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**Deep Learning models for short-term
Drought Prediction in the Horn of Africa**

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Abstract

This thesis advances the monitoring and forecasting of vegetation dynamics and drought impacts in the Horn of Africa by leveraging high-temporal-resolution satellite data and Machine Learning models. The first study introduces a novel approach to derive daily Normalized Difference Vegetation Index (NDVI) time series from the SEVIRI geostationary sensor, mitigating cloud contamination on vegetation pixels. The resulting dataset exhibits similar performance to other existing vegetation products (e.g., MODIS) in capturing regional climatology and detecting vegetation anomalies with the added benefit of the increased temporal resolution. Building on this foundation, the second study compares the derived high-frequency NDVI dataset with global and regional precipitation products in detecting meteorological and agricultural droughts across Ethiopia, Somalia, Kenya, and Djibouti. The analysis highlights the value of daily temporal resolution in capturing short-term fluctuations and improving drought characterization across different land cover and soil types. Moreover, the study emphasizes a trade-off between accuracy and precise detection of meteorological drought events for precipitation indices at different accumulations. The final study integrates the vegetation dataset with meteorological data from the reanalysis model ERA5 and soil moisture from ASCAT radiometer to develop a series of Deep Learning models for short-term drought forecasting. A diffusion-based probabilistic model, conditioned on prior vegetation and meteorological history, demonstrates superior performance over traditional recurrent architectures, particularly under extreme drought scenarios. Collectively, these studies provide an end-to-end pipeline—from data reconstruction to predictive modeling—that enhances early warning capabilities in climate-vulnerable regions.

1. Introduction

The Horn of Africa stands as one of the most vulnerable regions to the devastating effects of drought, a natural hazard that has long plagued the area but has become more frequent and severe in recent years. Research indicates a significant increase in both the intensity and frequency of droughts across the region, with occurrences now happening roughly every three years, compared to every six years before 2005 (IPCC 2023). The 2023 IPCC report further underscores

this concerning trend, projecting an increase in the intensity of extreme weather events such as heatwaves and droughts, particularly in regions like East Africa, which are already highly vulnerable. Over the past decade, mortality rates due to droughts, floods, and storms in these high-risk areas have surged, being 15 times higher than in lower-risk regions. The socio-economic repercussions are staggering: from widespread crop failure to the loss of livestock and exacerbated food insecurity, droughts deepen the challenges faced by already vulnerable communities. This calls for urgent improvements in the accuracy and responsiveness of early warning systems to reduce the human and economic toll of such disasters.

Traditional drought monitoring and forecasting tools, which predominantly rely on monthly or seasonal data, often fail to capture the rapid onset of extreme events, such as flash droughts or the abrupt intensification of heat waves (Park et al. 2020). New developments in satellite technology, particularly from geostationary sensors, have shown significant promise in enhancing the temporal resolution of data available for early warning systems. These high-frequency observations can provide near-instantaneous updates on changes in vegetation and climate variables, allowing for more timely and precise responses to impending drought conditions.

However, assessing vegetation health alone does not provide a full picture of drought conditions. Precipitation, a key determinant of vegetation growth, plays an equally crucial role in drought dynamics, especially in regions like East Africa, where agriculture and pastoralism are central to the economy and livelihoods. One of the major challenges in the region is the scarcity of accurate rainfall data. The limited network of weather stations, combined with the spatial variability of rainfall and the decreasing number of such stations, hampers reliable monitoring of precipitation. Furthermore, the sporadic nature of convective rainfall events complicates the collection of in-situ data, making it even harder to predict droughts with high precision.

This research seeks to explore the potential of high-temporal-resolution satellite data to study drought dynamics and to improve drought detection and monitoring across the Horn of Africa, with a focus on Ethiopia, Somalia, Kenya, and Djibouti. By examining alternative sources of precipitation data and comparing them with a newly derived high temporal resolution vegetation dataset, the study aims to refine our understanding of drought dynamics in this region. By doing so, it contributes to more effective early warning systems that are better equipped to track the rapid development of droughts and provide timely information to decision-makers.

1.1. Meteorological and agricultural drought

Drought phenomena have different components and are generally classified into four types (meteorological, agricultural, hydrological, and economic) (Van Loon 2015). Several indices have been developed in the literature to decompose different aspects of droughts. The baseline index to analyze deficits or excesses in precipitation that are related to meteorological drought is the Standard Precipitation Index (SPI) developed by McKee, Doesken, and Kleist (1993), which is also recommended by the WMO (Svoboda, Hayes, and Wood 2012). The SPI quantifies precipitation deficits or surpluses over various timescales by comparing observed precipitation to a long-term historical record. It transforms precipitation data into a standardized normal distribution, allowing consistent drought classification across regions and periods. Negative SPI values indicate dry conditions, while positive values reflect wet conditions. To evaluate vegetation stress conditions, the Normalized Difference Vegetation Index (NDVI) (Rouse Jr et al. 1974; Tucker 1979) is a standard index that can be obtained from remote sensing optical data. It has been tested to correlate with chlorophyll, leaf area index, or biomass content (Thenkabail et al. 2004). Researchers proposed the Vegetation Condition Index (VCI) (Kogan 1990; Kogan 1995), which expresses the NDVI relative anomaly as a percentage, to detect significant anomalies in the vegetation status and to understand the intensity, spatial, and time extension of agricultural droughts. The relationship between meteorological and agricultural drought has been widely studied (Tucker 1979; Henricksen and Durkin 1986; Tucker and Choudhury 1987; Gutman 1990; Dutta, Kundu, and Patel 2013). It is particularly important to understand its dynamics in arid and semiarid areas where vegetation condition is closely related to soil moisture (L. Ji and Peters 2003). This can be done by directly estimating the relationship between vegetation vigor and precipitation indices (Henricksen and Durkin 1986; Tucker and Choudhury 1987; Tucker 1989; Gutman 1990) or by looking at the non-linear interactions between precipitation lags and vegetation (the so-called “memory effects”) (Kraft et al. 2019). Previous research concluded that the effect of precipitation on plants is phase-lagged and depends on the type of soil (L. Ji and Peters 2003; Van Hoek et al. 2016; Barbosa et al. 2019). However, these studies have mostly used monthly data and often struggled to find significant short-term effects of precipitation. Dutta, Kundu, and Patel (2013) collect a 21-year NDVI series from the AVHRR radiometer for the Indian Eastern Rajasthan region and try to understand the relationship between SPI at different accumulations and NDVI. They found scarce short-term correlation (e.g. 1-month cu-

mulation) between the two indices but show strong correlation for periods longer than one month (3-6 months). Studying a subset of central and northern U.S. regions with a time series of NDVI (1989-2000), L. Ji and Peters (2003) conclude that a 3-month SPI displays the strongest effect on vegetation and can be used as a good predictor for drought severity. Moreover, they point out that this relationship is more significant in the growing season since the vigor of plants in the reproductive stage can be easily compromised by water scarcity. Barbosa et al. (2019) were among the few to exploit geostationary satellite products to explore the relationship between precipitation deficits and vegetation stress at higher temporal resolution in a region in the northeast of Brazil. They built 10-day NDVI composites from daily MSG SEVIRI imagery and correlated it with 10-day interpolated daily local weather station data. The authors concluded that the SEVIRI-derived NDVI normally reacts to rainfall between one and three months and highlighted how it is possible to successfully discern different lagged responses of vegetation to precipitation based on the vegetation type. Moreover, the derived vegetation series allowed them to analyze vegetation behavior before and after a strong drought event and found a robust correlation between NDVI anomalies (SDVI) and short-term precipitation anomalies measured with the SPI-1.

1.2. Geostationary satellite for vegetation monitoring

West, Quinn, and Horswell (2019) argue that to enhance our understanding of drought events and improve the ability to anticipate their effects, there is a need to use remote sensing products with better spatial, temporal, and spectral resolution. Most of the seminal applications of drought monitoring focus on the construction of vegetation time series using polar orbiting satellite products (e.g. MODIS, AVHRR, SPOT), whereas a viable alternative is to construct vegetation series from the MSG Spinning Enhanced Visible and Infrared Imager (SEVIRI) radiometer. This low spatial-resolution sensor is particularly attractive for real-time meteorological applications or high temporal frequency applications, as it provides 20 years of imagery at 15-minute intervals with a latency of just three hours. On the other hand, the clear drawback of SEVIRI images is the coarse spatial resolution (3 km at sub-satellite point) compared to other products (e.g. MODIS, Sentinel, Landsat) which prevents its applicability to fine-detail applications (e.g. local scale agriculture monitoring).

Fensholt, Sandholt, et al. (2006) show the advantages of constructing vegetation series with SEVIRI compared to imagery derived from Polar Operational Environmental Satellite (POES) sensors. The temporal resolution of POES and their data gaps problems due to the presence of

clouds allow users to normally generate 10 or 16-day non-cloud contaminated vegetation composites. Consequently, this might not be the best choice when using them to plan fast responses to natural hazards such as droughts or floods. Previous studies have tested its application to monitor vegetation status and the outbreak of drought events (Lacaze and Bergès 2005; Fensholt, Sandholt, et al. 2006; Fensholt, Anyamba, et al. 2011; Rulinda, Bijker, and Stein 2010; Rulinda, Bijker, and Stein 2011; Demisse et al. 2018; Barbosa et al. 2019). Some of these works have tried to validate the quality of SEVIRI images for the African continent (Lacaze and Bergès 2005; Fensholt, Sandholt, et al. 2006; Rulinda, Bijker, and Stein 2010; Rulinda, Bijker, and Stein 2011; Fensholt, Anyamba, et al. 2011; Demisse et al. 2018) or for semi-arid regions (Barbosa et al. 2019) at similar latitudes than the Horn of Africa, however restricting their analyses in space or time. Rulinda, Bijker, and Stein (2011) showed how in a Rwandan region SEVIRI-derived NDVI correlates with the mean chlorophyll content and the mean percentage of vegetation cover for 15 days in May 2011. Looking at the whole African continent for 10 days in July 2004, Lacaze and Bergès (2005) demonstrate the improved quality of SEVIRI images compared to higher resolution SPOT NDVI series due to an improved ability to remove cloud-contaminated pixels. The study by Barbosa et al. (2019) enlarged the time dimension to the years 2008-2016 and used the SEVIRI NDVI series to successfully monitor the effects of a series of vegetative droughts in a semi-arid region in the Northeast of Brazil. Similar to Lacaze and Bergès (2005), the authors found that SEVIRI radiometer yields improved NDVI series compared to SPOT VGT-10.

1.3. Precipitation products at a daily scale

Nowadays it is increasingly difficult to obtain reliable ground data in the African continent as weather stations are sparse and the total number is decreasing (Dinku, Funk, et al. 2018; Le Coz and Van De Giesen 2020). Therefore, researchers increasingly rely on satellite products to provide accurate estimations of rainfall. A study by Mekonnen et al. (2023) assessed the performance of a series of global and regional precipitation satellite and reanalysis products in the African continent at a daily scale compared to in-situ data over the period 2001-2020. The authors concluded that their performance varied greatly in time and space, although it seems that some products consistently show better skill in detecting no rains, small rains, or heavy rains events. Overall, they demonstrated that, compared to monthly and annual scales, the performance of all rainfall products on a daily scale was not satisfactory and showed a general overestimation of rain events. They attributed these failures to satellite model errors in predicting rainfall

accumulation and distribution or to the presence of high variance and lack of a dynamic range in rainfall estimates at a daily scale. Notably, previous studies that experimented with different temporal resolutions concluded that the prediction skills of satellite or rain gauge products were poorer in the case of using products at improved temporal resolution (e.g. daily instead of dekadal or monthly) (Dinku, Connor, and Ceccato 2011; Dembélé and Zwart 2016; Dinku, Funk, et al. 2018). Other works (Maidment et al. 2013; Dembélé and Zwart 2016; Le Coz and Van De Giesen 2020) agree that it is hard to find an optimal precipitation product that can outperform all the others. Reviewing previous regional studies in Africa, Le Coz and Van De Giesen (2020) conclude that, in general, using precipitation products with coarser grids generally delivers improved performance in different applications. The authors also highlight how satellite products might deliver inaccurate estimates in the case of complex orography, or that different rainfall regimes across the same region might affect the quality of their results. They stress out that satellite products are expected to perform better during summer and in the tropics given their improved ability to reproduce convective rainfalls.

1.4. Hydrological indices

Besides the SPI, a variety of hydrological indices have been used to monitor drought across the Horn of Africa. More advanced indices such as the Reconnaissance Drought Index (RDI) (Tsakiris, Pangalou, and Vangelis 2007) and the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2013) attempt to account for the growing impact of temperature and evapotranspiration (ET) on water availability, particularly under climate warming. However, these indices still have important limitations. Their estimates of atmospheric water demand often rely on uncertain input data, especially in regions like the HoA, where weather station coverage is sparse.

The Evaporative Stress Index (ESI), which measures how much actual ET deviates from expected values, is a promising tool for identifying early signs of vegetation stress. Unlike other indices, it does not rely on rainfall data, which makes it useful in areas where precipitation records are lacking. However, ESI depends heavily on satellite data quality and can be affected by cloud cover, land surface heterogeneity, and gaps in validation due to limited ground measurements in the region.

