.3 | Drought services

Drought is the major disaster affecting food production, thus its prediction has been relevant to decision-makers (Demisse et al., 2019; WMO, 2019). Drought alone accounted for 19% of the crop and livestock losses from disasters in Africa during the period 2005–2014 (FAO, 2017). Drought services address two main types of drought: meteorological and agricultural. Meteorological drought is defined by a precipitation deficiency threshold over a predetermined period of time. In turn, agricultural drought is defined by the availability of soil water to support

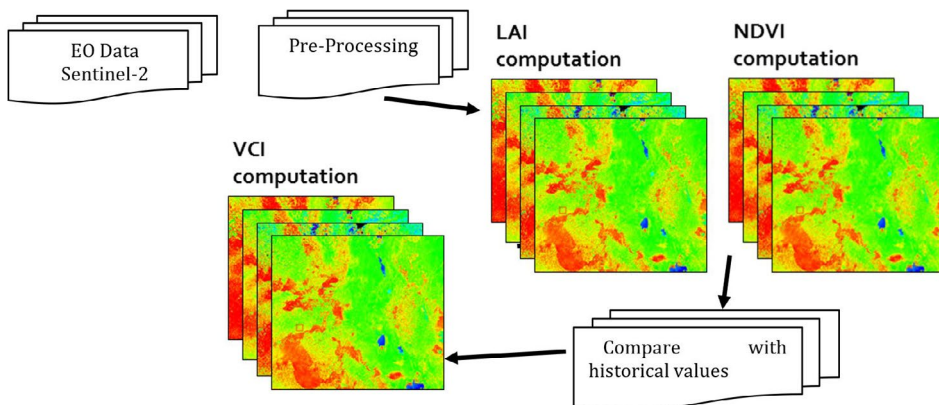


FIGURE 2 Schematic view of the procedure for carrying out AfriCultuReS crop condition monitoring using VCI, NDVI or LAI based on available Sentinel-2 imagery. The NDVI or LAI, computed on that image by using SNAP software, is compared with the historical values (mean, maximum and minimum) corresponding to the same period of the year. The year has been divided in decades

crop and forage growth rather than by the departure of normal precipitation over some specified period of time. Note that the impact of drought on food production depends on the intensity, duration, and spatial coverage of drought. Moreover, long drought periods strongly affect the resilience of the terrain to intense precipitation (Haile et al., 2019). As a result, both the drought monitoring and the seasonal forecast are considered within AfriCultuReS services.

In the case of the Seasonal Drought Forecast service, it is based upon the calculation of the standardized precipitation evapotranspiration index (SPEI), which is able to provide an estimation of the onset, duration, and intensity of a drought event (Vicente-Serrano, Beguería, & López-Moreno, 2010). In addition, the SPEI allows for a multi-scalar analysis, by calculating its values on different temporal windows. The multi-scalar nature of SPEI enables the identification of the return time of different drought types (Schwalm et al., 2017).

2.3.4 | Land services

Land services provide facts on the current land cover situation and land cover changes, as well as abiotic factors that affect, or can affect, food production. Land use competition between agricultural and/or pastoral land and other uses, mainly urban expansion, constitutes a key factor when tackling sustainable land use planning. The increasing demand for space for urban and other non-food production activity development is increasingly relegating food production to land areas less suitable for human and economic activities. These changes lead to lower productivity of agricultural land. In addition, other factors, such as land degradation, soil erosion, and the occurrence of recurrent natural disasters, while not always coincident with land use cover transformations, exacerbate the decrease in land productivity. With three proposed land services, AfriCultuReS will contribute to improved and informed decision-making with the aim of mitigating the adverse effects of the above factors on land and food security.

To be specific, the high-resolution burnt areas mapping service uses multi-temporal Sentinel-2 data sets to compute the normalized burn ratio (NBR), which is a spectral index that combines the near infrared (NIR) and shortwave-infrared (SWIR) bands to distinguish between burned and unburned areas (Key & Benson, 1999):

$$NBR = \frac{R_{NIR} - R_{SWIR}}{R_{NIR} + R_{SWIR}} \quad ((1))$$

where R_{NIR} and R_{SWIR} are the reflectance of the NIR and SWIR spectral bands, corresponding to band 8 (0.842 μm) and 12 (2.190 μm) of the MultiSpectral Instrument (MSI) sensor of Sentinel-2.

The differenced normalized burn ratio (dNBR) index was also calculated, defined as:

$$dNBR = NBR_{pre} - NBR_{post} \quad ((2))$$

that is, the difference between the NBR values computed by using a pre-fire and a post-fire image. In this way burned areas can be detected, and the severity of the damage can be quantified, by introducing appropriate thresholds on the possible values of dNBR. The dNBR index provides a continuous scale of differences that can be related to a magnitude of ecological change, which in turn offers a conceptual model for the severity of damage caused to vegetation in the burned area: the greater the change detected due to fire, the greater the severity. A relativized form (RdNBR) of the dNBR has been introduced (Miller & Thode, 2007) to remove the biasing effect of the pre-fire condition. The RdNBR is defined as:

$$RdNBR = \frac{dNBR}{\sqrt{\text{abs}(NBR_{pre}/1,000)}} \quad ((3))$$

In principle, employing the RdNBR allows categorical classifications to be created using the same thresholds for fires occurring in similar vegetation types without acquiring additional calibration field data on each fire. However, an alternative relativized burn severity index, the relativized burn ratio (RBR), was recently introduced (Parks, Dillon, & Miller, 2014). This index is defined as:

$$\text{RBR} = \frac{\text{NBR}_{\text{pre}} - \text{NBR}_{\text{post}}}{\text{NBR}_{\text{pre}} + 1.001} \quad (4)$$

The dNBR maximizes reflectance changes in plants and soil due to drastic changes such as forest fires. Like the RdNBR, the RBR is a relativized version of the dNBR, designed to detect changes even where pre-fire vegetation cover is low. It was demonstrated that both the RBR and RdNBR are less correlated to pre-fire NBR than dNBR, indicating that the relativized metrics are better at detecting high-severity effects across the full range of pre-fire vegetation cover. The RBR is an improvement on the dNBR in terms of correspondence to field measures of burn severity and overall classification accuracy. Furthermore, the reduced variability in RBR threshold values among fires indicates that RBR thresholds are more stable than RdNBR thresholds and are thus more transferable among fires and eco-regions. By using suitable thresholds, the range of values of RBR can be exploited to provide the burn severity in the form of discrete thematic categories, distinguishing, generally, between “no burn”, “low severity”, “moderate severity” and “high severity”.

Burnt area maps give an effective support in estimating damage and plan management. This service provides key information to many diverse applications such as forestry, agriculture, risk management and enables assessment of the amount of crop, forested and pastoral areas affected by fire. The high spatial resolution service consists of an automated satellite-based data set of RBR maps computed continuously for the area of interest. The data are computed using Sentinel-2 Level-2A (L2A) images downloaded automatically from the Copernicus Hub. The procedure is shown schematically in Figure 3. The AfriCultuReS burned area service at medium spatial resolution is taken from the Copernicus Global Land Service based on *Proba-V* images.

2.3.5 | Livestock services

Across Africa, pastoralism is a vital socioeconomic activity, practised on about 43% of Africa's landmass (FAO, 2018). Moreover, livestock is generally the most valuable asset of rural households, providing nutritional requirements, transport, and profit. However, rangelands, as the major source of feed for grazing and browsing livestock, are faced with several challenges, including, bush encroachment (Belayneh & Tessema, 2017; Mugasi, Sibiiti, & Tayebwa, 2000), the proliferation of invasive alien plants (Kganyago, Odindi, Adjorlolo, & Mhangara, 2018), wildfires (Kganyago & Mhangara, 2019), drought (Huho, Ngaira, & Ogindo, 2011), as well as displacement due to competing land uses (Sullivan & Rohde, 2002). Therefore, mapping of grazing and rangeland resources and their changes over time becomes essential, to ensure sustainability and support decision-making and effective implementation of land use management approaches (Müller, Quaas, Frank, & Baumgärtner, 2011).

