INTEGRATED USE OF MULTISOURCE REMOTE SENSING DATA FOR NATIONAL SCALE AGRICULTURAL DROUGHT MONITORING IN KENYA
ADM- KENYA

State-of-the-art review report on the relevant EO-based methods and solutions

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1. Executive Summary: Overview of the document

This document presents a comprehensive synthesis of both scientific research and practical applications in the field of agricultural drought monitoring. By analyzing the most recent literature and evaluating cutting-edge methods, the document aims to provide a thorough understanding of the current state of drought monitoring methods and its practical implications. The document includes also the review of the methods for cropping systems mapping, which can give a contextual information regarding drought vulnerability and impact. Additionally, the document examines several programs and projects (global and regional) that have been implemented to manage and mitigate the impacts of agricultural drought in Kenya. By integrating theoretical knowledge with practical experience, this report offers valuable insights for the development and improvement of future drought monitoring strategies, ultimately contributing to more effective and sustainable agriculture practices.

2. Review of methods for agricultural drought monitoring

2.1. Advancement of Drought monitoring: Systematic Literature Analysis

Satellite data have been used for drought detection and monitoring since the 1980s (Kogan, 1997). The advantages of remote sensing-based drought indices are the large spatial coverage and the almost continuous data availability. In contrast, difficulties and challenges arise with small areas, data gaps, consistent historical datasets, integration of recent satellite missions, and the development of a standard for a validation scheme (Hazaymeh & Hassan, 2016). The usability of data depends on its availability, cost, quality, pre-processing, and post-processing requirements (Hazaymeh & Hassan, 2016). Nevertheless, remote sensing is the most effective way to detect and analyze the impacts of droughts on ecosystems (Zhang et al., 2013).

Droughts are usually triggered by a precipitation deficit in combination with increased solar radiation and a temperature rise (Zhang et al., 2013). Using remote sensing to map this phenomenon is based on the fact that droughts affect the biophysical and chemical properties of soils and plants, such as soil moisture, organic matter content, vegetation biomass, chlorophyll content, canopy cover, and soil temperature (Anjum et al., 2011). Droughts can alter the spectral or thermal responses of ecosystems, from which indicators of their occurrence can be derived (Hazaymeh & Hassan, 2016). Remotely sensed drought indices depend primarily on the characteristics of energy reflected or emitted from the Earth's surface (Hazaymeh & Hassan, 2016). They are based on individual spectral signatures of the ground surface and tree canopy characteristics (Hazaymeh & Hassan, 2016). These signatures vary with changes in vegetation. For example, photosynthetic barriers are the result of declines in evapotranspiration and stomatal closure, leading to a reduction in absorbed photosynthetically active radiation (APAR). This is a defensive response of plants, leading to slower growth under stress - triggered, for example, by water deficits. Droughts also reduce enzyme activity in plants, which can cause damage to biomolecules and chlorophyll (H. G. Jones & Corlett, 1992; Reddy et al., 2004). This causes the leaves to dry out, fall off, and the plant dies (Zhang et al., 2013). Plant death and growth are mainly controlled by the three environmental factors of temperature, water, and sunlight, all of which are interrelated (Zhang et al., 2013). The temperature increase can be measured in the thermal wavelength range of the measurement instruments on the satellites (Zhang et al., 2013). In the optical wavelength region, the green of the plants can be inferred (Chang et al., 2017), and in the infrared region, the water content of the leaves can be inferred (Zhang et al., 2013).

Effective monitoring and assessment of droughts are crucial for guiding drought response and mitigation strategies. The primary goal of drought research is to reduce the negative impacts of drought through improvements in water management, drought management, and agricultural practices (Di Wu et al., 2015). For proper drought strategies, temporal information on the onset, severity, and duration is very important (Di Wu et al., 2015). Moreover, a comprehensive understanding of the causes and consequences of historical and current droughts is essential for food production and crop planning/management (Hazaymeh & Hassan, 2016).