Soil moisture-based indices, like the Standardized Soil Moisture Index (SSMI), are also gaining traction for tracking agricultural drought. Supported by satellite data such as ESA-CCI and

NASA SMAP, they provide more spatial coverage than traditional in-situ observations. Still, they struggle to accurately capture moisture conditions below the surface, especially in areas with dense vegetation or complex terrain. Without reliable ground data to calibrate against, their accuracy remains uncertain. Hydrological drought, which affects rivers and groundwater, is often assessed using the Standardized Streamflow Index (SSI) or the Palmer Hydrological Drought Index (PHDI). Yet in the HoA, long-term and consistent streamflow data are often lacking, limiting the practical application of these indices.

Composite drought indices like the Integrated Drought Severity Index (IDSI) and the Drought Severity Index (DSI) aim to combine several variables such as precipitation, temperature, soil moisture, and streamflow into a single, more holistic indicator. While this approach helps capture the complexity of drought, it also introduces new challenges. These indices often rely on fixed rules or weights that may not reflect local realities. Without proper calibration, they risk producing oversimplified or misleading assessments, especially in diverse landscapes like those found in the HoA.

One of the persistent challenges in drought monitoring is the difficulty of tailoring indices to local conditions. Most drought indices are designed to be globally applicable, but their effectiveness often depends on region-specific factors such as climate regime, land use, soil type, and data availability. This makes it difficult to calibrate them accurately without extensive local knowledge and validation data, which are often lacking in the Horn of Africa. As a result, an index that performs well in one area or season may not be reliable in another. Moreover, no single index is capable of capturing all dimensions of drought—meteorological, agricultural, and hydrological—equally well. The choice of an appropriate index often involves trade-offs between simplicity, data requirements, and sensitivity to different drought phases. In practice, this makes it challenging for practitioners and decision-makers to identify the most suitable indicator for a given context. Unlike predefined indices that rely on fixed mathematical formulations and assumptions, ML models can learn complex, non-linear relationships between multiple environmental variables and observed drought impacts. This flexibility allows them to adapt more easily to local conditions, provided sufficient training data are available. ML approaches can also integrate diverse data sources, such as remote sensing, climate reanalyses, and socio-economic indicators, without the need to reduce them to a single standardized format. In regions like the HoA, where conventional monitoring networks are sparse, ML models can fill observational gaps

and infer spatio-temporal patterns of drought from incomplete or noisy data. Moreover, they can be trained to directly predict drought impacts on agriculture, water resources, or livelihoods, offering more actionable insights than generic indices. While they come with their own challenges, such as data quality, model interpretability, and the risk of overfitting, ML approaches offer a promising path toward more locally relevant and impact-driven drought monitoring systems.

1.5. The potential of Machine Learning

Advances in Artificial Intelligence (AI) and Machine Learning (ML) have opened new avenues for enhancing drought early warning systems, particularly through the integration of high-temporal-resolution Earth Observation data.

A series of early studies exploited the operational use of the Vegetation Condition Index (VCI) by the Kenyan National Drought Management Authority (NDMA). For example, Adede et al. (2019) used lagged monthly vegetation and precipitation values as inputs to an Artificial Neural Network (ANN) to predict future vegetation anomalies at counties' level. Barrett et al. (2020) developed a pipeline to forecast the 3-month average VCI (VCI3M) in pastoral regions, using daily MODIS and 16-day Landsat imagery, which was composited into weekly temporal resolution datasets. They formulated the prediction task as a time-series regression problem, relying on previous index values to estimate future ones. However, their approach had limitations, notably the use of a random pixel subset and spatial averaging, which reduced the spatial precision of the predictions.

Building on this work, Salakpi et al. (2022) incorporated daily vegetation data from MODIS, soil moisture from ESA-CCI, and precipitation from CHIRPS to predict VCI3M using a Bayesian Auto-Regressive Distributed Lag (BARDL) model. Although still focused on regional-scale predictions, this method reduced the forecasting window by approximately two weeks compared to previous efforts. The authors also explored the contribution of precipitation and soil moisture anomalies to the predictive performance at different forecast horizons. In parallel, Lees et al. (2022) opted for enhanced spatial resolution by resampling daily data to a monthly scale and employing a recurrent structure with a Long Short-Term Memory (LSTM) network, an architecture well-suited for temporal dependencies, to predict VCI based on three-month historical sequences.

These studies typically involved trade-offs between spatial and temporal resolution due to limitations in satellite data availability. Park et al. (2020) used the area of South Korea to introduce

one of the first efforts to employ a Deep Learning model exploiting spatio-temporal features, specifically a ConvLSTM architecture, at short temporal scales, showcasing the benefits of integrating higher temporal resolution data for near-term drought prediction.

More recently, the EarthNet2021 dataset (Requena-Mesa et al. 2021) enabled spatio-temporal DL benchmarking by providing a data cube of meteorological and static variables (e.g., elevation) to predict vegetation conditions at 20 m resolution every five days in Europe. This dataset spurred various applications of both deterministic (e.g., ConvLSTM) (Diaconu et al. 2022; Robin et al. 2022; Benson et al. 2024) and probabilistic models (e.g., diffusion-based approaches) for Earth surface forecasting (Benson et al. 2024; Zhao et al. 2024). However, since the data was derived from the Europe-specific E-OBS model, global generalization was limited. Robin et al. (2022) addressed this by extending EarthNet to Africa using global ERA5 reanalysis data, albeit at a reduced 10-day temporal resolution. A more recent contribution by C. Ji et al. (2025) introduced a global dataset with 5-day frequency to monitor compound drought and heat events at 2.5 km resolution.

Despite these efforts, most existing applications rely on low-Earth orbit (LEO) satellites, which typically offer high spatial but lower temporal resolution, making it difficult to detect short-term vegetation dynamics critical for early drought warning. In contrast, geostationary satellite systems, while coarser in spatial detail, provide continuous observations throughout the day and maintain a fixed viewing geometry, which mitigates issues related to cloud cover and varying solar angles. These attributes enhance the consistency of vegetation time series and improve phenological monitoring (Fensholt, Anyamba, et al. 2011; Anyamba and Tucker 2012; García-Haro et al. 2019; Lu et al. 2024).

2. Methodology

The thesis unfolded into three separate works. The first explains the strategy used to develop a novel vegetation product derived from geostationary satellites (D’Ercole et al. 2024). The derived vegetation status data for the Horn of Africa offers daily temporal resolution and robustness to cloud cover contamination. The second work examines the evolution of both meteorological and agricultural droughts in the HoA region, using the derived vegetation dataset in combination with a range of global and regional precipitation datasets. A quantitative analysis is carried out computing the Standard Precipitation Index (SPI) over multiple accumulation periods (30, 60,

90, and 180 days), thereby assessing the sensitivity of drought detection to different temporal windows.

Finally, integrating the developed vegetation status dataset with ERA5 climate features and soil moisture from ASCAT radiometer, the third work adapts to the task of drought forecasting state-of-the-art Deep Learning architectures, including graph-based and diffusion models, aiming to predict vegetation dynamics up to 60 days in advance. The contributions of this last work are multiple: (i) I developed a robust, cloud-resilient Earth surface prediction dataset with coarse spatial but high temporal granularity; (ii) I evaluated the predictive capacity of various DL architectures, including graph-based models and diffusion processes, across multiple sub-seasonal forecasting horizons; and (iii) I performed a feature attribution analysis to assess the role of variables in driving vegetation dynamics. Overall, the work demonstrates that high-temporal-resolution inputs can help build responsive and accurate models, allowing for earlier detection of vegetative stress, which is crucial for anticipatory drought mitigation.



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A high temporal resolution NDVI time series to monitor drought events in the Horn of Africa

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ABSTRACT

This study investigates the reconstruction of climatological patterns and vegetation dynamics in the Horn of Africa region using high temporal resolution (i.e. daily) Normalized Difference Vegetation Index (NDVI) datasets. The analysis compares a straight-forward processing approach to derive a daily vegetation index from a geostationary (SEVIRI) satellite with existing NDVI series from geostationary or polar-orbiting (MODIS, MetOp-AVHRR) satellites, highlighting the impact of cloud contamination on data quality in high temporal resolution datasets. Using a smoothing process designed to reconstruct the upper envelope of the vegetation status series, we obtained a daily vegetation dataset that effectively mitigated cloud-induced fluctuations, outperforming polar-orbiting (e.g. MODIS) satellite-derived dataset in capturing regional climatology. We demonstrated this through statistical analysis, including autocorrelation and mean absolute difference between consecutive observations. We showed that cloud contamination significantly affects high temporal resolution NDVI series, particularly in forest areas, which makes it difficult to identify a suitable dataset to validate our approach. Therefore, we mitigated this problem using a Maximum Value Compositing technique, designed to remove cloud-induced biases and further compared our results with another independent vegetation index at coarser temporal resolution derived from AVHRR. We found that our vegetation index closely relates with MODIS 10-day composites after removing cloud-contaminated pixels. Furthermore, the study evaluates the sensitivity of the selected NDVI datasets to drought events, demonstrating the strength of the proposed SEVIRI dataset in capturing the intensity and persistence of vegetation anomalies. In conclusion, the study presents an innovative strategy for deriving daily-resolution NDVI datasets in cloud-prone regions, validating it with independent datasets at different sub-monthly temporal scales.

1. Introduction

Satellite remote sensing has played a significant role in narrowing the gap in drought monitoring, deviating from site-based measurement approaches (e.g. Palmer Drought Severity Index) (Palmer, 1965) and creating a paradigm-shift (West et al., 2019; Anyamba and Tucker, 2012). Due to the need of consistent long-term vegetation series, most drought monitoring applications have utilized a narrow set of sensors (Kogan, 1997; Zhang et al., 2006; West et al., 2019). Moreover, a significant share of monitoring systems have been designed to track drought evolution at a seasonal or monthly scale, whereas considerable gaps remain in the ability to predict droughts on a short-term scale (e.g. within 10 days) (Park et al., 2018). Nowadays, this is suboptimal for several reasons. If on the one hand droughts are mostly considered a

climate phenomenon with a slow onset, a drought event can quickly develop in the case of persistent atmospheric anomalies that last for more weeks (Otkin et al., 2013). Rapid deterioration of vegetation can happen during prolonged periods with lack of precipitation, unusually warm surface temperatures, strong winds, and clear skies (Otkin et al., 2013). These factors can result in increased evapotranspiration (ET), and, consequently, in a swift decrease in root zone soil moisture (Mozny et al., 2012). Additionally, when short periods of water stress happen in crop growing seasons, they can significantly compromise crop development (Otkin et al., 2013). This appears particularly relevant in certain regions of Africa (Southern, Eastern) where leaf phenology is largely driven by precipitation (Buitenwerf et al., 2015; Zhang et al., 2006, Rishmawi et al., 2016).

The evolution of extreme hazards and the shortfalls of current

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systems are raising the need for better sensors, which are required to describe their full extent and to detect them promptly. West et al. (2019) argue that to enhance our understanding of extreme dry events and to improve the ability to anticipate their effects, it is fundamental to extend our usage of remote sensing products, either by creating instruments with better spatial, temporal (or spectral) resolution or by adopting new methodologies that can better exploit current ones. Today, there is a vast array of sensors capable of capturing global images at varying spatial or temporal resolutions. Satellite imagery can be exploited to generate derived indices that offer more comprehensive descriptions of land surface physical processes. Mostly due to their higher spatial resolution compared to geostationary satellites, researchers and operators usually rely on vegetation products derived from polar orbiting satellites including Advanced Very High-Resolution Radiometer (AVHRR), Visible Infrared Imaging Radiometer Suite (VIIRS), Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat Operational Land Imager (OLI) and Multi-Spectral Imager for Sentinel-2 (MSI). However, cloud contamination remains a major factor limiting vegetation dynamics monitoring from polar-orbiting satellites (Fensholt et al., 2006, 2011; Miura et al., 2019). The challenge notably increases during crop-growing seasons, as for most areas globally cloud cover is present for about 30 % of the time (Anyamba and Tucker, 2012). Fensholt et al. (2011) have demonstrated how persistent clouds in West or East Africa during the crop-growing season were an obstacle to effective drought or flood monitoring using Terra-MODIS, SPOT, or AVHRR vegetation products. This pioneering study showed how exploiting data from the geostationary Meteosat Second Generation (MSG), which collects full-disk images every 15 min, can help generate more reliable cloud-free imagery over cloud-contaminated areas. Numerous studies agree on the advantages of using geostationary sensors for cloud contamination attenuation (Fensholt et al., 2006, 2011; Miura et al., 2019; Barbosa et al., 2019). There are added benefits in using observations from geostationary satellites: the Viewing Angle for a certain region can be considered as constant over time, and the observation time can be selected in order to reduce the variability of the Sun Zenith Angle. Additionally, geostationary orbit (GEO) data offer specific benefits for drought monitoring. These benefits include faster and more accurate detection of seasonal changes in vegetation (García-Haro et al., 2019; Miura et al., 2019), better understanding of vegetation dynamics and plant phenology (Fensholt et al., 2011; Miura et al., 2019; Barbosa et al., 2019; García-Haro et al., 2019), decreased sensitivity to data gaps (Fensholt et al., 2011) or improved representation of the relationship between precipitation and vegetation (Barbosa et al., 2019).

The Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974; Tucker, 1979) has established itself as a baseline indicator to monitor vegetation conditions in the case of drought events (Ji and Peters, 2003), whereas the derived Vegetation Condition Index (VCI) (Kogan, 1995) has been widely used to detect anomalies in the vegetation status and to understand the intensity, spatial and time extension of vegetative droughts. However, besides cloud cover, also atmospheric attenuation and variations in the viewing angle can compromise their validity. Researchers often used products that directly corrected for these distortions or employed post-processing strategies to reconstruct high-quality vegetation status series. For instance, the Terra MODIS 16 days NDVI product (MOD13A1) is based on the MOD09GA reflectance daily product, which is already corrected for atmospheric factors (e.g. gas absorption, aerosol scattering, interactions between atmospheric and surface bi-directional reflectance functions (BRDF), and the adjacency effect) (Vermote et al., 2002). Alternatively, researchers adopted empirical correction strategies that can account for biases and help reconstruct high-quality vegetation indices, including the Maximum Value Compositing (MVC) technique (Holben, 1986) or the Whittaker Smoother (Atzberger and Eilers, 2011; Eilers et al., 2017).

In our work, we use a processing approach inspired by Fensholt et al. (2011) and Sobrino et al. (2013) to generate daily vegetation status series from MSG SEVIRI. Assuming that maximum top-of-atmosphere

(TOA) radiance is measured around local noon, we selected SEVIRI observations at 12:12 local time. Despite not taking full advantage of the temporal resolution of MSG SEVIRI (i.e. 15 min), we mitigate biases resulting from cloud cover using a smoothing technique based on the Whittaker filter, designed to reconstruct plant phenology. We then compare our derived vegetation index with other reference datasets, using statistical analysis to demonstrate how current high temporal resolution vegetation datasets are strongly biased by cloud cover. Finally, we demonstrate the effectiveness of our approach in reducing the impact of atmospheric factors and highlight the benefits of utilizing a vegetation index generated from a geostationary satellite.

2. Data and methods

2.1. Study region

The Horn of Africa (HOA) encompasses a variegated climate and topography, which includes humid highlands and arid lowlands, as well as coastlands (Dinku et al., 2011). The main highlands are located in Ethiopia and Kenya, whereas Somalia and Djibouti are mostly made of arid areas (Dinku et al., 2011). Regarding the climate, the area presents three wet seasons, with a bimodal distribution for Somalia, Djibouti, Kenya, and southern Ethiopia with a long rainy season in March-May and a short rainy season in October-December (Liebmann et al., 2014). On the other hand, northern Ethiopia receives most of its rain during the July-September period. Overall, depending on the area, the mean yearly rainfall ranges from less than 300 in the lowlands to more than 1200 mm in the highlands (Fenta et al., 2017).

Fig. 1a depicts the spatial representation of the multi-annual mean of our NDVI derived from MSG SEVIRI (see Section 2.2), and panel b displays which of these areas constitute a forest land cover according to the Copernicus Land Cover Map 2019 (Buchhorn et al., 2020). We used both closed and open forest type pixels to limit certain parts of our analyses. Moreover, using the SEVIRI Cloud Mask product as described in Section 2.2, we computed the percentage of cloudy days for each pixel in our sample. The output is shown in Fig. 1c.

2.2. Data description and methodology

To meet the demand for vegetation monitoring at increased temporal resolution, we derived a daily NDVI index from the MSG SEVIRI radiometer, which we refer to as HRSEVIRI-1D-NDVI. Using the EUMETSAT Data Access Client (EUMDAC), we collected full-disk images covering the visible and near-infrared channels (0.635 μm and 0.81 μm) and gathered daily imagery for the years 2005–2023. As other studies have empirically demonstrated that the NDVI derived from SEVIRI has a bowl-shaped pattern throughout the day (Fensholt et al., 2006; Rulinda et al., 2010; Barbosa et al., 2019), we obtained single images of the 0-degrees MSG SEVIRI at 09:12 UTC and assumed that the maximum daily reflectance was achieved around local noon. Since MSG SEVIRI provides TOA radiances, we calculated the Bidirectional Reflectance Factor (BRF) for the SEVIRI visible channels and derived the TOA reflectances (EUMETSAT, 2012). Additionally, we obtained the MSG Cloud Mask product for the same time and used it to remove cloud-contaminated pixels. Given the fact that it is currently not possible to directly obtain water vapor, ozone, and aerosols data from the MSG SEVIRI (Fensholt et al., 2006) and that deriving these data from other sensors would imply imprecisely estimating their effect on vegetation pixels, we did not directly correct for atmospheric factors but performed an ex-post bias correction (see section 3.2). After removing pixels contaminated by clouds, we computed the NDVI series and we applied a Whittaker filter with a V-curve (see sub-section 2.2.1).

To assess the quality of the NDVI series derived from SEVIRI, we compared the performance of the HRSEVIRI-1D-NDVI to a set of alternative vegetation status products. Firstly, to test the product at daily temporal resolution, we retrieved the MSGNDVE NDVI product from the

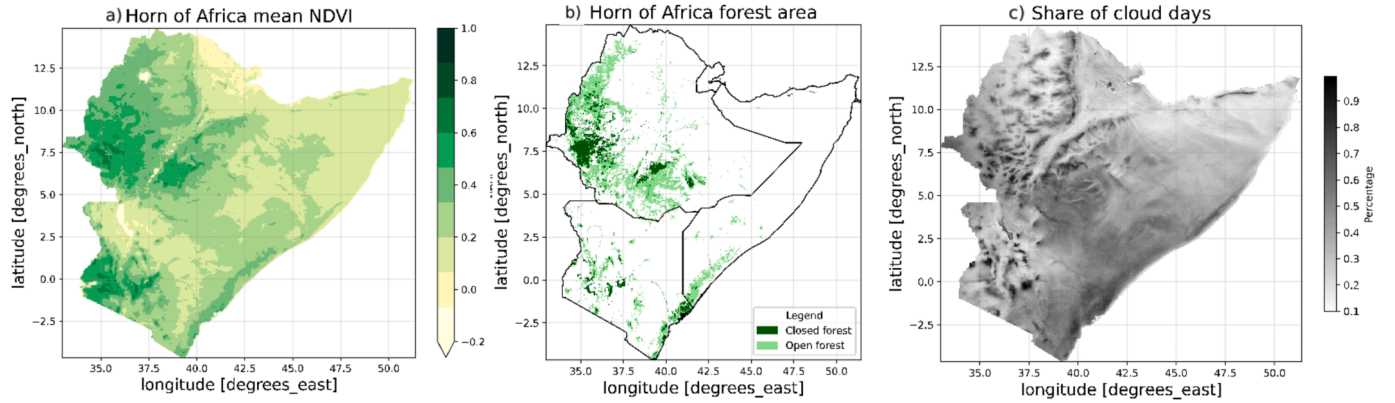


Fig. 1. (a) Mean NDVI for the Horn of Africa. MSG SEVIRI daily dataset. (b) HOA forest area. Copernicus Land Cover Map 2019. (c) Percentage of cloud days. SEVIRI Cloud Mask daily product 2005–2023.

EUMETSAT Data Store and used it as our first benchmark. The product, which has been discontinued, derives the NDVI as part of the Scenes Analysis algorithm (MSG MPEF, 2015), which calculates the index from the top-of-atmosphere reflectances, corrected with a BRDF method. Also, the algorithm accounts for the effect of clouds using the SEVIRI Cloud Mask product. Furthermore, we used as a second benchmark a MODIS Terra daily NDVI dataset¹ obtained from the Google Earth Engine (GEE) platform which is derived from the MOD09GA surface reflectances. The MODIS land surface products are a well-established reference to monitor vegetation dynamics. Moreover, the MOD09 series products are corrected for surface anisotropy and atmospheric effects, providing an estimate of surface spectral reflectance in the absence of atmospheric scattering or absorption at ground level. Additionally, we removed low-quality pixels with the aid of the Quality control Band of the MOD09GA product (QC_500m MODLAND QA). We refer to this product as MOD09GA-NDVI.

To mitigate the problem of cloud contamination in high temporal resolution (e.g., daily) datasets and to facilitate comparisons with other datasets of coarser temporal resolutions, we applied a Maximum Value Compositing technique (Holben, 1986). We divided each month into three dekads, where the first two were always ten days long (1–10, 11–20), while the third varied in length, spanning from the 21st to the end of the month. The resulting 10-day composites for the HRSEVIRI-1D-NDVI and MOD09GA-NDVI datasets were respectively denoted as HRSEVIRI-10D-NDVI and MOD09GA-10D-NDVI. We used the 10-day temporal resolution EPS-NDVI (EUMETSAT Polar System) dataset from the Land Surface Analysis Satellite Application Facility (LSA SAF) for comparative purposes as this dataset is derived from different sensors. The product is generated from the Meteorological-Operational (MetOp) satellites, combined with observations from the Advanced Very High Resolution Radiometer (AVHRR). The NDVI is computed from the AVHRR RED and NIR atmospherically corrected surface reflectances. We regridded all our datasets to the spatial resolution of the coarser dataset and the timeframe of the shorter dataset also removing water bodies identified in the Land Cover Copernicus map (Buchhorn et al., 2020). Table 1 shows a summary of the datasets used in this analysis, including the acronym of each product, the sensor and platform, the spatial and temporal resolutions, and the temporal extent of each dataset.

2.2.1. The Whittaker Smoother

The Whittaker filter with V-curve (Eilers et al., 2017) has shown sound ability to reconstruct vegetation phenology at different temporal

Table 1

Summary of the NDVI datasets used in the analysis.

Name	Sensor	Spatial resolution	Temporal resolution	Temporal extent	Atmospheric / Surface Correction
HRSEVIRI-1D-NDVI	MSG-SEVIRI	5 km	1 day	19/01/2004-Present	None/None
MSGNDVE	MSG-SEVIRI	5 km	1 day	17/02/2011–21/10/2020	None/None
MOD09GA-NDVI	MODIS Terra	250 m	1 day	24/02/2000-Present	6S/BRDF
HRSEVIRI-10D-NDVI	MSG-SEVIRI	5 km	10-days	19/01/2004-Present	None/None
EPS-NDVI	MetOp-AVHRR	1 km	10-days	01/05/2007-Present	SMAC / None
MOD09GA-10D-NDVI	MODIS Terra	500 m	10-days	24/02/2000-Present	6S/BRDF

scales (Eilers et al., 2017, Kong et al., 2019) following the upper envelope of the series. The goal is to minimize the objective function S :

$$S = \sum_i v_i \omega_i (y_i - z_i)^2 + \lambda \sum_i (\Delta^2 z_i)^2 \quad (1)$$

$$v_i = \begin{cases} \alpha & y_i - z_i > 0 \\ 1 - \alpha & y_i - z_i \leq 0 \end{cases} \quad (2)$$

In the provided equations y_i is the original time series, z_i the series to be interpolated, v_i a parameter for asymmetrically weighting positive and negative values of the first term, ω_i a vector identifying missing values with zeros and λ a parameter that influences the degree of smoothness of the interpolated series. To reconstruct the upper envelope of the NDVI series we set the α parameter for expectile smoothing to 0.99. Instead, λ is part of a penalty term where larger values of λ generate a stronger degree of smoothing, and vice versa. We used the data-driven method of the V-curve (Frasso and Eilers, 2015) to determine the series-level optimal smoothing, where the derived λ parameter corresponds to the V-curve minimum. As reported by Kong et al. (2019), different types of vegetation will require distinct λ parameters. A low value of the parameter is desirable for vegetation with multiple growing seasons in order to quickly witness biomass changes, whereas higher values of λ are needed in the case of ever-green forests to offset sharp fluctuations of the series, in our case mostly caused by the residual presence of clouds. To test that our smoothing strategy did not alter the information content of

¹ https://developers.google.com/earth-engine/datasets/catalog/MODIS_MOD09GA_006_NDVI.

our vegetation series, we computed a few summary statistics and tested the dataset ability to detect drought events derived from the Emergency Events Database (EM-DAT) (EM-DAT, 2024) and the EU Joint Research Centre ASAP Early Warning System (EWS) (Rembold et al., 2019).

2.3. Evaluation metrics

We used a series of metrics to evaluate the ability of our dataset to describe vegetation conditions. Initially, we qualitatively assessed the performance of the generated NDVI series by comparing annual vegetation growth in both the forest area and the entire region. To quantify the noise of the generated vegetation index, we employed two quantitative metrics that aid in describing data fluctuations between consecutive days. One of these metrics is the pixel-based Mean Absolute Difference (MAD) between consecutive NDVI observations (i.e. two consecutive days) at a given pixel, defined for pixel i and time t as:

$$MAD_i = \frac{1}{T} \sum_{t=1}^T |NDVI_{i,t} - NDVI_{i,t-1}| \quad (3)$$

where T is the temporal extent of the series. Low values of the MAD indicate minimal fluctuations in the NDVI index between consecutive observations, while higher values of the metric indicate consistent fluctuations in the vegetation index series. Additionally, we assessed the noise generated by the presence of clouds by focusing this analysis on pixels with a low average share of cloud-contaminated days. Specifically, using the SEVIRI Cloud Mask product, we selected pixels with less

than 25 % of cloudy days to evaluate our metric (see Fig. 1c).