The advent of medium- to high-resolution data from sensors such as the *Landsat-8* Operational Land Imager and the Sentinel-2 MSI, coupled with robust machine learning algorithms such as support vector machines and random forest (RF), offers the prospect of operational high-resolution grazing and rangeland mapping. In this project, the high-resolution grazing and rangeland mapping product is generated based on the Sentinel-2 MSI, while the training data are generated from the ESA Climate Change Initiative (CCI) prototype high-resolution land cover map of Africa, and classification is performed using an RF classifier (Figure 4). The RF classifier is an ensemble tree-based algorithm which generates classification results by assimilating several classification trees. Each tree is grown to maximum depth using bootstrapped samples (i.e., out-of-bag) and randomly selected variables at each node. The RF classifier was chosen based on its robustness and better accuracy in applications such as land cover

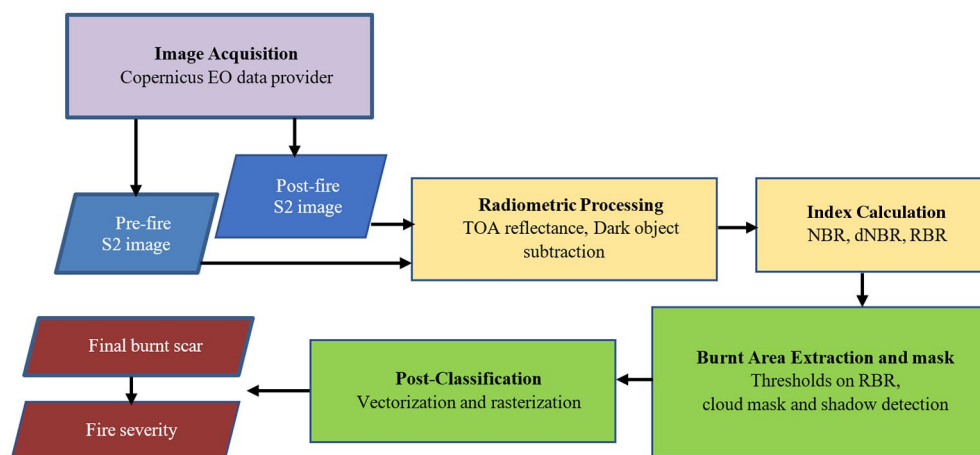


FIGURE 3 Schematic view of the procedure followed to detect burnt areas at high spatial resolution using Sentinel-2 images

mapping (Abdi, 2020), characterizing grazing quality and quantity (Ramoelo et al., 2015) and species discrimination (Mansour, Mutanga, Everson, & Adam, 2012). On the other hand, the coarse-resolution product (i.e., the Joint Research Centre (JRC) Global Rangeland Mask at 1 km) and the South African National Land Cover at 30 m were used as a reference for quality assurance purposes (Vancutsem, Marinho, Kayitakire, See, & Fritz, 2013).

2.3.6 | Water services

Water services provide geospatial products for water body extent mapping and lakewater quality assessment and monitoring. Other products are designed to deliver information on soil water availability for crop growing, as well as crop water consumption. According to the FAO (Turrall, Burke, & Faurès, 2011), the impacts of climate change on the global hydrological cycle are expected to modify the patterns of water supply and demand for agriculture, the dominant user of freshwater. The extent and productivity of both irrigated and rainfed agriculture can be expected to change. As a result, the livelihoods of rural communities and the food security of a predominantly urban population are at risk from water-related impacts linked primarily to climate variability. The rural poor, who are the most vulnerable, are likely to be disproportionately affected. Adaptation measures that build upon improved land and water management practices are fundamental in boosting overall resilience to climate change.

2.3.7 | Weather services

Weather services provide seven-day to near real-time deterministic weather forecasts at continental scale (0.25° longitude \times 0.25° latitude). In addition, probabilistic weather forecasts will serve to deliver early warnings on weather extremes at continental scale (0.5° longitude \times 0.5° latitude). In the short term, weather factors may reduce crop yield, while extreme weather events combined with a climate change environment produce food shortages. In fact, yield losses of more than 25% have been projected for various crops and regions (Porter et al., 2014). Therefore, weather forecasts, both short and medium range, are required for making decisions. Day-to-day farm management requires weather information for the schedule of farming practices; for example, the application of fertilizers requires water in the upper to mid layers of the soil, the spraying must be done on non-windy days, etc.

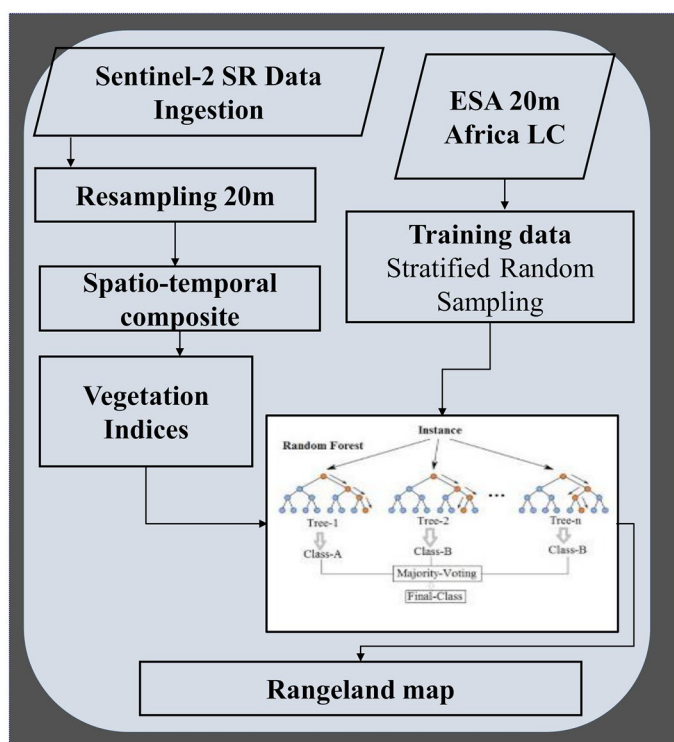


FIGURE 4 Methodological flow for grazing and rangeland mapping product

Weather conditions are also a key driver for the outbreak of pests and diseases, such as fungal diseases. Knowing in advance the likelihood of these events can support early decision-making towards the mitigation of the adverse effects of weather on food production.

3 | RESULTS

3.1 | Identified user requirements and list of EO data

Gathering user needs has provided us with valuable information about crop types, fertilization requirements, calendar advice, irrigation scheduling, and the facilitation of timely agricultural management practices. One of the main concerns reflected during some of the national workshops was related to water availability and droughts at different time-scales, from climate seasonal forecast to decadal and long-term climate change projections, as it strongly affects crop planning and growth, and livestock management. Moreover, climate and weather information is also needed as input for crop models.

The list of users' requirements identified through review of secondary sources and engagements with potential users in the AfriCultuReS pilot countries can be summarized as follows:

- EO monitoring of crop conditions, crop pests, crop diseases, and crop management.
- Provide ready-to-use information for irrigation management.
- Provide a smart system to predict crop yield for tackling hunger and disasters that affect crops.
- Integrate information on traditional cultivation techniques for the assessment of the most appropriate land for agricultural production.

TABLE 2 Selected EO data and providers by scale level

EO products	Coarse	Medium	High
LULC	FAO GLC-SHARE	500 m MCD12Q1 v6 Land Cover (LC) v2 (2015)	Tunisia: OSS 30 m (2015–2016), Kenya: 15 m 2015, Ethiopia: OSS 30 m (2014–2015), Ghana: OSS 30 m (2014–2015), Niger: OSS 30 m (2014–2015)
Rangeland		250 m JRC rangeland mask	
NDVI	1 km 10 day Copernicus v2.2	300 m 10 day Copernicus v1	Sentinel-2
NDVI anomaly		250 m 8 day NDVI Anomaly (GMOD09Q1)	
VCI (vegetation condition)	1 km 10 day Copernicus		Sentinel-2
LAI	1 km 10 day Copernicus v2	300 m 10 day Copernicus v1 NOAA Climate Data Record (CDR) of AVHRR	Sentinel-2
FAPAR		NOAA Climate Data Record (CDR) of AVHRR	Sentinel-2
Burnt area		300 m 10 day Copernicus v1 (pre-operational)	Sentinel-2
Water bodies	1 km 10 day Copernicus v2	300 m 10 day Copernicus v1	Sentinel-1
Soil moisture	SWI Surface 10 km 10 day Copernicus		
Soil erosion	25 km Global Soil Erosion (2012, 2001) (ESDAC)		
Evapotranspiration	3 km daily LSA-SAF DMET 5.6 km monthly SSEBop v4 ET anomaly	500 m 8 day MOD16A2	Ethiopia, Ghana, Kenya, Mozambique, Rwanda, and Tunisia: 100 m 10 day FAO/WaPOR (2009–2016)
DEM			30–90 m SRTM

AVHRR, advanced very-high-resolution radiometer; ESDAC, European space data center; FAPAR, fraction of absorbed photosynthetically active radiation; GLC-SHARE, global land cover – SHARE; LSA-SAF DMET, land surface analysis – satellite Application facility – Daily MSG evapotranspiration; LULC, land use/land cover; OSS, L'Observatoire du Sahara et du Sahel; SSEBop, simplified surface energy balance model; WaPOR, water productivity through open access of remotely sensed derived data.