Initially, on-site observations were essential for drought modeling, with the Palmer Drought Severity Index (PDSI) being widely used, but limited in efficiency and coverage. The greater use of satellite remote sensing now provides more spatially explicit information about soil moisture, vegetation, and precipitation. Vegetation-related drought indices, such as the Vegetation Condition Index (VCI) derived from the Normalized Difference Vegetation Index (NDVI), are well-suited for monitoring agricultural droughts. Going into more detail, Rojas et al. (2011) use the Vegetation Health Index (VHI) to calculate drought probabilities of agricultural land during the growing season in Africa. Ghazaryan et al. (2020) tested the suitability of different MODIS based indices to detect drought impacts on crop production. They found the best results for the evaporative stress index (ESI), while the ESI and LST revealed more intense drought conditions than the NDVI. However, monitoring based on a single factor, such as vegetation growth, does not provide a complete picture of drought conditions. To address this, new indices that combine various factors with traditional meteorological datasets are needed to monitor different types of droughts. For example, Rhee et al. (2010) proposed the Scaled Drought Condition Index (SDCI), which combines NDVI, LST, and TRMM data, and is suitable for use in humid regions. Du et al. (2013) then developed the Synthesized Drought Index (SDI) through principal component analysis, incorporating data from MODIS and TRMM to reflect the impact of precipitation deficits, soil thermal stress, and vegetation growth on drought. Despite these advances, many commonly used indices are better suited for long-term events than short-term droughts. To address this, Zhang & Jia (2013) developed a new drought index, MIDI, based on PCI, SMCO, and TCI and satellite multi-sensor microwave data, which effectively monitors short-term droughts in cropland and grassland in northern China. Brown et al. (2008) also developed the Vegetation Drought Response Index (VegDRI) that considers vegetation condition anomalies, precipitation anomalies, and biophysical parameters, such as land cover and soils, using data mining techniques.

Studies aimed at better drought management exist, for example, by Bachmair et al. (2017), who modeled probabilities of drought impacts from drought reports. More consistent methods are presented by Diermanse et al. (2018) and Towler and Lazarus (2016), who conduct general drought risk analyses at regional and local scales based on meteorological and hydrological data. Even more specific are Wu and Wilhite (2004), who model drought risks for individual crops. Regional droughts were observed for example by Shen et al. (2019) who used multi-source remote sensing data with MODIS NDVI and EVI (Enhanced Vegetation Index) as well as TRMM (Tropical Rainfall Measuring Mission) data. Their deep learning model for drought showed good applicability in monitoring regional droughts. Monteleone et al. (2020) on the other hand successfully developed a new composite index for agricultural drought (PPVI (Probabilistic Precipitation Vegetation Index) in Haiti by combining the SPI and the VHI. By only using globally available remote sensing data sets their methods could also be transferred to and applied in other areas. Other studies focused on the relationship between droughts and crop yield loss. Du et al. (2013) found low correlation between the Synthesized Drought Index (SDI) and crop yield, but high correlation with the variation of drought-affected areas. Park et al. (2017) proposed the High-resolution Soil Moisture Drought Index (HSMDI) and used crop yields for validation, which showed a high correlation. Zhang et al. (2022) also developed three new indices for large-scale drought monitoring in China, with the Multiple Remote Sensing Drought Index integrated by the gradient boosting method (GBMDI) having a trend well-aligned with standardized crop yield. Other high-resolution drought monitoring has also been conducted in the recent past as for example Kowalski et al. (2023) modeled local to regional drought conditions based on Sentinel-2 and field survey data from the Land Use/Cover Area frame statistical Survey (LUCAS) for central European grassland gradients. They found good accuracy as their results followed meteorological and solid drought conditions and showed the value of combining high-resolution Sentinel-2 data with field survey information. A combination of Sentinel-1/-2, Landsat 8 and MODIS was used in a logistic regression model for a drought/non-drought classification in local-scale agricultural drought monitoring by Ghazaryan et al. (2020). They found that their approach can be used for crop condition assessments in vulnerable areas and that the NDVI and NDMI depict stress affected areas with a larger spatial extent. Urban et al. (2018) also used a combination of Sentinel-1/-2 and Landsat 8 and found that their combined radar-optical approach can separate and retrieve surface moisture conditions suitable for drought monitoring. Zhou et al. (2020) on the other hand fused MODIS and Sentinel-2 data with the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM) to operate on a higher spatial resolution to be able to separate drought conditions between winter wheat, woodland and bare soil. By comparing their results to cumulative rainfall of the past 20 days the found an improvement of 0.03 in their R^2 when using their high-resolution index. Nevertheless, these high-resolution drought monitoring approaches also come in hand with some limitations as for example shorter time-series, the amount of data or the limitation of scale.