Subsequently, we used an autocorrelation statistic to understand the degree of correlation between observations of the vegetation status over time. In this case, we expected the autocorrelation plot to depict strong persistence and a slowly decreasing trend as time lags increase, indicating that the NDVI does not abruptly oscillate, which is in line with the evolution of the vegetation phenology. Conversely, lower autocorrelation values would suggest that the series does not adequately describe plant phenology and exhibits considerable noise. For pixel i , the autocorrelation is defined as:

$$\rho_{i,k} = \frac{1}{T} \sum_{t=0}^{T-1} NDVI_{i,t} * NDVI_{i,t+k} \quad (4)$$

In equation (4) k indicates any selected lag of the variable and T is the total number of samples in the series. For computational reasons, we only calculated each record autocorrelation with the previous 30 observations.

Furthermore, as a central objective of the experiment was to assess the similarity between the reconstructed and theoretically clean NDVI time series, we adopted two consistency metrics to evaluate the degree of alignment between the generated NDVI datasets (HRSEVIRI-1D-NDVI and HRSEVIRI-10D-NDVI) and the relative benchmarks. Specifically, we used Pearson's correlation coefficient (r), and root mean square error (RMSE).

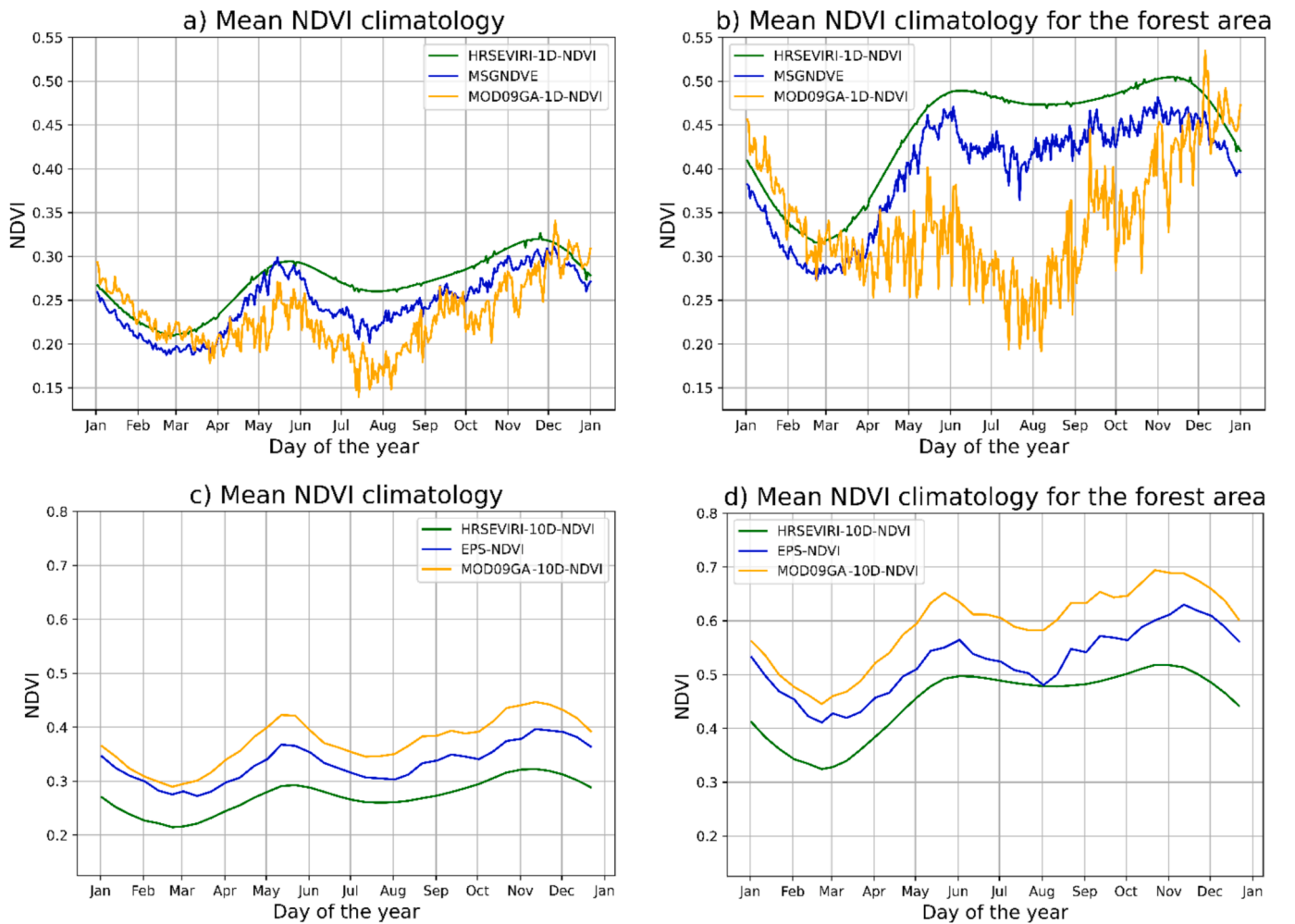


Fig. 2. Daily products mean-NDVI climatology for the whole study area (a) and the forest area (b). Dekadal products mean-NDVI climatology for the whole study area (c) and the forest area (d).

3. Results

3.1. Qualitative comparison

The four panels in Fig. 2 report the daily and dekadal (i.e. 10-day) mean NDVI for the whole study area or the forest areas. In panel a, the vegetation phenology for the area is well represented, with the mean NDVI decreasing in the dry season (January-March), then increasing after the long rainy season (March-May) and reaching the maximum during the short rainy season (October-December), which also corresponds with the harvest period of a considerable share of crops in the Ethiopian and Kenyan agricultural lands. In the top panels, the daily NDVI series constructed with MODIS appears noisy for the entire study area and the forest areas. The series peaks at the end of the short rainy season but it experiences a considerable decline during the summer (June-September). From Fig. 2 we note a clear similarity between the HRSEVIRI-1D-NDVI and the MSGNDVE series.

Observing the climatology of the forest area reveals some interesting features. There are significant differences in the mean NDVI between the dry and the wet season for the MODIS dataset, whereas they are considerably reduced for the SEVIRI NDVI datasets. Particularly, the observed lower fluctuations in the SEVIRI NDVI in the summer align with the pattern of a forest area, where the absence of precipitation is expected to have less impact on vegetation greenness. Since the end of the long rainy season (May), the mean HRSEVIRI-1D-NDVI value consistently remains high.

The picture for the MODIS dataset changes when analyzing the climatology of the 10-day composites. In this case, the three series concur on the evolution of phenology. Unlike its daily series, the MOD09GA-10D-NDVI properly describes the bimodal pattern of vegetation consequent to rainy seasons. Compared to the HRSEVIRI-10D-NDVI dataset, the EPS-NDVI and MODIS 10-day composites for the forest area exhibit higher fluctuations. Moreover, the MODIS NDVI over a 10-day period demonstrates higher absolute values in contrast to the daily MODIS product. This is attributed to the compositing process, which selects the maximum NDVI from the series and decreases the effect of cloud cover.

3.2. Bias correction

Having detected a shift in the climatology curve of the HRSEVIRI-10D-NDVI with respect to the MOD09GA-10D-NDVI (see Fig. 2 panel c-d), we computed the data density scatterplots (Fig. 3) to verify the correspondence between the two datasets. As the aim was to model the relationship between the two datasets minimizing the effects of clouds,

we restricted our analysis to pixels that are covered by clouds for less than 25 % of the days in the sample. Firstly, a high linear correlation between the two datasets is evident, as demonstrated by the distribution of most points regularly placed around a straight line. Secondly, we noted the existence of a multiplicative bias. We attributed this bias to the absence of corrections for surface anisotropy and atmospheric effects in our dataset, as opposed to the MOD09 product. Therefore, we computed a linear relationship between the two dekadal datasets for pixels with a low incidence of clouds and, after fitting a linear regression model, we found the following relationship:

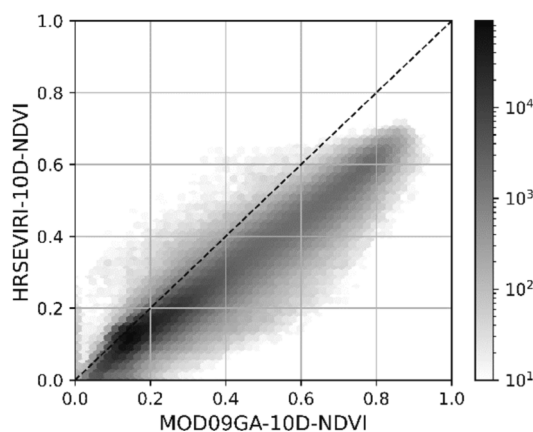
$$HRSEVIRI_NDVI = 0.0165 + 1.12538 \times MODIS_{NDVI} \quad (5)$$

We applied this bulk bias correction to the full SEVIRI dataset in the case of 10-day and daily temporal resolution. Even if the correction is quite simple compared to complex atmospheric corrections and BRDF corrections, it should be considered that: 1) the relation is quite robust, as it has been calculated for about 20 years of observations, and 2) after additional checks, we did not find any dependence of the bias from the SEVIRI Viewing Angle (that is constant over time for a given pixel), or from the Sun Zenith Angle (all SEVIRI observations have been taken around the local Noon). Therefore, the bulk bias correction mitigates atmospheric and surface-related effects that are constant in time and space, primarily the mean molecular gases effects, while it cannot account for the rapidly varying and intense aerosols effects. However, as shown in the next section, the SEVIRI dataset with this bulk and simple correction is more consistent with the MODIS-10D NDVI than other products that have been accurately corrected for the atmosphere radiative effect and surface anisotropies.

3.3. Signal persistence

As a further step, we calculated the autocorrelation statistics for the selected datasets. In the absence of an abrupt event that can stress vegetation (e.g., wildfires, flash droughts), the NDVI series should show minimal or gradual daily changes. Overall, the results for the SEVIRI NDVI indices (see Fig. 4) are in line with the expected behavior of vegetation, consistent with patterns of vegetation growth, and strongly influenced by plants' recent condition. The smaller autocorrelation of the MODIS series after a few days confirms the significant short-term fluctuations and describes the difficulty of reconstructing accurate plant phenology with the MODIS NDVI at daily temporal resolution. Considering also the differences between the MODIS daily and 10-day composites climatology (see Fig. 2), we attributed the weak autocorrelation of the daily MODIS product to the presence of clouds. On the other hand, the autocorrelation of the HRSEVIRI-1D-NDVI dataset is strongly

MOD09GA-10D-NDVI and HRSEVIRI-10D-NDVI



MOD09GA-10D-NDVI and HRSEVIRI-10D-NDVI-corr

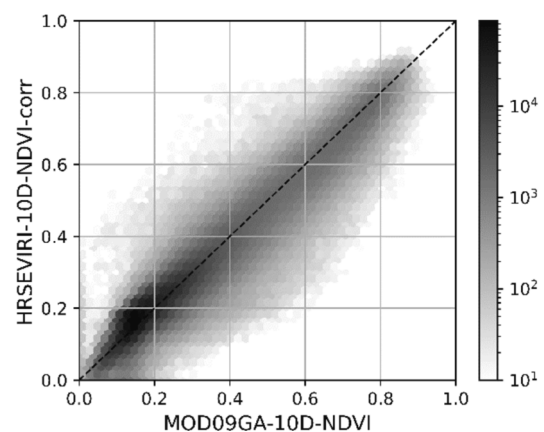


Fig. 3. Scatter density plots between MODIS and SEVIRI 10-day datasets for pixels with low cloud incidence (covered by clouds for less than 25% of the days), non-bias-corrected (left panel) and bias-corrected (right panel).

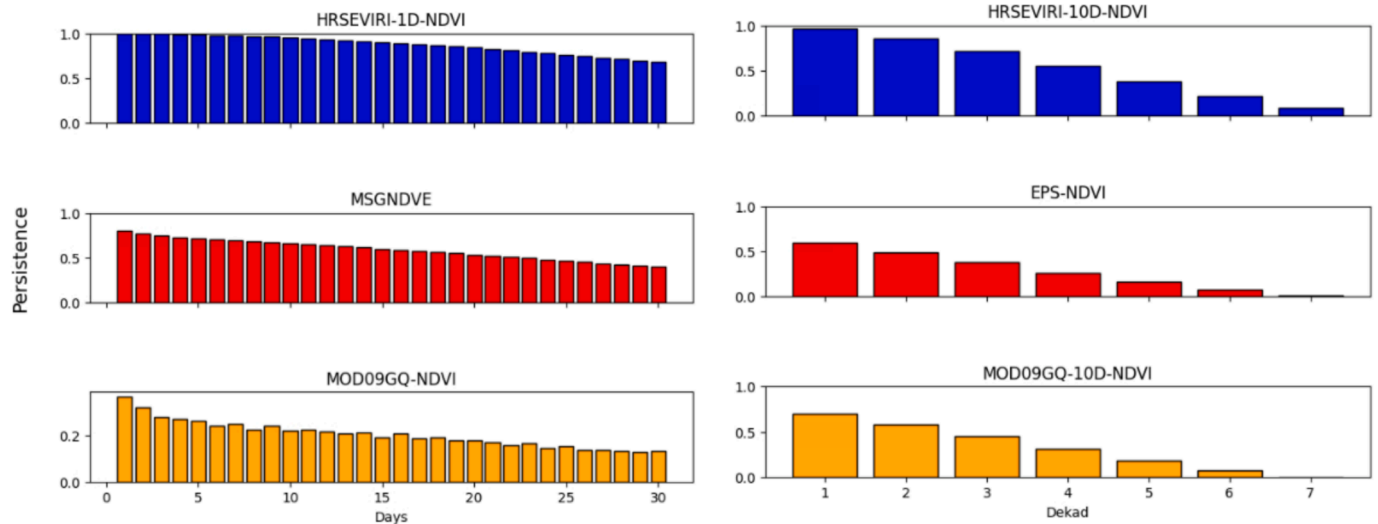


Fig. 4. Autocorrelation for 1-day (left panels) and 10-day (right panels) datasets. The x-axis represents the time lag in units of days and dekads.

influenced by the application of the Whittaker Smoother, as this filtering step incorporates neighboring information in daily observations. Similarly, it is not surprising to witness less but still considerable persistence in the MSGNDVE product. The Scenes Analysis algorithm used to derive the index uses image data of the previous repeat cycle to validate new observations. As shown in Fig. 4, the autocorrelation for the MODIS daily series is much lower than the two daily SEVIRI datasets, although it does not completely disappear after 30 days.