- Support the development of index-based insurance.
- Enhance service provision to farmers by local government (policy monitoring, seed and fertilizer subsidy, field extension services, crop insurance, precision farming, early warning for drought, pests, diseases, disaster management, agricultural downstream logistics, farm-level calendars).
- Produce information for main crop yield forecasting.
- Set up index-based livestock insurance against extreme events for pastoralists to minimize their risk.
- Calibrate and evaluate climate services at local and regional scale; meteorological information based on the available national and/or international observational networks is needed as input.
- Provide information on the likelihood of extreme weather conditions (frost, high temperatures and heat waves, extreme precipitation events) related to agricultural activities.

The user requirements were then connected to actual services, intended to be designed and developed by the AfriCultuReS project. For the implementation of these services a set of EO products was identified as most appropriate. The EO products are presented in Table 2 along with the data source or provider for each scale considered.

3.2 | The AfriCultuReS service portfolio

Following the guidelines described in Section 2 and taking into consideration the users' requirements identified and the availability of relevant EO products, the AfriCultuReS service portfolio was designed. It is presented in Table 3. Due to the large number of services developed, one representative service per service category identified in Section 2.3 is provided below. A case study accompanies each service description.

3.2.1 | Climate services: AFRICRS-S1-P02—Seasonal climate forecast and early warnings

Climate services aim to provide seasonal forecast and decadal and long-term climate projections at continental and, when possible, local or regional scales. At seasonal scale, these services obtain one month in advance the expected climate evolution for the next (typically 6–9) months as given by the state-of-the-art seasonal forecast systems produced by the Copernicus initiative. As a result, this service will allow proper adaptation measures to be planned according to the expected seasonal climate conditions.

As an example, the seasonal forecast of 2-m mean daily air temperature for autumn 2019 is shown in Figure 5 at continental scale, including the tercile plot corresponding to Rwanda. In this figure, the most probable tercile (lower than normal, normal, and higher than normal) for each grid box is shown in colour (blue, yellow and red, respectively), while the transparency of the dots represents the uncertainty of the forecast as given by the hind-cast (retrospective forecast). This is illustrated in more detail in the tercile plot in which the forecast for each year and the observed tercile are shown, reflecting the capability of the forecast system to predict each class in the past and, as a result, the uncertainty associated with the new forecast. Note that this forecast can be adapted to the target season and climate indices needed (e.g., plant dates) by end-users, extending the capabilities of other existing services (WMO, 2019).

3.2.2 | Crop services: AFRICRS-S2-P02—Crop condition monitoring (high resolution)

The crop condition assessment service provides information about the status of vegetation and crops through the VCI (see Section 2.3.2).

TABLE 3 List of the AfriCultuReS services per scale level.

	Product ID	Product name	Coarse	Medium	High
Climate	AfriCRS-S1-P01	GAEZ Agro-Climatic Condition	✓		
	AfriCRS-S1-P02	Seasonal Climate Forecast and Early Warnings	✓		
	AfriCRS-S1-P03	Decadal Climate Change Predictions	✓		
	AfriCRS-S1-P04	Long Term Climate Change Projections	✓		
Crop	AfriCRS-S2-P01	Crop Type Mapping			✓
	AfriCRS-S2-P02	Crop Condition Monitoring	✓	✓	✓
	AfriCRS-S2-P03	Crop Yield Forecast	✓		✓
	AfriCRS-S2-P04	Crop Calendar			✓
	AfriCRS-S2-P05	Crop Phenology Monitoring			✓
	AfriCRS-S2-P06	Crop Early Warning	✓	✓	✓
Drought	AfriCRS-S3-P01	Seasonal Drought Forecast	✓		
	AfriCRS-S3-P02	Drought Monitoring and Early Warning	✓		
Land	AfriCRS-S4-P01	Land Use & Land Use Change Monitoring	✓	✓	✓
	AfriCRS-S4-P02	Land Degradation	✓		
	AfriCRS-S4-P03	Disasters Mapping and Monitoring (Fire, Flood)		✓	✓
Livestock	AfriCRS-S5-P01	Grazing and Rangeland Mapping	✓	✓	✓
	AfriCRS-S5-P02	Grazing and Rangeland Condition Monitoring	✓	✓	✓
Water	AfriCRS-S6-P01	Water Bodies Mapping	✓	✓	✓
	AfriCRS-S6-P02	Lake Water Quality Monitoring	✓	✓	✓
	AfriCRS-S6-P03	Soil Moisture Monitoring	✓	✓	
	AfriCRS-S6-P04	Water Consumption Monitoring	✓	✓	✓
Weather	AfriCRS-S7-P01	Weather Forecast	✓		
	AfriCRS-S7-P02	Weather Extremes Early Warning	✓		

As an example, the agricultural area of Jendouba, one of the Tunisian test areas, was chosen to test the services in its rather wet climate and evaluate the impact on the availability of cloud-free images. Figures 6a and b shows the historical maximum and minimum NDVI computed for the area by using Sentinel-2 images acquired from January 2018 to 13 July 2019. In addition, Figure 6c shows the VCI map computed using the Sentinel-2 image acquired on 23 July 2019. The VCI is divided into four classes according to Qian et al. (2016): (d) normal vegetation condition; (c) moderate vegetation condition; (b) poor vegetation growth; (a) extremely poor growth condition. From the VCI map the statistics on the distribution of VCI values for the pixels classified as crop, grass, or shrub were retrieved. They are 81.5% for (a), 4.37% for (b), 3.11% for (c), and 11% for (d).