While most comparisons between real drought-affected croplands and their indices have shown good relations, few tests have been conducted on the transferability of indices to other regions. Also, global drought models are available, but mostly on a lower resolution and therefore they often lack precise regional information. Examples are the Global Drought Observatory (Vogt et al., 2018) and Climate Engine data (Huntington et al., 2017). Schwarz et al. (2020) therefore developed a regional transferable drought-modeling framework on a national scale using only globally available data sets to account for country-specific, regional drought characteristics and showed a good fit during the model setup in the USA, but also when transferring the model to other countries like Zimbabwe, South Africa, Chad, the Central African Republic or Germany. This model closed the gap of global drought models with a coarse resolution, which cannot capture regional droughts, and local drought models, which on the one hand are not spatially transferable or on the other hand have not been tested in other areas.

2.2. From Research to Practice: Emerging Methods and Programs implemented in Kenya

Besides these scientific advances, some drought relevant projects and products are already in use by the national incubators. The SERVIR[1] project for example was started in 2016 in a cooperation with NASA and RCMRD to support the management of food security, data collection and crop insurance. Monthly reports reflect a consensus on the most recent crop conditions in the respective counties. The Kenya Crop Monitor (Figure 1) additionally provides NDVI maps for cropland areas to report on the crop condition based on MODIS data. The

[1] https://servirglobal.net/Regions/ESAfrica

National Drought Management Authority (NDMA) provides additional reporting sources by publishing monthly drought update reports on a monthly basis (National Drought Bulletin[2]) along with monthly early warning reports on a county basis (County Early Warning Bulletins). The Airbus group together with several other stakeholders carried out the Kilimo project to showcase the use of earth observation for geo-data collection, crop, monitoring, precision agriculture and early warning though the building of regional GIS lab and demonstrations on the use of GIS and remote sensing. Some of the outputs are agricultural geo-statistics, crop monitoring at the field level, field delineations and an early warning on crop development anomalies. Additionally, the Famine Early Warning Systems Network (FEWS NET)[3] provides a food security assessment through a classification of acute food insecurity phases. This classification is carried out on administrative units and provides information on the status of food security in each respective unit. The East Africa Drought watch is an additional drought monitoring system operating in near-real time. It uses earth observation and weather information to monitor drought conditions. This system was developed as part of the Intra-ACP Climate Services Project in collaboration with the Drought group of the Natural Disaster Risk Unit at the Joint Research Centre of the European commission and is an adaption of the European Drought Observatory (EDO) to the conditions in the East Africa region – including Kenya.