For the 10-day resolution datasets, the MODIS dataset shows higher autocorrelation compared to its daily product, which attests to a considerable decrease in noise due to clouds. For the EPS-NDVI, the autocorrelation statistics are weaker than the other two products, and they become close to zero after four dekads.

In Table 2, the summary statistics for the MAD are presented, while Fig. 5 illustrates its spatial distribution for both the daily and dekadal datasets. For the HRSEVIRI-1D-NDVI dataset, the metric is much lower in absolute terms, indicating small day-to-day NDVI variations compared to the other two daily datasets. Looking at the spatial distribution of the statistic we observed a clear pattern over the forest area (see Figs. 5 and 1). For instance, for the HRSEVIRI-1D-NDVI dataset, we found the highest MAD figure around the southwestern Mau National Reserve in Kenya, an area with a mountainous and forested area characterized by intense rainfall rates. For MSGNDVE and MOD09GA-NDVI, the increase in the metric encompassed the entire highlands area, extending to the south coast of Kenya and Somalia, over the Kenyan Mau reserve, the Bale Mountains, and the southwestern highlands in Ethiopia. Interestingly, the MAD calculated for the forest area increases by 53 % for HRSEVIRI-1D-NDVI, 64 % for MSGNDVE, and 72 % for the

MOD09GA-NDVI dataset (Table 2). Besides the performance on forest areas, the MODIS product shows higher MAD values for the extended semi-arid area in the center of the HOA. Instead, in the HRSEVIRI-1D-NDVI product, the extended green area next to the south Kenya and Somalia coast did not show considerably high MAD. This reveals that daily fluctuations in NDVI for this forest area are relatively smaller after applying the temporal filter.

For the dekadal datasets, a general increase in the MAD metric was expected, as a 10-day window is sufficient to observe significant changes in vegetation growth. Bringing the HRSEVIRI-1D-NDVI dataset to 10-day resolution increases the MAD metric considerably. In absolute terms, the MAD for the HRSEVIRI-1D-NDVI dataset remains largely lower than the other two dekadal datasets even though it reveals a decrease in the effect of the Whittaker filter. Despite the larger temporal window, there is a reduction in MAD for the MODIS dataset, which aligns with previous results and indicates the benefit of compositing the MOD09GA-NDVI daily product. When analyzing the spatial distribution of the metric for the MODIS dataset (Fig. 5), a decrease in the error on the Ethiopian and Kenyan highlands compared to the daily dataset can be noted. Finally, the EPS-NDVI dataset presents the highest MAD among the three dekadal datasets in the whole sample and along the forest area. In the computation of the MAD statistic for pixels experiencing low cloud cover, notable enhancements are observed across all datasets, except for HRSEVIRI-1D-NDVI and HRSEVIRI-10D-NDVI datasets, where the change is not significant. This strongly suggests that cloud cover is contaminating the vegetation indices derived from the other datasets.

3.4. Consistency

We used consistency metrics to assess the degree of alignment between the bias corrected and reference datasets. Table 3 provides details of the correlation coefficient and RMSE for the entire sample and a subset of pixels with less than 25 % of records contaminated by clouds. Additionally, Fig. 6 illustrates their spatial distribution for the whole study area. Analyzing the datasets at daily temporal resolution, a high correlation between the two SEVIRI datasets is observed, as expected. Conversely, the high RMSE is mostly attributed to the lack of atmospheric corrections in the MSGNDVE product. Overall, the consistency between the HRSEVIRI-1D-NDVI and the MOD09GA-NDVI datasets is the lowest in our experiment, with low correlation and high RMSE.

For what concerns the 10-day composites, a considerable improvement in the agreement between the MODIS and SEVIRI datasets is observed due to the MVC technique's ability to decrease the effect of

Table 2
NDVI datasets persistence metrics.

Data	MAD	MAD (forest)	MAD (low cloud)	MAD (forest, low cloud)
HRSEVIRI-1D-NDVI	0.0015	0.0023	0.0010	0.0022
MSGNDVE	0.0304	0.0499	0.0175	0.0317
MOD09GA-NDVI	0.1089	0.1889	0.0531	0.1308
HRSEVIRI-10D-NDVI	0.0189	0.0280	0.012	0.0298
EPS-NDVI	0.0642	0.1127	0.0300	0.0671
MOD09GA-10D-NDVI	0.0536	0.0860	0.0244	0.0486

"Low cloud" indicates the subset of pixels in the sample with less than 25% of days covered by clouds as defined by the SEVIRI Cloud Mask product. See Section 2.2.2.

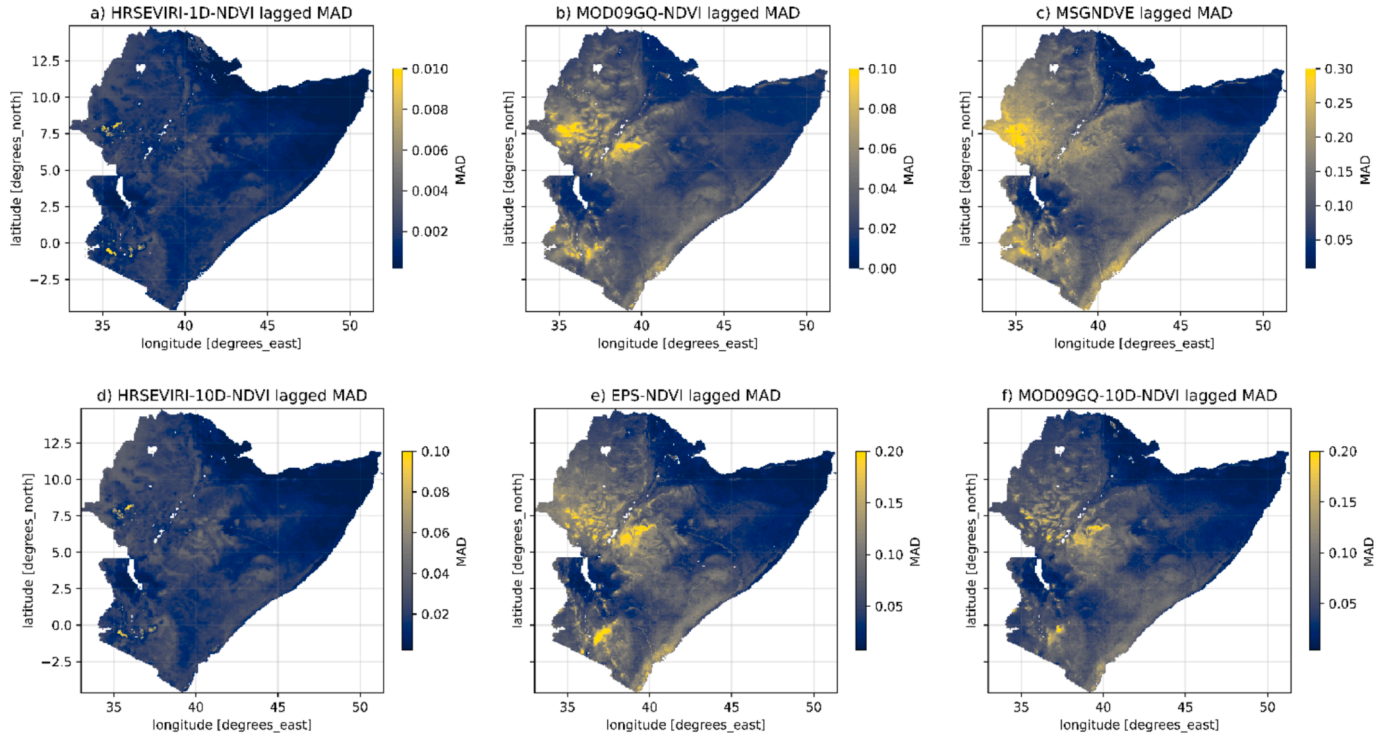


Fig. 5. Spatial distribution of mean absolute daily difference for the daily (panels a, b, c) and dekadal datasets (panels d, e, f).

Table 3
Consistency metrics for daily and dekadal datasets.

Daily datasets					
Data 1	Data 2	RMSE	Correlation	RMSE (low cloud)	Correlation (low cloud)
HRSEVIRI-1D-NDVI	MOD09GA-NDVI	0.190	0.343	0.102	0.406
HRSEVIRI-1D-NDVI	MSGNDVE	0.121	0.770	0.085	0.752
MSGNDVE	MOD09GA-NDVI	0.127	0.496	0.073	0.533
Dekadal datasets					
HRSEVIRI-10D-NDVI	MOD09GA-10D-NDVI	0.078	0.753	0.046	0.747
HRSEVIRI-10D-NDVI	EPS-NDVI	0.103	0.634	0.073	0.636
EPS-NDVI	MOD09GA-10D-NDVI	0.976	0.674	0.049	0.688

“Low cloud” indicates the subset of pixels in the sample with less than 25% of days covered by clouds as defined by the SEVIRI Cloud Mask product. See Section 2.2.2.

cloud cover. Despite the considerably higher correlation and lower RMSE between the HRSEVIRI-10D-NDVI and MOD09GA-10D-NDVI datasets compared to their daily resolution version, some consistent statistics of RMSE remain after the bias correction (see Fig. 6). However, these differences have a clear spatial pattern in correspondence with areas with a high percentage of cloudy days (e.g. localized areas in southern Ethiopia and Kenya highlands, Kenya south coastal area – see Fig. 1c). Worse metrics are found between the SEVIRI 10-day dataset and the EPS-NDVI, with the former overestimating the latter (on average) (see Fig. 7). This overestimation pattern is also observed between the MOD09GA-10D-NDVI and the EPS-NDVI dataset. Similarly to the analysis of the MAD, the consistency metrics tend to improve or remain stable when calculated on pixels with a low incidence of clouds

(with the expected higher correlation between the HRSEVIRI-1D-NDVI and MSGNDVE).

3.5. Drought detection

3.5.1. EM-DAT comparison

In an additional experiment, we verified whether the smoothing strategy used to reconstruct the HRSEVIRI-1D-NDVI reduced the information content of the daily resolution dataset. We computed vegetation anomalies using the VCI index and used long-term records on droughts in the HOA from the EM-DAT to assess our dataset’s ability to describe vegetation stress during dry spells. Since the database reports drought events for each country, we restricted our computations to the mean VCI for each country in the study area (HOA) during the selected timeframe. Table 4 presents the average VCI for the country during the identified drought events according to the two SEVIRI daily datasets and the 10-day MetOp-AVHRR and MODIS datasets. Fig. 8 illustrates the average of the VCI-1D-SEVIRI (calculated from HRSEVIRI-1D-NDVI) and VCI-10D-MODIS (calculated from MOD09GA-10D-NDVI) for the country during four drought events.

A strong agreement between the average VCI-1D-SEVIRI and the VCI-10D-MODIS can be noted. Our SEVIRI dataset exhibits the lowest average VCI for drought events in Kenya and detects a mild drought status in the case of the Somalian dry events. For the case of the Ethiopian drought, it is important to consider that the event lasted around 20 months, resulting in VCI values obtained averaging over a long period. Furthermore, Fig. 8 indicates that the evolution of the two VCI indices at daily or 10-day temporal resolution is similar, with both indices promptly describing the duration, onset (e.g., VCI below 40), or ending of drought events from the EM-DAT database. Moreover, the two indices often concur in the intensity of drought events. For example, in Ethiopia and Kenya during 2016, the average VCI dropped to a global minimum during the short rainy season, registering values below 30 and 20 on average, respectively, indicative of severe and extreme drought events.