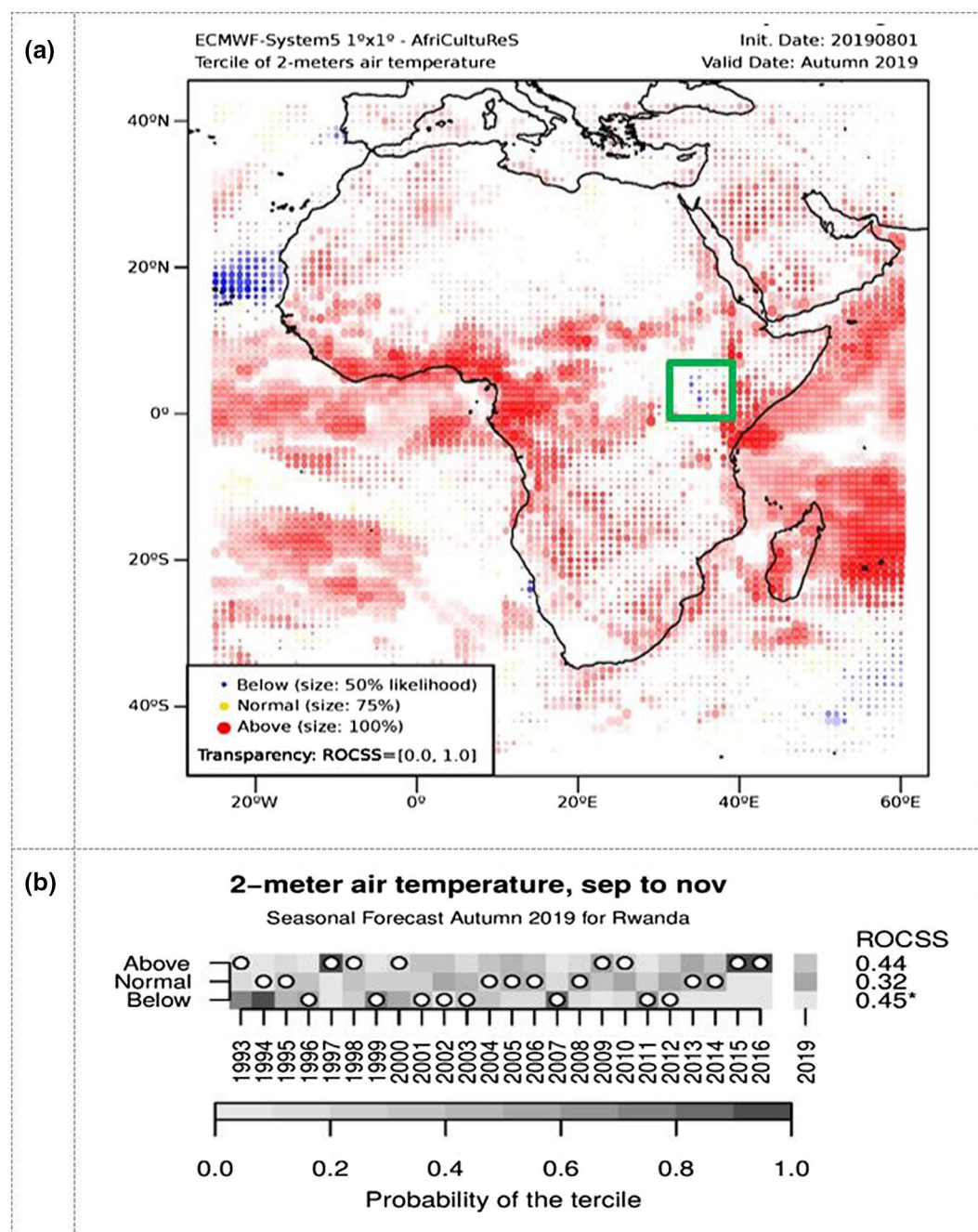


FIGURE 5 (a) Seasonal forecast for the African continent for the 2-m air temperature for September to November 2019 (the study area of Rwanda is indicated by a green box) - the dot size and the transparency show, respectively, the percentage of members corresponding to the most probable tercile and the skill of the prediction; and (b) Seasonal forecast for the Rwanda study area for autumn 2019. White dots represent the tercile (rows) observed for each year (columns) during the hindcast period (1993-2016)

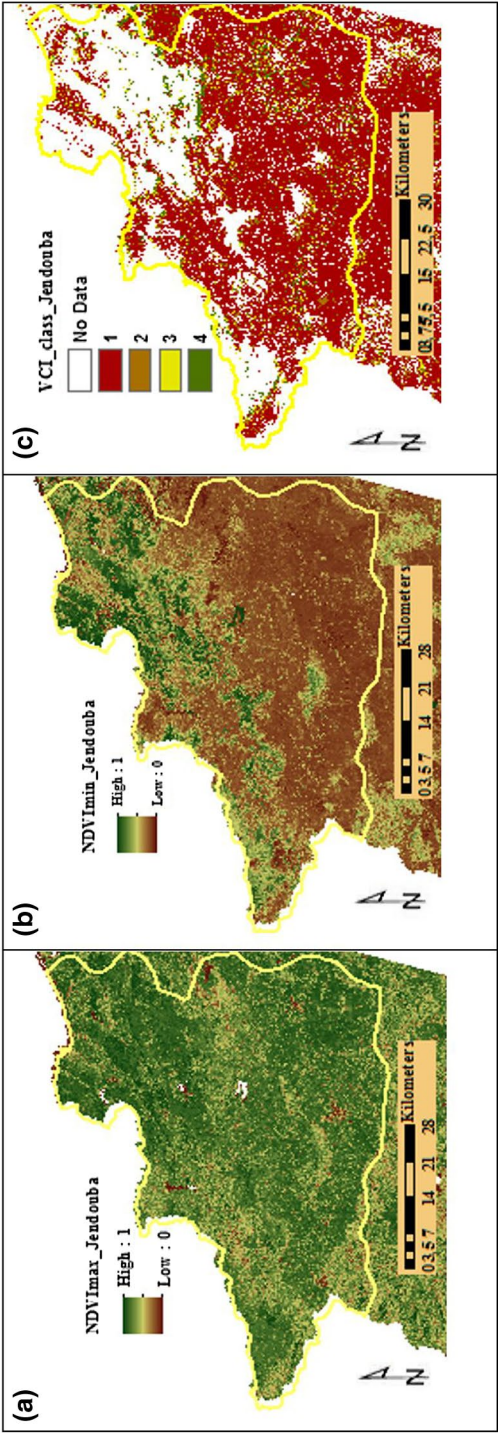


FIGURE 6 Example of crop condition maps computed for the Jendouba test area in Tunisia: (a) historical maximum of NDVI, Centre; and (b) historical minimum of NDVI; (c) VCI computed for 23 July 2019. White area refers to cloudy pixels

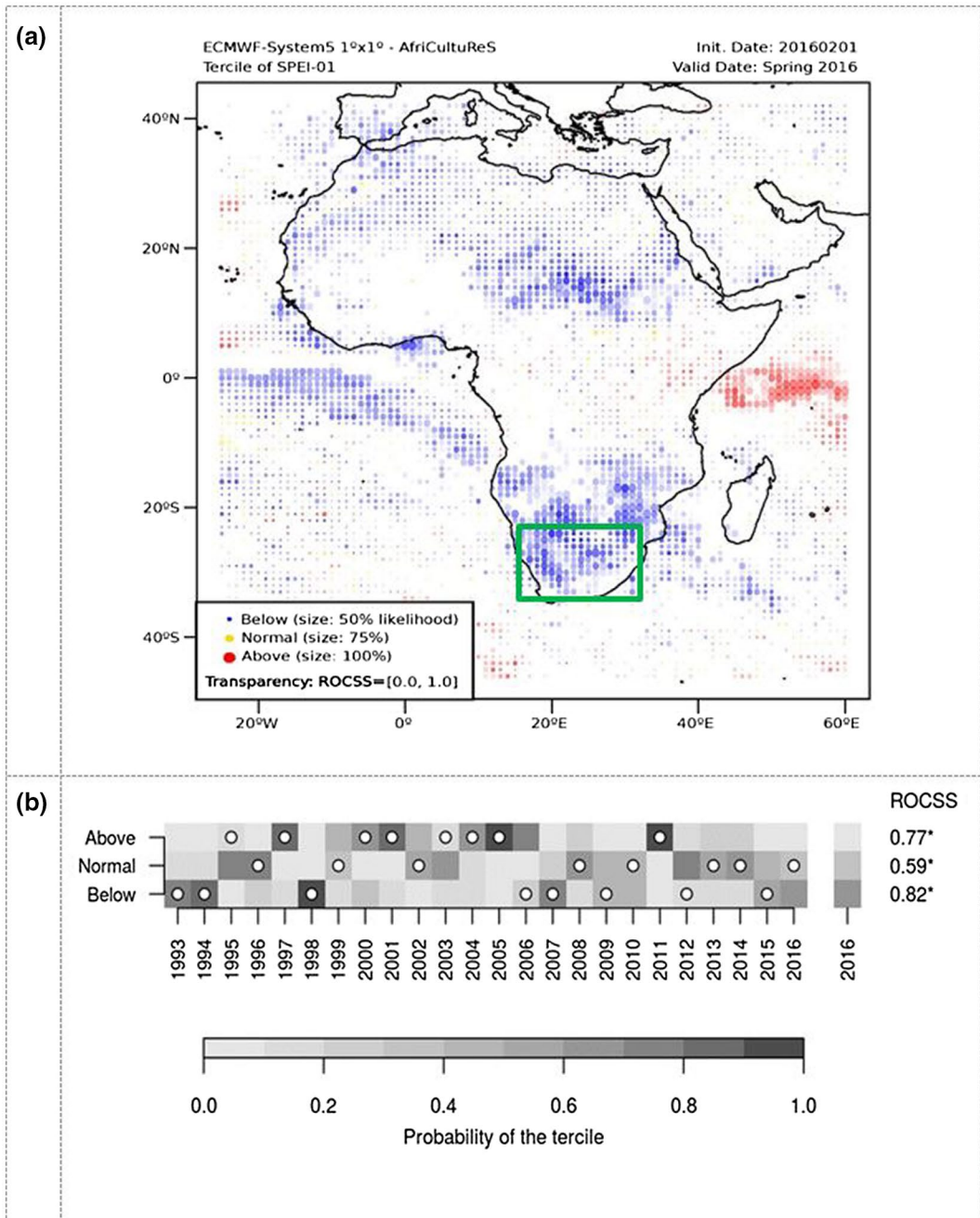


FIGURE 7 (a) Seasonal drought forecast for the African continent during spring of 2016 (the study area of South Africa is indicated with a green box); and (b) 1 Month Standardized precipitation evapotranspiration index from March to May 2016 in South Africa. Note that for the calculation of the SPEI-01 index the climatic conditions of the previous month, February 2016 in this case, are considered