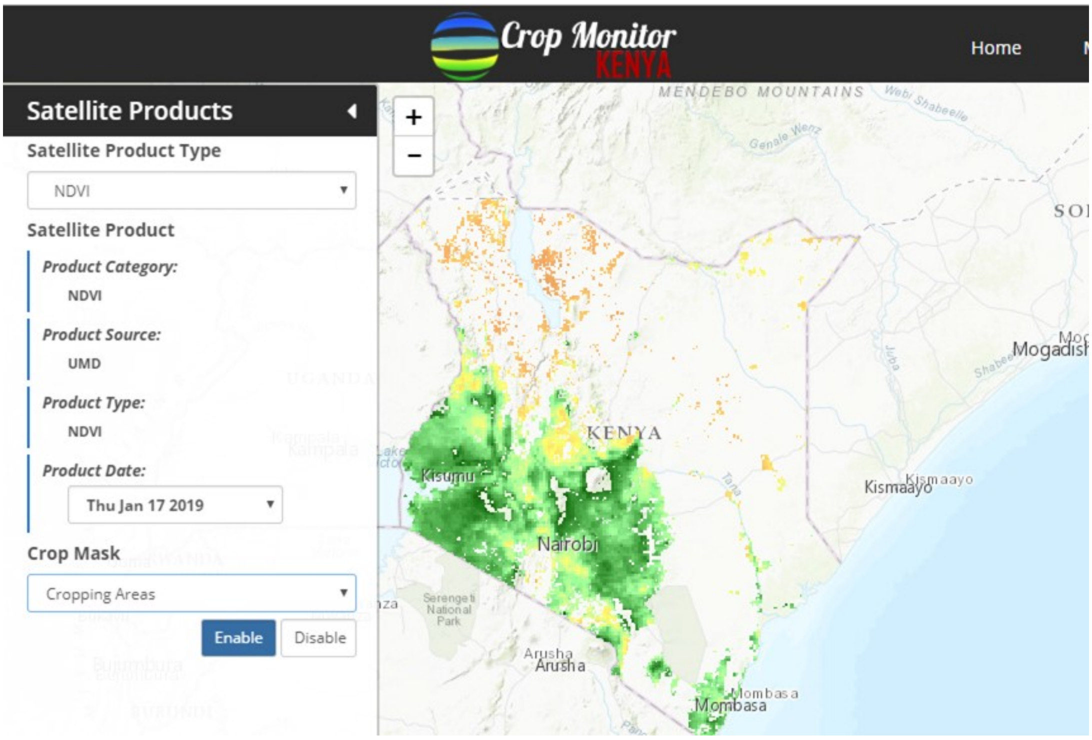

Figure 1: Exemplary screenshot of the Kenya Crop Monitor.

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[2] https://www.ndma.go.ke/index.php/resource-center/early-warning-reports/category/2-early-warning-bulletins
[3] https://fews.net/

3. Review of methods for cropping systems maps

The information on farming systems plays a crucial role in evaluating the impact of drought. According to Landmann et al. (2019), these vital land use categories have not been explicitly mapped (Xiong et al. 2017), despite their significance for various applications, such as evaluating agricultural productivity, food supply, biodiversity, the impacts of extreme events like droughts (Fritz et al. 2015; Meier et al. 2018) and improved water management (Pageot et al. 2020). Irrigation in general also significantly contributes to crop development, food diversity and the sustainability of agro-ecosystems (Jin et al. 2016).

The vegetation index, which has a distinctive seasonal pattern, is a widely used approach for obtaining vegetation information. The time series analysis of NDVI (Normalized Difference Vegetation Index) can be used for irrigation and crop classification by analyzing the vegetation on the ground surface. Jin et al. (2016) used for example the maximum NDVI and time-integrated NDVI to classify rainfed and irrigated cropland with a support vector machine (SVM) algorithm and achieved an overall accuracy of 96% within their test samples. Their algorithm, though, only considered one crop type (wheat) in a semi-arid region of China. However, satellite data is often disrupted by cloud contamination and orbital differences, which can result in irregularly distributed data, increasing uncertainties in cropland monitoring (Egorov et al., 2019). To make the most of the operational satellite systems' information, it is necessary to address image-specific data quality issues, such as clouds, cloud shadow, and instrument artifacts, as well as data gaps (Verbesselt et al. 2012). Data gaps due to cloud cover can limit the use of time series data for vegetation and cropland monitoring, especially during vital phenological periods (McNairn et al. 2009). These data gaps and recurring noise effects render the raw NDVI time series unsuitable as a classification input. Also, most classifiers struggle to cope with large data gaps and underperform when using hundreds of varying parameters (Shao et al. 2016). To mitigate these issues, it is important to smooth NDVI time series to accommodate varying data availability. Temporal-based methods, such as temporal interpolation-replacement methods, are commonly used for reconstruction, but they are data-sensitive and perform poorly with many gaps (Li et al., 2021). Another reconstruction technology, frequency-based, includes Fast Fourier Transform (FFT) and Harmonic Analysis of Time Series. HANTS algorithm, based on Fourier Analysis, is widely used to reconstruct NDVI time series (Q. Zhou et al., 2022). The HANTS filtering can effectively remove periodic fluctuation noise and recover anomalous values (Ghafarian Malamiri et al., 2020; Jakubauskas et al., 2001). Using harmonics can preserve the core information of a phenology trend without the need to process every observation in a time-series data set (de Jong et al. 2011). Harmonics can be defined as the addition of sine and cosine functions at regular intervals to model an existing curve (Landmann et al. 2019). If the current curve is an NDVI time series, the resulting harmonic can be employed to anticipate stable seasonal vegetation trends for a specific timeframe (Brooks et al. 2012). However, separating the foundational signals from noise is a challenge. Bradley et al. (2007) used a curve-fitting method based on harmonic analysis to extract inter-annual phenological patterns from noisy satellite NDVI data, with high frequencies fitting extraneous noise rather than meaningful signals (Wilson et al., 2018). The performance and availability of HANTS can be reduced by various parameters (Wen et al., 2004). By using monthly composites, harmonics have shown to produce 10-20 percent more accurate results than methods based on individual image data stacks over the same observation period (Wilson et al. 2018). Therefore, Pageot et al. (2020) used monthly cumulative indices based on Sentinel-1, Sentinel-2 and weather data to map irrigated and rainfed cropland with a random forest classifier. They found an improved irrigated cropland classification (~70% overall accuracy) compared to classifications that use these datasets only separately (~50%). To understand specific harmonics optimizations and their effect on classifications, Landmann et al. (2019) investigated the impact of linear trend, time series length, and harmonics on a random forest algorithm, a nonparametric machine learning technique. They effectively mapped rain-fed and irrigated croplands in Zimbabwe and achieved an overall accuracy of 97%. RSS further improved the resolution of their method by using Sentinel-2 instead of Landsat data.