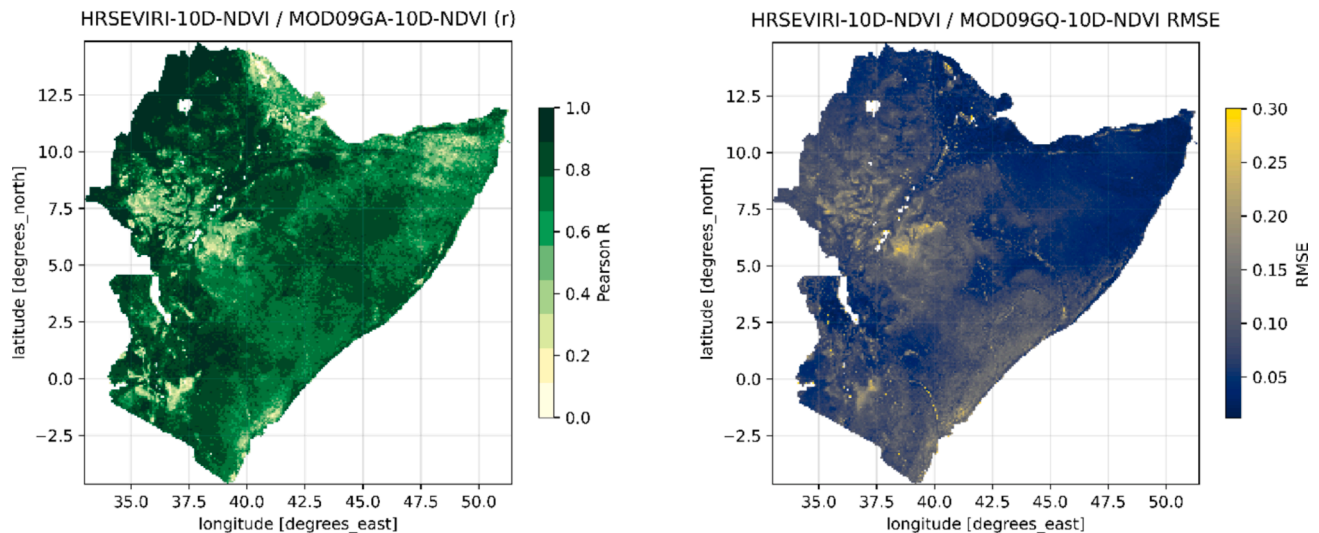


Fig. 6. Spatial distribution of the correlation and RMSE between the HRSEVIRI-10D-NDVI and MOD09GA-10D-NDVI.

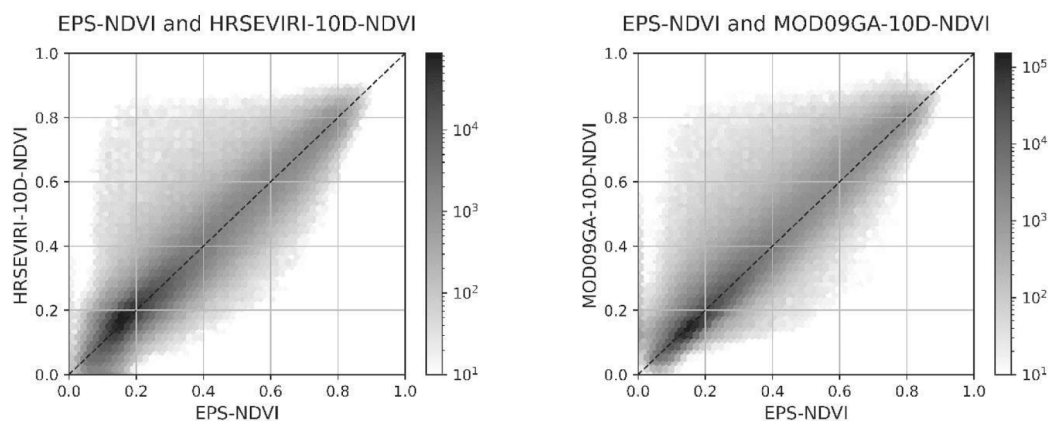


Fig. 7. HRSEVIRI-10D-NDVI and MODIS-10D-NDVI Comparison with EPS-NDVI.

Table 4

VCI from selected drought events from the EM-DAT database for the years 2014–2019. In bold the dataset with the lowest average VCI value for the event.

Country	Drought start	Drought end	People affected (Million)	VCI-1D-SEVIRI	VCI-1D-MSGNDVE	VCI-10D-EPSCG	VCI-10D-MODIS
Kenya	2014-01	2015-05	1,6	38.81	41.56	40.53	38.60
Somalia	2015-08	2017-05	6,7	39.05	44.27	33.43	38.36
Ethiopia	2015-09	2017-04	10,2	41.97	46.23	37.42	43.21
Kenya	2016-06	2018-01	3,4	30.16	39.21	34.87	32.67
Kenya	2019-01	2019-09	2,6	31.53	43.84	39.04	36.10
Somalia	2019-02	2019-10	1,5	38.11	47.02	44.30	40.81

3.5.2. ASAP early warning system and Somalia 2019 drought

We narrowed down on the spatial features of the 2019 drought event in Somalia by computing the average VCI per sub-national level, as defined in the FAO Global Administrative Unit Layers (GAUL) level 2 (FAO, 2014). The analysis was restricted to crop-intense areas as identified in the ASAP EWS. It is important to highlight that the ASAP approach differs from ours as the EWS issues unit-level biomass (i.e. zNDVI) or water balance warnings if at least a quarter of the crop area is classified as under stress during an active growing season, whereas we only compute a spatial average of the NDVI anomaly. As observed from Fig. 9, the average VCI-SEVIRI-1D falls below 40 for a range of areas in south Somalia and an end-of season biomass warning in the ASAP tool supports this over part of the Bay region in the south (see Fig. 10). At the end of February 2019, the month recorded in the EM-DAT as onset of the

drought, the VCI index confirms mild anomalies in the south of the country but signals strong variations in the vegetation condition for crop areas next to the north coast. This result cannot be compared with ASAP warnings as the tool categorizes the area as off-season. The local average decrease in the VCI index at the end of the first week of March for areas in the north and south of Somalia portrays an expansion of the vegetation stress. However, the ASAP system only depicts this condition as of March 20, when the crops enter the planting period. About 1 week after, the daily VCI signals a further worsening of the situation, but this stress condition can be fully identified on the ASAP system only on the 20th of April, when also the crop areas on the north are identified as under biomass stress. At the end of the rainy season (20 June) the ASAP system signals significant crop-harvesting phase failures for the south and north areas, a situation which concurs with the average vegetation anomalies

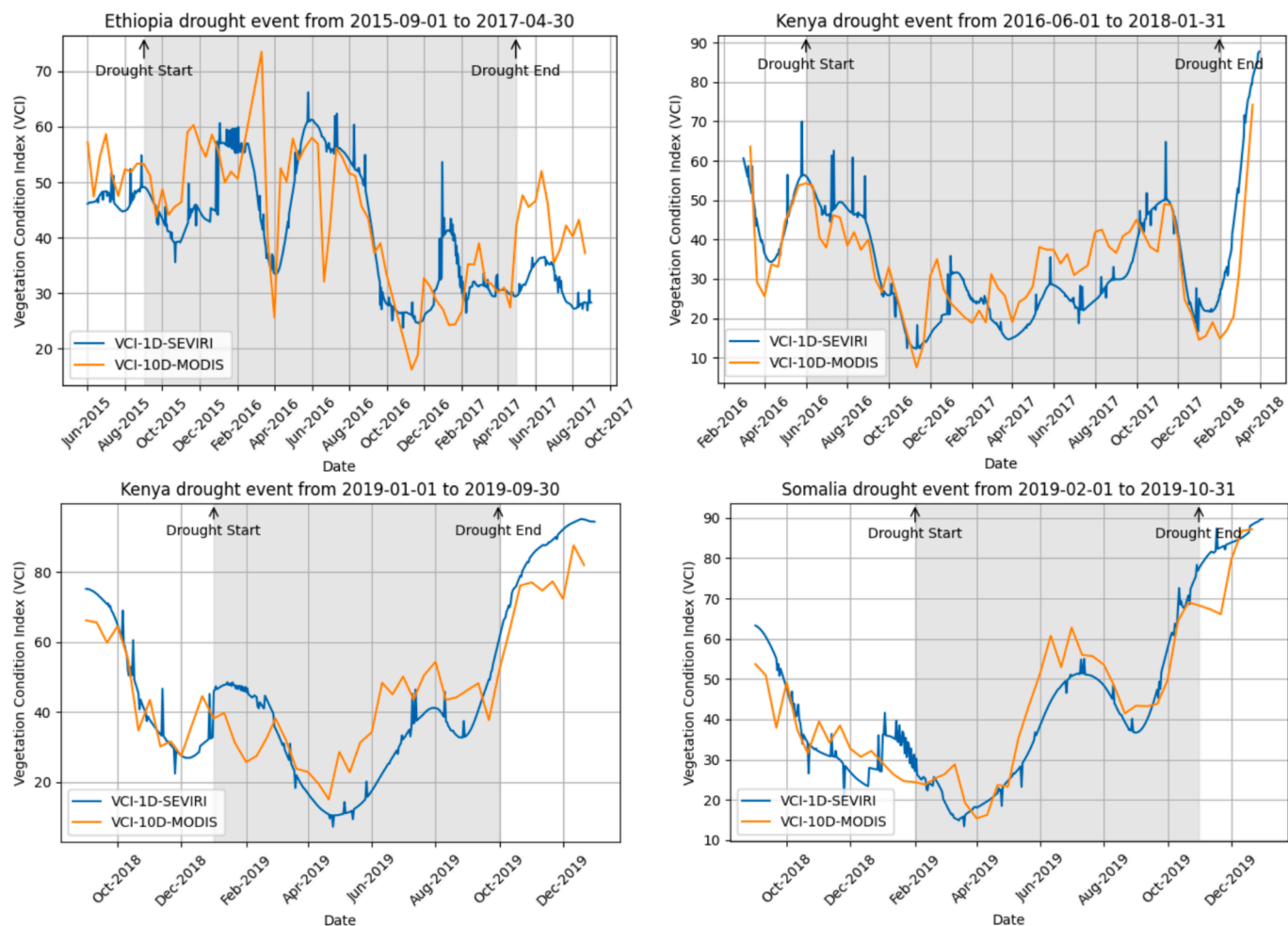


Fig. 8. Temporal evolution of VCI-1D-SEVIRI and VCI-10D-MODIS for four drought events in Ethiopia (2015–2017), Kenya (2016–2018, 2019), and Somalia (2019). The grey shaded area indicates the drought period as identified in the EM-DAT.

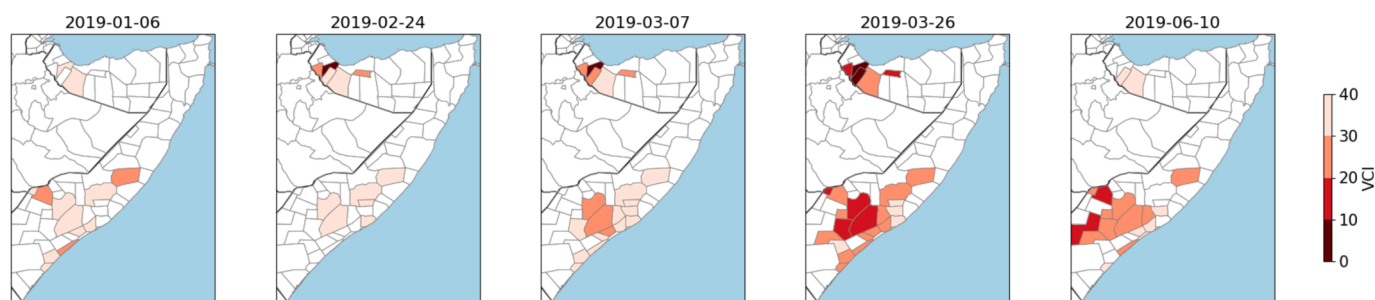


Fig. 9. Unit-level mean VCI-SEVIRI-1D temporal evolution of crop areas for 2019 drought in Somalia.

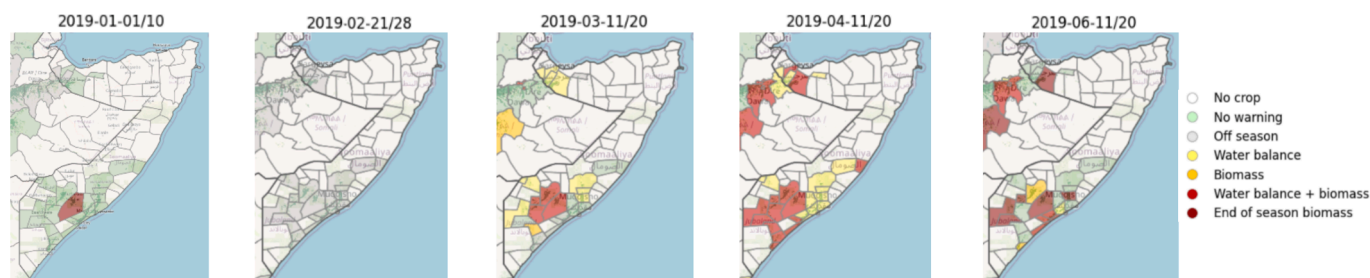


Fig. 10. ASAP Early Warning System temporal evolution of crop areas for 2019 drought in Somalia.

from SEVIRI since the beginning of the dekad.