3.2.3 | Drought services: AfriCRS-S3-P01—Seasonal drought forecast

Complementary to the Seasonal Climate Forecast and Early Warnings, the Seasonal Drought Forecast service aims to provide the probability and intensity of drought conditions for the next season one month in advance, in

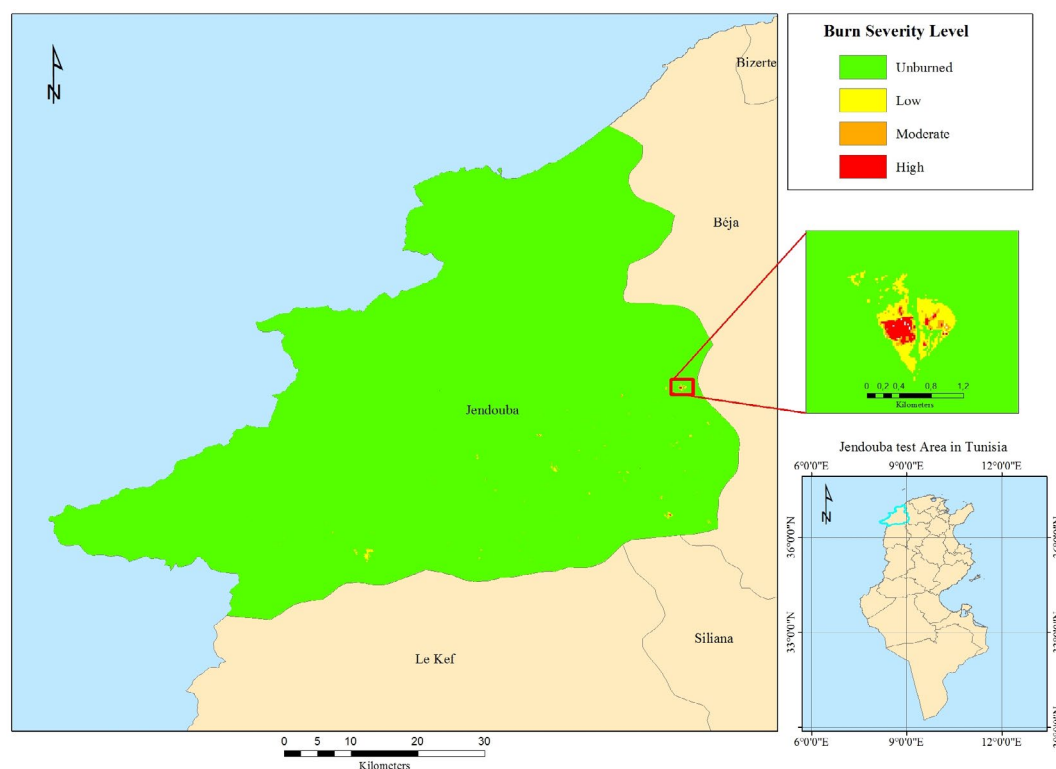


FIGURE 8 Example of high-resolution fire disaster mapping computed for the test area of Jendouba, Tunisia, between 17 and 22 August 2019 using the RBR index

order to plan proper adaptation measures according to the predicted drought conditions, using the time series of the SPEI index. This service has been identified by end-users during the workshops as an important relevant product to properly establish actions for the next season. Note that the conjunction of both climate and drought Services gives the user a general view of the expected climate conditions for the next months.

As an example, the one-month-in-advance seasonal forecast of the SPEI for spring 2016 is shown in Figure 7, corresponding to the end of a large drought period of approximately 2 years (2015–2016) affecting South Africa, which has been reported in scientific and institutional publications (Archer et al., 2017; Hornby, Vanderhaeghen, Versfeld, & Ngubane, 2017; Yuan, Wang, & Wood, 2018). On the one hand, Figure 7a shows that drought conditions (blue) were predicted for the whole continent. The dot size and the transparency show, respectively, the percentage of members corresponding to the most probable tercile and the skill of the prediction as given by the evaluation of the hindcast against the observations, in this case the EWEMBI data set (Frieler et al., 2017; Lange, 2018) which can be downloaded from the ISIMIP ESGF server (https://esg.pik-potsdam.de/search/isimip/?project=ISIMIP2b&dataset_type=Climate+atmosphere+observed). Based on this, only the south and mid-centre of the continent show a reliable forecast of those drought conditions. The tercile plot (Figure 7b) shows, for a location or a (climatologically homogeneous) region, the probability predicted for each tercile in the historical period and the target season, in this case spring 2016. The white dots show the observed tercile, reflecting the capability (or not) of the seasonal forecast system to reproduce the observations. This skill is shown together with the forecast in order to reflect its uncertainty according to historical predictions. As could be expected, for this particular season and region (the green box in Figure 7a), all the members predicted normal or dry conditions for the season and the uncertainty of the prediction is very low, leading to a high confidence in these results. Thus, a source of valuable information is established for farmers and authorities to plan adaptation measures based on the given forecast.

3.2.4 | Land services: AFRICRS-S4-P03—Disasters mapping and monitoring (burnt area mapping, high resolution)

This service provides key information to many diverse applications such as forestry, agriculture, and risk management, and makes it possible to assess the extent of crop, forested, and pastoral areas affected by fire. The service consists of an automated satellite-based map data set for burnt areas, with data available on the area of interest being continuously updated using Sentinel-2 L2A images.

As an example, one of the AfriCRS Tunisian test areas was considered. Figure 8 shows an example of an RBR map, based on Sentinel-2, computed for the test area of Jendouba. The map was computed using two Sentinel-2 images acquired on 17 and 22 August 2019. Four fire severity levels are distinguished: (1) unburned; (2) low; (3) moderate; and (4) high. Monitoring burned areas could help in assessing the loss of agricultural areas as well as, in the case of wooded areas, the damage severity and the potential susceptibility to soil erosion.

3.2.5 | Livestock services: AFRICRS-S5-P01—Grazing and rangeland mapping (high resolution)

Livestock services provide satellite-based products to support livestock agricultural management decisions. These services entail multi-scale historical assessment, seasonal and on-the-go pasture and rangeland mapping and condition monitoring.

As an example, South African rangelands were mapped using Sentinel-2 MSI data at 20 m resolution and an RF classifier. This case study was chosen based on the availability of recent high-resolution land cover data for comparison with mapped rangelands and the extensive mosaic of commercial, small-holder and subsistence livestock farming activities. The training data were generated from ESA CCI-LC, the Africa Prototype Land Cover Map (released 2017). A visual comparison of the preliminary rangeland map for South Africa (Figure 9d) with a reclassified National Land Cover map (NLC 2017/2018) and the JRC-Global Rangeland Mask (Figure 9e) indicates huge differences between the maps. The observed differences may be due to several factors, related to dates of acquisitions of input data, differences in spatial resolutions and temporal compositing methods used. For example, the rangeland map in Figure 9a is based on Sentinel-2 data acquired in 2019 March and April at 20 m spatial resolution, while the map in Figure 9b is based on *Landsat-8* data collected between 2017 and 2018, and Figure 9c, the JRC Rangeland Mask, is based on MODIS data and provided at a spatial resolution of 1-km (<https://data.jrc.ec.europa.eu/dataset/jrc-10112-10005>). Further information can be found in Pérez-Hoyos (2018). Another contributing factor of the difference is the accuracy of ESA CCI-LC (65%; Lesiv et al., 2017), while that of the NLC is about 96%. Therefore, future work will involve the improvement of the rangeland map.