There are also global assessments of cropping systems as for example Salmon et al. (2015) combined MODIS data with climate and agricultural survey data to map rainfed, irrigated and paddy croplands. To analyze farming systems on a local scale and also include smallholder farmers, these global assessments are not accurate enough and have a comparable low resolution.

Other research was conducted on quantifying the water used for irrigation. Therefore, Dari et al. (2022) used three different data sources on evapotranspiration and quantified the amounts of water used for irrigation using the soil-moisture-based inversion algorithm. Another study was conducted by Brombacher et al. (2022) who used high-resolution Sentinel-2 data to quantify irrigation based on the comparison of evapotranspiration of irrigated and natural areas and found their results suitable for the comparison with seasonal water allocations and as support to monitor overconsumption in water-scarce regions.

The FAO WaPOR program also focuses on the mapping cropping systems. At a country scale the available datasets have 100m resolution, and at regional scale (which comprises the Busia County in Kenya in the current version) at 30m (FAO. 2020). The dataset is based on the integration of several EO datasets, such as MODIS, Landsat and Sentinel 2 (at national scale, resampled to 100m). Additionally, the FAO together with the World Bank created a new methodological framework to identify irrigated fields (FAO, World Bank 2022). Here, crop maps together with estimations of ET and yields per pixel from WaPOR were used initially, where post-rainy season irrigation ET estimates were added. Combining these to information yields accurate identification of irrigated fields by calculating the soil moisture in the root zone.

Cropland maps have already been used in the past in general, but according to RCMRD the current used map is from the year 2015 and therefore most likely lacks accuracy. The Copernicus4GEOGLAM (Figure 2) project managed by the EC-JRC was launched in September 2020 to strengthen the EU support to GEOGLAM especially in developing countries and focuses on the mapping cropland. Seasonal crop masks were produced for the whole country. Nevertheless, up-to-date information on irrigated and rainfed cropland are still lacking in Kenya.