4. Discussion

4.1. Strengths and Weaknesses of geostationary

The exploitation of geostationary data can dramatically increase the likelihood of collecting cloud-free daily images. Consequently, it can offer a more accurate means of measuring plant processes, including photosynthetic activity and plant phenology, compared to images derived from polar-orbiting satellites (Fensholt et al., 2011; Barbosa et al., 2019; Miura et al., 2019). This feature is crucial to many applications, including agriculture, food security or drought monitoring (Rulinda et al., 2010; Fensholt et al., 2011; García-Haro et al., 2019; Miura et al., 2019). In our study, although we were unable to fully utilize the more-than-daily frequency of SEVIRI data due to computational constraints (Sobrino et al., 2013), we showed that by selecting single daily images taken at the peak of daytime reflectance—based on previous studies that identified a bowl-shaped pattern in NDVI curves during the day at similar latitudes (Fensholt et al., 2006; Rulinda et al., 2010; Sobrino et al., 2013; Barbosa et al., 2019)—and applying an appropriate processing strategy, we can produce a vegetation status series that is effective for monitoring drought. Our SEVIRI-derived index describes plant phenology with similar degree of reliability of the MVC-corrected 10-day MODIS-derived NDVI (MOD09GA-10D-NDVI), while offering an enhanced temporal resolution, improved signal persistence and fewer oscillations between consecutive observations.

Another clear advantage of the SEVIRI dataset is that it offers about 20 years of measurements and new observations of the sensor are available in near real time (NRT). Given the fact that MSG observations are produced every 15 min with a latency of about 5 min, our processing ensures that the updated vegetation status index becomes available shortly after each new daily observation is collected. Therefore, it is not necessary to implement “online learning” filtering strategies such as those proposed by Klisch and Atzberger (2016), which are used to predict present values of the vegetation status from polar orbiting satellites like the MOD09 or MYD09 series. However, a clear bottleneck in operationalizing our approach is the computational time required to recalibrate the entire NDVI sequence every time new observations of vegetation are integrated. On the other hand, this could be avoided by applying periodic recalibrations every few days, as significant changes in the computed Whittaker filter parameters are not expected.

The principal shortcoming of the HRSEVIRI-1D-NDVI is its coarse spatial resolution, which is approximately 3 km nadir and around 5 km in the HOA. This makes the index unsuitable for the analysis of plant phenology at the local scale. This is in contrast to the capacity of more recent sensors, such as Landsat 8, Sentinel 1 and 2, to provide finer spatial resolution data. Apart from this, the methodology described in this work can be easily reproduced to other regions using SEVIRI, or with other geostationary products (e.g. GOES, Himawari, Feng-Yun, INSAT, GEO-KOMPSAT). In the future, adapting the algorithm to the Flexible Combined Imager (FCI)/Meteosat Third Generation satellites (MTG) will be a relatively straightforward process. The FCI offers enhanced spatial and temporal resolutions in comparison to SEVIRI, and is scheduled to become operational in the near future. From a broader perspective, the utilization of geostationary satellite observation for vegetation index calculation can serve as a valuable alternative to the NDVI calculated from polar orbiting satellites. In the future, the optimal NDVI index could likely be achieved by using Deep Learning data fusion methods to combine GEO and Low Earth orbit observations (LEO), thereby improving both temporal and spatial resolutions (Xiao et al., 2023).

4.2. Strengths and Weaknesses of high temporal resolution

If on the one hand the potential benefits of high temporal resolution

data are clear cut, by analyzing high-frequency NDVI datasets derived from either polar-orbiting or geostationary satellites we have demonstrated that a major factor currently limiting their exploitation is the presence of consistent fluctuations between consecutive observations. From our analyses we attributed most of these oscillations to the residual effect of cloud cover on vegetation pixels as cloud removal strategies can never guarantee a perfect outcome. To attenuate for this effect it is possible, instead of sacrificing short-term information through the generation of sub-monthly vegetation composites, to complement cloud removal strategies with filters that are able to exploit the dense information of high-frequency data. In our case, this was achieved with a Whittaker filter designed to reconstruct the NDVI series upper envelope. Similar to our work, Liu et al. (2022) showed how daily NDVI derived from the MOD09GA product presented considerable fluctuations between consecutive observations, and used the QA & QC bands in conjunction with different temporal reconstruction methods to produce meaningful vegetation status series. After comparing the daily NDVI obtained from MODIS with low-temporal resolution series calculated from Landsat 8 or Sentinel-2, the authors highlighted that, post reconstruction, low temporal resolution data only depicted longer-term phenological changes, meanwhile they missed short-term phenological information. Another key benefit of high-frequency data is the ability to reduce the impact of consistent data gaps or consecutive low-value noise (e.g. residual impact of clouds) (Fensholt et al., 2011; Liu et al., 2022) compared to coarser temporal resolution data, as the reconstruction methods can interpolate between more data points. For instance, also in the case of data at sub-monthly scale (e.g. dekadal) resolution, a few data gaps (e.g. 3–4 consecutive observations) can make it difficult to reconstruct the phenological information (Liu et al., 2022).

In the qualitative comparison with the ASAP EWS for the 2019 Somalian drought, we demonstrated that the SEVIRI-derived VCI was able to anticipate warnings on crop areas by at least a dekad. Although the daily monitoring of vegetation anomalies was able to anticipate future warnings, the ASAP system is much more conservative in their methodology in order to avoid issuing false alarms. In the context of early warning actions it is fundamental to evaluate trade-offs between timeliness and precision in order to efficiently allocate scarce resources. While designing an EWS is not the objective of this work, validating our satellite NDVI index with ground data is crucial for increasing public confidence in our methodology. Additionally, it will be important to describe the ability of our index to successfully identify drought events (hit rate) while minimizing the false alarms.

As previously mentioned, the improved timeliness offered by high temporal frequency data is of great importance for many applications, including the early action of drought risk financing (Vrieling et al., 2016; Jensen et al., 2019; Fava and Vrieling, 2021). For instance, the employment of high temporal resolution EO data has been recommended as a desirable solution to trigger an early distribution of payouts or to obtain more precise forage estimates in the case of drought insurance (Jensen et al., 2019; Fava and Vrieling, 2021). Vrieling et al. (2016) used 10-day MODIS composites to generate a forage index which due to the needs of the temporal filter can only be produced with a delay of one month and three days after the end of the season. Jensen et al. (2019) used a near real time solution based on BOKU (Klisch and Atzberger, 2016), which, however, is not freely available. In the context of the HOA, where droughts affect large areas homogeneously and country-wide protection schemes are in place, insurance companies typically trigger payouts for pastoral communities at a geographic-unit level (Fava and Vrieling, 2021). In this context, high temporal resolution data derived from geostationary, due to their ability to reduce the effect of cloud contamination, might be more functional than high-spatial resolution data to precisely estimate the unit level of risk.

5. Conclusions

In this paper, we presented a straight-forward strategy to derive a

high temporal resolution NDVI dataset from a geostationary satellite and validated it with reference vegetation products derived from polar-orbiting satellites at daily or dekadal scales. We demonstrated that cloud contamination constitutes a major factor limiting the ability to exploit high temporal resolution (i.e. daily) vegetation datasets, hindering their utility for phenology analysis or vegetation status monitoring. To mitigate the biases due to cloud cover, we used a cloud mask product and then employed a smoothing strategy designed to reconstruct the series upper envelope. The obtained vegetation index HRSEVIRI-1D-NDVI demonstrated satisfactory reconstruction of the climatology of the Horn of Africa when compared to the MSGNDVE and MOD09GA-NDVI datasets, which instead presented considerable oscillations, mostly attributable to cloud contamination. Taking into account the limitations of the MODIS product at daily temporal resolution, we employed a MVC technique to produce 10-day NDVI composites. The corresponding MOD09GA-10D-NDVI product demonstrated an enhanced capacity to eliminate the distortions caused by cloud cover. Further, a good level of agreement was observed between the MODIS and SEVIRI products at a 10-day temporal resolution for pixels exhibiting a minimal cloud cover. However, a considerable multiplicative bias was identified in all NDVI indexes derived from SEVIRI in comparison to those derived from MODIS and AVHRR. We hypothesized that the bias is due to the absence of an atmospheric and surface reflectance anisotropy correction in the processing phase of the SEVIRI NDVI datasets. After correcting for the bias, a RMSE of 0.046 and a correlation coefficient of 0.75 were found between the SEVIRI and MODIS dekadal datasets, which in our experiment were the best statistics for datasets derived from different sensors. However, some considerable error statistics (e.g. RMSE, MAD) persisted for isolated pixels located in regions with a high incidence of cloudy days.

Finally, to test that our smoothing strategy did not compromise the index ability to describe sudden alterations in vegetation conditions, we used VCI anomalies to identify drought events. Overall, we observed a strong relationship between the VCI computed from our dataset at daily temporal resolution and the one obtained from MODIS 10-day composites. The SEVIRI-derived dataset exhibited the lowest country-average VCI in the case of three out of six drought events, and closely followed the others in the remaining cases. Furthermore, the VCI at daily temporal resolution matched the anomalies derived from the 10-day MODIS dataset in terms of the ability to describe the intensity, duration, onset, and ending of selected drought events from the EM-DAT database. Also the analysis on the spatial components of the 2019 drought event in Somalia revealed good agreement with the alerts provided by the ASAP EWS, anticipating the drought phases by at least a dekad. Therefore, we concluded that our smoothing strategy did not hinder the index ability to capture fast changes in vegetation conditions in our sample. In future endeavors, fully leveraging the high temporal resolution (i.e., 15 min) of geostationary data by gathering multiple daily imagery could further reduce the impact of cloud cover.

CRedit authorship contribution statement

Riccardo D'Ercole: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Daniele Casella:** Writing – review & editing, Supervision, Methodology. **Giulia Panegrossi:** Writing – review & editing, Funding acquisition. **Paolo Sanò:** Writing – review & editing, Supervision, Resources, Conceptualization.

Declaration of competing interest

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

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Data availability

Data can be downloaded from the Zenodo public repository <https://doi.org/10.5281/zenodo.14001095>.

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Using daily vegetation and precipitation products to study drought events in the Horn of Africa

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Abstract

Recent studies indicating an increase in the frequency, severity, and duration of drought events in the Horn of Africa. This research aims to assess the capability of high-frequency Earth observations in detecting drought events in Ethiopia, Somalia, Kenya and Djibouti. By utilizing daily vegetation and precipitation products, we explore the benefits of high frequency data to monitor meteorological and agricultural drought. A vegetation product derived from geostationary satellites with an increased capacity to minimize the effect of clouds is compared with global and regional precipitation daily datasets to analyze the relationship between vegetation and precipitation indices. Our findings demonstrate the importance of monitoring drought phenomena at improved temporal resolution, revealing that certain daily precipitation products offer enhanced accuracy and a higher probability of detecting rainfall events. Additionally, we investigate the impact of different Standard Precipitation Index (SPI) (McKee, Doesken, and Kleist 1993) accumulation periods, finding that longer accumulation windows provide greater robustness to wet-dry fluctuations but introduce a trade-off between precision and timeliness in detecting drought events. Through a detailed analysis of drought events, we assess their effects across different soil types, indicating that cropland and forest soils exhibit greater resilience to water stress compared to other soil types. This study underscores the significance of using daily temporal resolution to identify drought events that are not visible at monthly scale.

Keywords: Agricultural drought, meteorological drought, geostationary satellite, high temporal resolution, daily data, Horn of Africa

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24 1. Introduction

25 The Horn of Africa is an area that has historically been vulnerable to droughts. Recent studies
26 suggested that droughts in the region increased in frequency, severity, and duration (Guha-Sapir,
27 Hargitt, and Hoyois 2004; Anyah and Semazzi 2006; Meier, D. Bond, and J. Bond 2007; Haile
28 et al. 2019). Particularly, the frequency of these events has doubled since 2005, with reported
29 droughts occurring every three years instead of every six years (Guha-Sapir, Hargitt, and Hoyois
30 2004; Anyah and Semazzi 2006; Meier, D. Bond, and J. Bond 2007; Haile et al. 2019). The latest
31 IPCC report (Lee et al. 2023) emphasized that climate change is projected to increase the occur-
32 rence of hot extremes, including concurrent heatwaves and droughts. Vulnerable regions, such
33 as East Africa, have experienced 15 times increased human mortality from drought, floods, and
34 storms compared to lower-risk regions during the years 2010-2020 (Lee et al. 2023). Drought
35 events pose significant concerns as they result in livestock losses, crop failures, and food se-
36 curity emergencies (Guha-Sapir, Hargitt, and Hoyois 2004; Mo and Lyon 2015). More timely
37 warnings can enable decision-makers and the public to adapt and take quick action, protecting
38 livelihoods and decreasing the economic burden of weather hazards (WMO et al. 2023). There-
39 fore, to mitigate the severe effects of this phenomenon and respond promptly to humanitarian
40 needs, integrating advancements in new-generation satellite products with existing early warn-
41 ing systems can provide fundamental assistance. A possible avenue is to understand droughts’
42 evolution at an improved temporal scale (West, Quinn, and Horswell 2019). The predominant
43 approach when trying to operationally predict drought incidence is to use monthly or seasonal
44 data. In the Horn of Africa, the Kenyan authority uses a 3-month average of the Vegetation Con-
45 dition Index (VCI) (Barrett et al. 2020). However, in the African context high temporal frequency
46 data from geostationary satellites have a great potential to improve the timeliness and accuracy
47 of early warnings (Roberts et al. 2022; WMO et al. 2023). Google has recently started to incor-
48 porate in their weather forecasting services for Africa the outputs of the Deep Learning MetNet
49 model (Sønderby et al. 2020), which uses a combination of satellite and ground observations
50 data to produce highly accurate predictions over the future 12 hours at 5 km spatial resolution.
51 Recent studies have demonstrated how it is possible to increase the accuracy in the estimates
52 of the status of vegetation by exploiting high temporal information derived from geostationary
53 sensors Fensholt et al. 2011; Miura et al. 2019; Weber et al. 2020; Zhao et al. 2022. Additionally,
54 using improved temporal resolution data can help promptly detect sudden extreme events that are

55 difficult to anticipate with monthly or seasonal data, such as flash droughts.