3.2.6 | Water services: AFRICRS-S6-P03—Soil moisture monitoring (coarse resolution)

The Soil Moisture Monitoring service provides decadal information about moisture conditions in different soil depth for Africa's continental tile. This information is provided through the Copernicus Global Land Service 10-day Soil Water Index (SWI), with a mean value computed over a period of 10 days. Copernicus SWI product is derived from the Surface Soil Moisture (SSM) data at 25 km spatial resolution distributed by EUMETSAT and produced using near real time data from the ASCAT (Advanced scatterometer) instrument on board the MetOp-A satellite. The SWI quantifies the moisture condition at various time intervals from which the depths in the soil can be retrieved, according to the equation $T = L/C$, where T is a factor determining how fast the soil moisture content decays with time, L is the depth of the reservoir layer referring to the soil profile extending downward from the bottom of the soil surface layer which is accessible to C-band scatterometers, and C is a pseudo-diffusivity

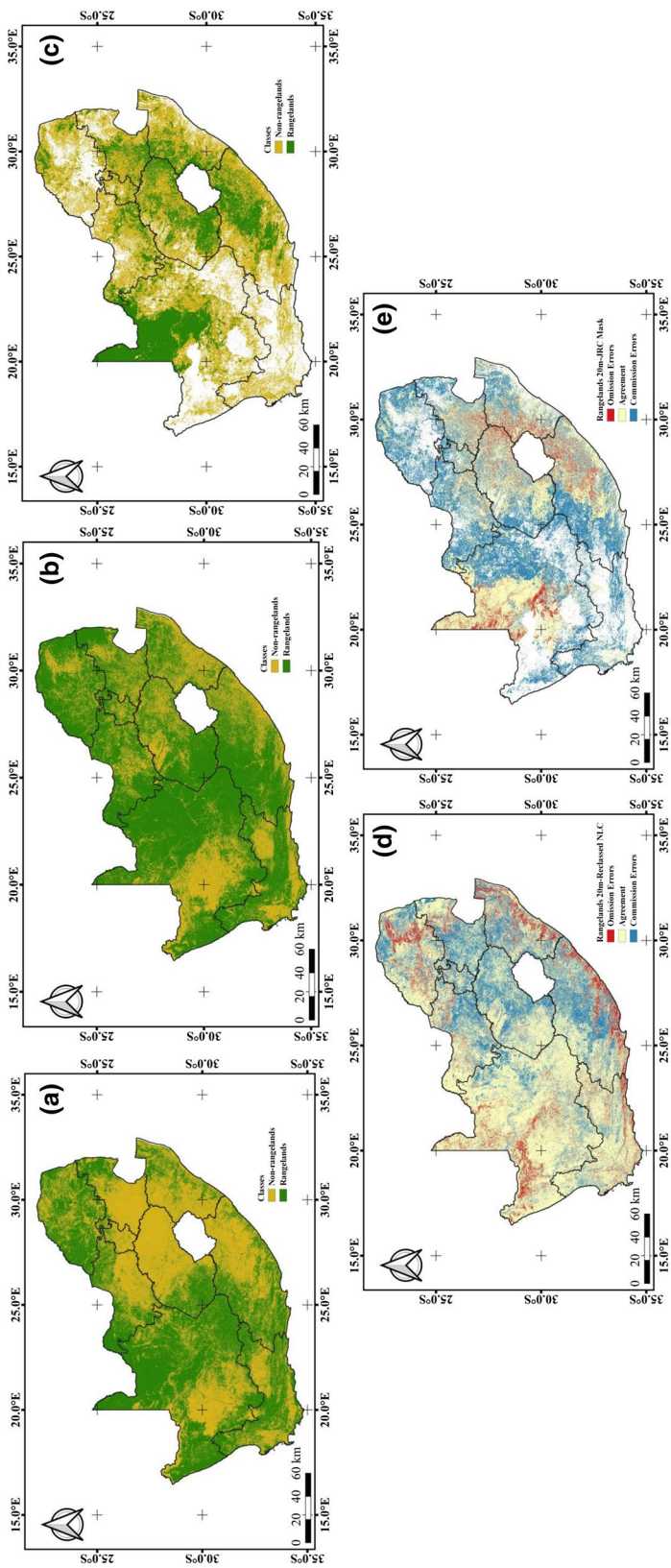


FIGURE 9 Sentinel-2 satellite images (a), National Land Cover (NLC) (b), and JRC Global Rangeland Mask (c). Differences, expressed as omission and commission errors, between: Sentinel-2 rangeland map and the NLC-derived map (d), and Sentinel-2 rangeland map and JRC Global Rangeland mask (e)

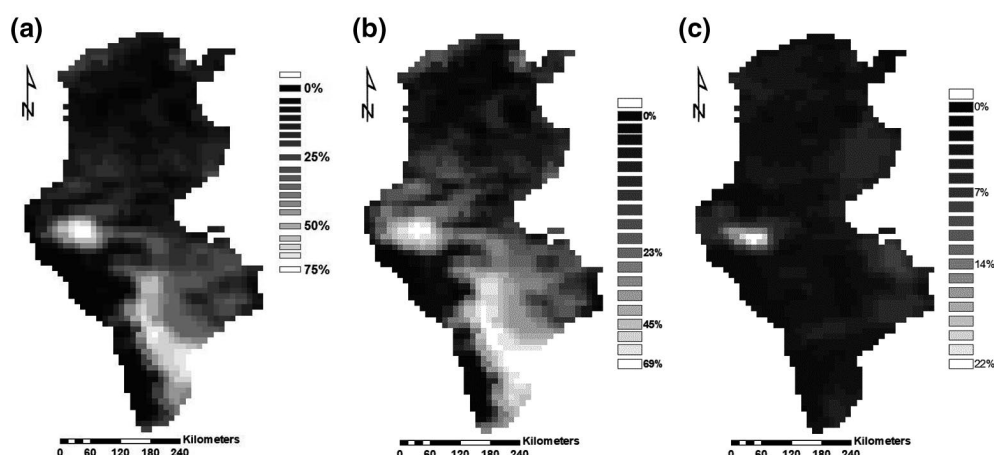


FIGURE 10 Example of soil moisture maps for Tunisia: (a) SWI10 map of 1 July 2019; (b) the historical 10-year mean SWI10 value; and (c) the historical 10-year standard deviation of SWI10

constant. The soil moisture is defined as the amount of water (m^3/m^3) contained in soil layers identified according to their depth measured from the surface. Soil moisture is intimately involved in the feedback between climate and vegetation, since local climate and vegetation both influence soil moisture through evapotranspiration, while soil moisture and climate determine the type of vegetation in a region. Changes in soil moisture therefore have a serious impact on agricultural productivity, forestry, and ecosystem health. Thus, the SWI is used in soil–vegetation–atmosphere transfer schemes to improve the accuracy of general circulation models, or to improve the understanding of the feedback between climate and vegetation. Soil moisture is directly derived from the SWI (SWI10) by comparing actual observations with long-term statistics, based on the 10-year period 2009–2018. This product is displayed in a regular latitude/longitude grid (plate carrée) with the ellipsoid WGS 1984 (terrestrial radius 6,378 km). The resolution of the grid is 0.1° and is provided as multi-band GeoTIFF. The SWI10 product for the country of Tunisia was considered as a case study (see Figure 10).

3.2.7 | Weather services: AFRICRS-S7-P02—Weather extremes early warning (coarse resolution)

Early warning systems regarding weather extremes are widely used around the globe, providing valuable information about potential extreme weather conditions and risk information in order to protect lives, livelihoods and assets. Some examples of such early warning systems are the French “Vigilance” system (Golnaraghi, 2012), the European Multi-Purpose Meteorological Awareness Programme (EMMA/METEOALARM; <https://www.eumetnet.eu/activities/forecasting-programme/current-activities-fc/emma/>), the Incident Meteorologist Program in the United States and the Early Warning System deployed by the Hong Kong Observatory. The Weather Extremes Early Warning service aims to inform end-users about temperature and precipitation extremes every day for the upcoming 7 days by utilizing the NCEP Global Ensemble Forecasting System (GEFS: Hou, Toth, & Zhu, 2006; Toth & Kalnay, 1993, 1997; Wei, Toth, Wobus, & Zhu, 2008; Wei et al., 2006). This information is crucial for proper adjustments of agricultural practices related to food security, as weather extremes (e.g., flooding events) have a direct effect on crop yield.