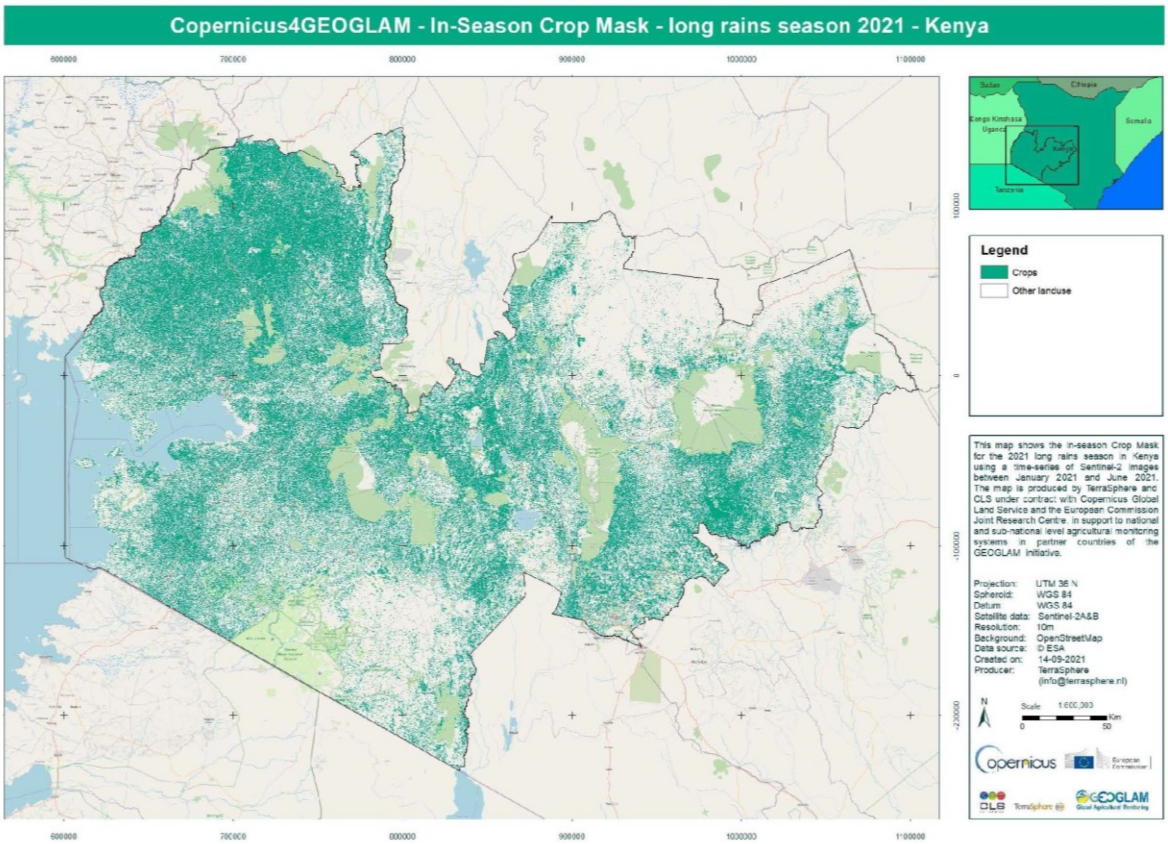

Figure 2: Exemplary presentation of the Copernicus4GEOGLAM cropland mask from 2021.

4. Conclusion & Project impact

The ADM-Kenya project will make use of current state-of-the-art research methodologies and will enhance the currently used products. Hereby the drought modeling framework will be based on Schwarz et al. (2020), but will be enhanced by using Sentinel-3 instead of MODIS data to guarantee a longer lifetime in the future. Following, the more reliable, accurate and detailed assessment of drought hazard, vulnerability and risk will allow for more effective planning of mitigation and response measures. The deliverables will inform on drought, hazard, vulnerability and risk at multiple scales, while the information will include the extent and severity of drought on various cropping systems across the country. Besides the new Sentinel-3 based drought hazard model, also Sentinel-2 will be used throughout the analysis. Compared to currently used solutions based on coarse and moderate resolution data, which are often aggregated to administrative levels, more detailed information can further support current activities such as crop condition mapping. In addition, drought models often lack validation measures. Within the scope of this project the drought hazard and risk modeling framework will be validated by in-situ data along with user-based validation – additional to the widely used verification measures through intercomparisons with similar datasets or drought reports – and therefore also improve the quality of the model.

The cropping systems maps generated by the project will provide detailed and up-to-date information on rainfed and irrigated cropland, but also on mono- and mixed-cropping throughout the country. Unlike the currently widely used map from 2015, these new products will offer a more current status of the agricultural landscape, ensuring that policymakers and stakeholders have access to the latest data when making decisions. By using Sentinel-2 data, the spatial resolution of the derived products will also enhance the currently available maps and therefore deliver detailed information on a finer scale. By providing products on the mapping of irrigated and rainfed and mono and mixed cropping systems, a more nuanced understanding of the distribution and condition of different cropping system can be achieved in the future. Besides enhancing the drought vulnerability product, this information can further inform several activities of different stakeholders, such as yield prediction, the enhancement of climate-suitability technologies or climate-resilience strategies.

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