The service addresses the probability of extreme temperatures in 3 hr time and at daily intervals and of precipitation extremes on a daily basis. Extremes (0.01, 0.05, 0.1, 0.9, 0.95, 0.99 quantiles) are defined by the ERA5 reanalyses data set (Copernicus Climate Change Service, 2017) for each month, or any other additional data set

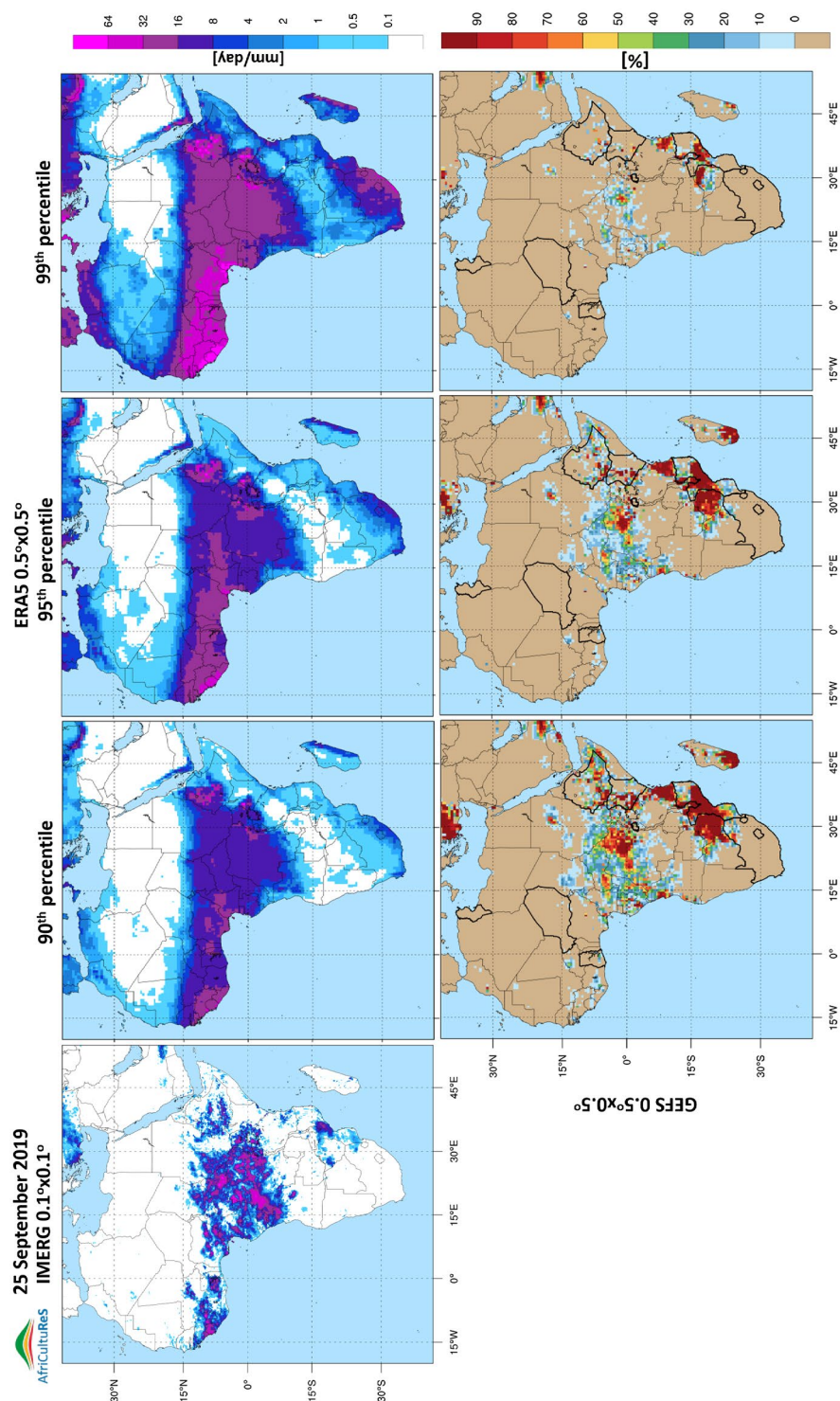


FIGURE 11 Daily estimated precipitation (millimetres, shaded contours) from the IMERG product (top left), quantiles (0.90, 0.95, 0.99) of daily precipitation (mm/day, shaded contours) for September according to ERA5 data set (top row) and probability of extreme precipitation occurrence (%), shaded contours, based on the NCEP/GEFS product (ensemble initialization at 1200 UTC, 24 September 2019), on 25 September 2019. The AfricaCultReS pilot countries are illustrated with bolder borderlines (bottom row)

fit for purpose. The service products come at $0.5^\circ \times 0.5^\circ$ horizontal resolution at continental (Africa, 20°W – 55°E , 40°N – 40°S) scale, in graphics (.png) and NetCDF format.

As an example, the extreme precipitation products (0.9, 0.95, 0.99 quantiles) on 25 September 2019 (forecast day 1) of the 24 September 2019 (1200 UTC) GEFS prognostic cycle are illustrated in Figure 11 (bottom row), along with the 24 hr estimated accumulated precipitation from the Integrated Multi-Satellite Retrievals for GPM (IMERG; Huffman, Stocker, Bolvin, Nelkin, & Jackson, 2019) product (top left) and the corresponding quantiles (0.95, 0.99, 0.999) from the climatology (top row). Shaded contours (Figure 11, bottom row) depict the percentage probability of precipitation occurrence above the specific threshold (Figure 11, top row), as defined by the climatology (ERA5).

According to the GEFS (Figure 11, bottom row), extreme precipitation is likely to occur in the central parts of Mozambique (over 90% probability, in all quantile plots), where the most fertile areas are located, in some regions of southern Ethiopia and over the mountainous areas of western Kenya, on 25 September 2019. The comparison with the IMERG product (Figure 11, top left) indicates that for central Mozambique the daily precipitation was actually above the 0.99 quantile values on that day, suggesting good performance of the early warning service.

4 | DISCUSSION

4.1 | Issues of scale, accuracy, and operationality

The service design of the AfriCultuReS project was performed to produce an integrated approach, merging individual services that respond to the problem of food security in Africa from different sectors. A notable advantage of the project as compared to its predecessors is the direct involvement of potential users in a co-design approach, promoted through the numerous workshops and surveys conducted in Africa. Another advantage is the direct communication with users and the establishment of the way the services will reach them.

For each AfriCultuReS service the relevant scale(s) for implementation was defined. While climate, weather, and drought services run using coarse-resolution global numerical weather prediction models, other services such as crop and land services are more meaningful at high resolution, where a higher level of detail about the crop types and farmlands is used. Other services, such as vegetation condition, are developed at all scales (from high to low resolution) in order to feed other services and provide information for multi-level decision-making.

Each scale has its pros and cons. Low-resolution products provide little detail but cover a wide area. High-resolution products, on the other hand, provide a high level of detail but for a limited area. The heavier processing burden and storage requirements when using high-resolution data need to be taken into account.

Regarding the temporal scale at which services will be provided, the appropriate time-scale is selected for each service and each user's requirements. Time-scales for weather forecasting and climate change monitoring vary from a few days up to the end of the century. A crop growth monitoring service has decadal (10-day composite) time-steps, while a land cover product is considered stable throughout the year. In addition, each pilot country has its specificities (e.g. different crop calendars and growth seasons) which result in specific requirements in temporal analysis. Monitoring services require frequently available data; this condition was fulfilled by the use of Copernicus 10-day products and Sentinel-1 and Sentinel-2 images with 5- to 6-day revisit times.

Regarding the forecasting products, the early warning system based on the climate seasonal forecast provides information one month in advance for the next season, in order to identify the occurrence and intensity of drought events and thus to plan the planting dates and growing season of crops. In addition, climate change services provide the information required for the authorities to define and establish mitigation and adaptation measures (e.g. identifying new optimal crops) for climate change.

A rather common constraint of satellite EO data is the cloud cover, where the surface reflectance of optical wavelengths or emissivity of thermal wavelengths is disrupted by the clouds, and there is large distortion at the

clouds' shadow. Depending on the nature of the service, the workaround was to use lower-resolution (but more frequent) satellite images, leading to a higher chance of acquiring data when there is no cloud cover, to use composite products (e.g., MODIS 8-day composite LAI product) which incorporate cloud filling techniques in order to overcome the issue of gaps from cloud cover, and to use microwave images (e.g., synthetic-aperture radar) that are not affected by cloud.

For all service products accuracy information is reported. For some service products that are federated and need additional processing (e.g., Copernicus products), the accuracy given by the service provider is directly reported. For those requiring some pre-processing, which may not provide equally accurate results when applied in the various agro-ecological zones in Africa, or for newly implemented methodologies, some extra validation work is being performed as part of the project's validation phase. Therefore, the data are tested at different levels according to available reference data and the level of processing. The reference data sets include non-EO data collected for AfriCultuReS purposes through new campaigns at test sites, historical non-EO data available to project partners and identified through questionnaires for data availability, EO products of higher spatial resolution, as well as data from other reliable sources.

4.2 | Case studies assessment and relation to food security

A case study was presented in this article for each category of services (Section 3.2), thus providing seven specific examples of food-security-related service outputs in specific areas of the African continent.

The climate services provided the seasonal forecast of precipitation and temperature at continental and national scales for autumn 2019, reflecting both the forecast and its uncertainty as defined by the corresponding hindcast. In general, warmer than normal conditions were predicted for this season. The climate services also provide information about mid-term climate variability and long-term climate change scenarios, enhancing the user's knowledge and understanding about the impacts of climate on their field, allowing enhanced decision-making. One of the most significant impacts of climate variability and climate change is the potential increase in food insecurity and malnutrition. All the components of food security are affected by climate-related issues: crop quantity and quality, as well as yield, are affected by the change and variability of climate patterns such as rainfall or temperature, threatening food availability; the deterioration of the agro-climatic conditions could lead to the increase of the price of major crops, affecting access to food for low-income populations; climate risks are tightly woven with calorie intake, and recurrent extreme events lead to the modification of the traditional diet which affects health conditions in societies with low coping and adaptation capacity; and food stability is also threatened by the occurrence of uneven phenomena affecting food production.

The crop condition service provided some statistics on crop condition over a specific area, showing some deviation of the current vegetation condition from the historical minimum and maximum values, thus highlighting the areas where vegetation growth status is poor. The high-resolution version of this product, based on Sentinel-2 images, enables the monitoring of crop status, taking into account the typical crop field sizes (1–2 ha) in African countries. Other vegetation condition products, like the 1 km spatial resolution Copernicus VCI and the 250 m spatial resolution MODIS NDVI anomaly, are suitable for monitoring the general status of vegetation without differentiating between crop or other land cover types (Zambrano, Lillo-Saavedra, Verbist, & Lagos, 2016).

In the case of the seasonal forecast and early warnings of drought conditions, the drought event that occurred in spring 2016 was considered as an example reflecting, one month in advance, the high probability and confidence for drought conditions during this season. This kind of forecast may allow farmers and authorities to establish adaptation measures according to the climate conditions predicted. Drought information may lead to adjustments in crop selection, cropping patterns and water use efficiency measures (de la Poterie et al., 2018).

A burnt area was successfully identified using a pre- and various post-fire events through Sentinel-2 images and by applying the RBR index in the Jendouba area in June 2019. This can lead to the estimation of biomass

loss and to support through monitoring recovery and rehabilitation operations. Similar to previous services, the burned areas estimate at high resolution allows the extent of crop and grassland areas affected by fire to be assessed (Archibald, Scholes, Roy, Roberts, & Boschetti, 2010). According to the period of the fire event (phenologic or post-harvesting), the impact on food production can be estimated.

An example of a rangeland map of South Africa was presented for the livestock service using Sentinel-2 MSI data and an RF classifier. As shown by the results in Figure 9, classification errors were large, attributed to temporal and spatial differences between products compared as well as data compositing methods. However, the large omission errors may be due to real changes (i.e. decline in rangeland extent), while commission errors may be due to errors in the prototype CCI-LC product used for training the RF classifier (Lesiv et al., 2017). In the future, crowdsourcing should be considered to gather more reliable training data to improve rangeland mapping. Nevertheless, the results from the Sentinel-2 MSI and RF are promising for monitoring of rangeland extent in Africa. The product is crucial for assessing, through time, the magnitude of changes and potential threats to rangelands. The produced grazing and rangeland maps should aid sustainable spatial planning, effective implementation of land management approaches, and informed decision- and policy-making in Africa, to avert the risks of food insecurity and to achieve global and continental mandates such as the United Nations Sustainable Development Goals and the African Agenda 2063 (Kganyago & Mhangara, 2019). The service will provide information not only on the extent of rangelands but also on its condition, on which forage production is also dependent.

The SWI10 product is used to monitor soil moisture at coarse resolution over Africa. Through the Copernicus SWI10 product the resolution at which soil moisture can be determined directly with Earth observation is considerably improved, providing critical information to farmers' organizations and agencies responsible for water management and irrigation.

The Weather Extremes Early Warning precipitation maps provide insight on the probability of extreme precipitation occurrence over Africa ($0.5^\circ \times 0.5^\circ$ horizontal resolution), based on an ensemble of model runs and according to climatology thresholds. Deterministic precipitation forecasts (in millimetres, at 3-hr intervals), are also available at finer scale ($0.25^\circ \times 0.25^\circ$ longitude/latitude). The precipitation product is a critical input to various AfriCultuReS services, including drought early warning and crop yield prediction.

As shown above, many products and services are interconnected. The early warning for drought uses input from the weather service and crop condition products. For the livestock service, information on land cover, pasture conditions and water availability are required.

5 | CONCLUSIONS

In the present article the concept behind the description of services of the AfriCultuReS project was presented with results regarding users' requirements collected through review of secondary sources and engagement with potential users. Based on these requirements, a list of services related to the climate, drought, land, livestock, crops, water, and weather was established and relevant EO products were selected for their implementation. Several case studies were presented from the application of the selected methodology in the project's pilot sites, pilot countries, or over the whole African continent according to the appropriate spatial scale. Future articles will report on the integration of these services into the project's platform, their validation by users and their demonstration over a different area in Africa.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

AUTHOR CONTRIBUTIONS

T. K. Alexandridis contributed to the conception, design and revision of the manuscript, G. Ovakoglou contributed to the design, drafting, revision, submission of the manuscript and acquisition, analysis and interpretation of data, I. Cherif contributed to the design, drafting, revision of the manuscript and acquisition, analysis and interpretation of data, M. Gómez Giménez contributed to the drafting and revision of the manuscript, G. Laneve contributed to drafting the manuscript and acquisition, analysis and interpretation of data, D. Kasampalis contributed to acquisition, analysis and interpretation of data, D. Moshou contributed to acquisition, analysis and interpretation of data, S. Kartsios contributed to the drafting of the manuscript and acquisition, analysis and interpretation of data, M. C. Karypidou contributed to the drafting of the manuscript and acquisition, analysis and interpretation of data, E. Katragkou contributed to the drafting and revision of the manuscript, S. Herrera García contributed to the drafting of the manuscript and acquisition, analysis and interpretation of data, M. Kganyago contributed to the drafting of the manuscript and acquisition, analysis and interpretation of data, N. Mashiya contributed to the drafting of the manuscript and acquisition, analysis and interpretation of data, K. Pattnayak contributed to the acquisition, analysis and interpretation of data, A. Challinor contributed to the drafting and revision of the manuscript, R. Pritchard contributed to the revision of the manuscript, D. Brockington contributed to the revision of the manuscript, C. Kagoyire contributed to the drafting of the manuscript and J. Suarez Beltran contributed to the conception and design of the manuscript.

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