56 To predict future vegetation degradation, it is essential to monitor precipitation. Given that
57 African countries' economies are highly dependent on rainfed agriculture for crop production
58 and livestock rearing, populations are highly exposed to the risk of fluctuations in precipitation
59 (Maidment et al. 2013; Haile et al. 2019; Barrett et al. 2020). A common origin of a drought
60 event is a prolonged precipitation deficit (Van Loon 2015). However, in some remote areas of the
61 globe, it is challenging to obtain precise rainfall estimates due to significant spatial variability. In
62 the African continent, convective storms can generate localized precipitation phenomena, which
63 can be difficult to measure with sparse weather station data. Overall, weather stations number
64 in the continent has been decreasing in recent years (Maidment et al. 2013; Le Coz and Van De
65 Giesen 2020) and this affects the quality of in situ estimates. Remote sensing products have been
66 identified as a potentially suitable tool to bridge this gap. On the other hand, the existence of
67 different global or regional rainfall products makes it non-trivial to identify an optimal product
68 (Le Coz and Van De Giesen 2020), especially because they present variable spatial or temporal
69 performance (Mekonnen et al. 2023). Studies on the African continent have shown how precipi-
70 tation products can present wet or dry biases (McNally et al. 2017; Mekonnen et al. 2023), which,
71 in turn, can influence the behavior of the derived indices (e.g. the Standard Precipitation Index
72 - SPI) and their usefulness for different applications (e.g. drought monitoring). In this research,
73 we aim to assess the capability of high-temporal-resolution sensors in detecting drought events
74 in the Horn of Africa (Ethiopia, Somalia, Kenya, Djibouti). Firstly, we discuss the benefits of
75 high temporal resolution data to understand meteorological and agricultural drought. Therefore,
76 we perform a practical experiment with a newly developed vegetation product derived from geo-
77 stationary satellites (D'Ercole et al. 2024) and compare it with a selection of global and regional
78 precipitation daily datasets. By following the evolution of droughts using vegetation and precip-
79 itation indices, we seek to understand meteorological and agricultural drought dynamics at an
80 improved temporal resolution. While multiple factors influence vegetation growth, such as tem-
81 perature, soil moisture, and pests, this study focuses solely on water availability, excluding these
82 additional variables. For what concerns meteorological drought, we further aim to understand
83 the suitability of different types of precipitation products to describe rainfall phenomena in areas
84 that lack reliable and dense in situ precipitation data. Further, we also study the impact of calcu-
85 lating the SPI index at different time accumulations (30, 60, 90, and 180 days). A comprehensive

intercomparison of the different precipitation products in the study area and their importance for the detection of vegetation growth with the Meteosat Second Generation - Spinning Enhanced Visible and Infrared Imager (MSG- SEVIRI) radiometer will be discussed.

1.1. Selected global and regional precipitation products

The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product is widely used operationally; as an example, it is used in many Early Warning Systems (e.g. Famine Early Warning Systems Network, World Food Programme Hunger Map). The product provides high spatial (0.05 degrees) and temporal (daily or monthly) resolutions, and has been widely tested with in-situ data (Dinku, S. Connor, and Ceccato 2011; Dinku, Funk, et al. 2018). However, as Le Coz and Van De Giesen (2020) suggested, even though the product has been developed for drought monitoring, other authors (Dembélé and Zwart 2016; Toté et al. 2015) advise using it for flood monitoring (at monthly scale). Interestingly, studying the suitability of a series of rainfall products in the Greater Horn of Africa, Dinku, Funk, et al. (2018) demonstrate that CHIRPS performs better than the others on a monthly scale, but at the daily scale it shows inferior performances (e.g. lower correlation, Probability of detection, and higher bias) than regional products (e.g. the Africa Rainfall Climatology 2.0 - ARC2 and the Tropical Applications of Meteorology using Satellite Data and Ground-based Observations - TAMSAT). Mekonnen et al. (2023) recommend it as a good choice for drought monitoring on a daily scale in the African continent given its dry bias. Fenta, Yasuda, Shimizu, Ibaraki, et al. (2018) evaluated the performance of satellite rainfall products (CHIRPS, TAMSAT, ARC) with ground data for the Lake Tana basin in northwestern Ethiopia at different temporal scales. They conclude that the satellite products underestimated moderate and heavy rain events. In their research, the TAMSAT product performed relatively better on a daily scale, and they motivate this to the fact the algorithm uses higher-resolution thermal infrared imagery to detect rainfall. They found that increasing the period of integration of rainfall yields a better correlation with ground data. Belay et al. (2019) studying the Beles Basin of Ethiopia demonstrate that CHIRPS product at a daily scale underestimates the occurrence of rainfall compared to rain gauges, with this bias being larger for lowlands compared to highlands. On the other hand, they also point out that these errors on a daily scale might be reduced when performing higher-duration (e.g. monthly) integrations (Belay et al. 2019). The performance of other recently developed precipitation products has recently begun to be systematically tested for the African Continent. For instance, is interesting to assess

the value of GPM-IMERG (Global Precipitation Mission, Integrated Multi-satellite Retrievals for GPM) product which replaces the previous TRMM-B42 (Tropical Rainfall Measurement Mission) product but also the ECMWF Reanalysis v5 (ERA5) product, which has been introduced to replace ERA-Interim. A study by Gleixner, Demissie, and Diro (2020) in East Africa shows that the new ERA5 product improves over its predecessor by reducing the bias during the wet season and by better representing extreme rainfall events. Another interesting product is the Multi-Source Weighted-Ensemble Precipitation (MSWEP), which blends data from satellite, reanalysis, and rain gauge products. Mekonnen et al. (2023) conclude that MSWEP and IMERG are overall the best products to describe rainfall in the African continent at a daily scale, with the former being particularly skilled in detecting light rain events (between 1 and 5 mm) whereas the latter in the case of no rains or heavy rains. Regarding reanalysis products, Le Coz and Van De Giesen (2020) discuss that they have been shown to suffer from similar shortcomings of global circulation models. Particularly, they might perform poorly over the tropics or during monsoon season due to the presence of convective storms. As an example, Bosilovich et al. (2008) demonstrate that the previous generation of reanalysis products (R1, R2, ERA-40, and JRA-25) showed in Africa decreased skills in precipitation detection during the boreal summer, which is motivated by the presence of clouds and the sparsity of ground observations. Interestingly, Mekonnen et al. (2023) concluded that the ECMWF ERA5 product at a daily scale does not have significantly different performance than the other satellite products and that it is robust to identify light rainfall events.

2. Data and Study Approach

2.1. Study region

The Horn of Africa (HoA) encompasses a variegated climate and topography, which includes humid highlands and arid lowlands, as well as coastlands (Dinku, Ceccato, and S. J. Connor 2011). The main highlands are in Ethiopia and Kenya, whereas Somalia and Djibouti are mostly made of arid areas (Dinku, Ceccato, and S. J. Connor 2011). For what concerns the climate, the area presents three wet seasons, with a bimodal distribution for Somalia, Kenya, and southern Ethiopia with a long rainy season in March-May and a short rainy season in October-November (Liebmann et al. 2014; Haile et al. 2019). On the other hand, northern Ethiopia receives most of its rains during the July-September period. Overall, depending on the area, the mean yearly

rainfall ranges from 800 to 1200 mm (Fenta, Yasuda, Shimizu, Haregeweyn, et al. 2017). Recent studies pointed out a general increase in the frequency, severity, and duration of droughts in the HoA (Guha-Sapir, Hargitt, and Hoyois 2004; Anyah and Semazzi 2006; Meier, D. Bond, and J. Bond 2007). Researchers have also concluded that the increase in drought events mainly happened in the primary rainy season (March-May) (Nicholson 2017), whereas the short rainy season (October-November) has witnessed an increase in wet events (Liebmann et al. 2014; Nicholson 2017).

2.2. Methodology

We created a vegetation status dataset with the methodology detailed in D’Ercole et al. (2024), following the approach by Sobrino and Julien (2021), we followed the assumption that the maximum daily reflectance is reached around noon and collected a single daily image at 12:12 UTC. We applied the bidirectional reflectance distribution function (BDRF) method for atmospheric correction as described in the documentation from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) (2012) and removed cloud-contaminated observations using the SEVIRI cloud mask product. To further account for missing data problems and to reconstruct the vegetation phenology, we applied a Whittaker filter as shown in Eilers, Pessendorfer, and Bonifacio (2017). In addition, a Vegetation Condition Index (VCI) (Kogan 1995) was computed to monitor the frequency, the onset, and the spatial extent of agricultural droughts.

The IMERG product fuses the early precipitation estimates from the satellite TRMM (Tropical Rainfall Measuring Mission) (2000-2015) and the estimates from the Global Precipitation Measurement (GPM) satellite (2014-present). The CHIRPS product is based on infrared Cold Cloud Duration (CCD) observations and blends a rain gauge and satellite product. We downloaded daily observations at 0.05° spatial resolution and collected data starting from 1981. We also collected data from the Global Precipitation Climatology Centre (GPCC) product, which has a climatology dating back to 1891. This product consists of station observations interpolated at 1°x 1° spatial resolution grid, with rain gauge data reported in near-real time via the Global Telecommunication System (GTS) (Schamm et al. 2014). TAMSAT is a regional product for Africa that has been developed and maintained by the University of Reading. The product provides images at 4 km spatial resolution and provides images back to 1983. We downloaded ERA5 hourly precipitation data and converted it to daily precipitation accumulations. This 5th

177 generation ECMWF Reanalysis is based on the Integrated Forecast System model and the assim-
178 ilation (4D VAR) of a considerable amount of historical data. The ERA5 dataset is distributed at
179 0.25° (in latitude and longitude) spatial resolution from 1940. The MSWEP global precipitation
180 product provides 0.1° resolution data from 1979 and merges rain gauge, satellite, and reanalysis
181 data.

182 For each precipitation product, we retrieved the complete available history, considering that a
183 sufficiently long series of precipitation data spanning at least 20 years is needed to create a robust
184 SPI index and to reconstruct the precipitation climatology (Svoboda, Hayes, and Wood 2012).
185 Subsequently, we derived SPIs at different daily accumulations (30, 60, 90, 180) using a gamma
186 distribution. Once vegetation and precipitation indices were evaluated with the aid of some basic
187 statistics, we selected several case studies for the period 2005-2020 in the HoA area to measure
188 the contribution of daily resolution precipitation indices to explain vegetation stress events due
189 to water scarcity. Lastly, given that the HoA presents different types of soil and considering that
190 it has been well-established that different soils present disparities in responses to water stress,
191 we decompose vegetation response by soil type using the ESA Land Cover map (Buchhorn et
192 al. 2020) resampled at the SEVIRI spatial resolution and study the impact of drought events on
193 vegetation as a function of soil type.

194 **3. Precipitation products validation**

195 We used different statistics to compare the precipitation products' performance during the
196 period 2005-2020. Similar to other studies in the HoA area (Fenta, Yasuda, Shimizu, Ibaraki,
197 et al. 2018; Belay et al. 2019), we defined rainy days as days with a total of at least 1 mm of
198 rainfall. Subsequently, we used a set of categorical metrics computed by comparing realized rain
199 events (days with 1 mm of precipitation or more) with the reference and computed the accuracy,
200 FAR (False alarm rate), POD (Probability of detection), and a continuous error metric, namely
201 the RMSE (root mean squared error). We used the GPCC product as a reference given that
202 the product is obtained from rain gauges interpolated on a regular grid (Schamm et al. 2014)
203 and we interpolate all the other products to the same coarser spatial resolution using a bilinear
204 interpolation method. In summary, the categorical statistics indicated the number of hits (true
205 positive), false alarms (false positive), misses (false negative), and true negatives to describe
206 the rainfall products' correspondence with GPCC. Further, utilizing the ESA Land Cover 100m

product (Buchhorn et al. 2020) resampled to the lower-resolution SEVIRI grid, we conducted a decomposition of the MSG-SEVIRI NDVI series by soil type. This allowed us to gain a deeper understanding of the heterogeneous responses of different soil types to precipitation.

4. Results

4.1. Alternative precipitation products

MSWEP, followed by ERA5, shows the highest accuracy and POD in detecting rain events, with the lowest RMSE. However, compared to MSWEP, ERA5 shows the highest false alarm rate in the study. IMERG ranks third in accuracy, which aligns with its lower POD and FAR compared to MSWEP and ERA5. We observed how the TAMSAT and CHIRPS products are more cautious in detecting rain events, which is well described by the lower FAR and POD metrics. For the CHIRPS product, we observed the highest RMSE and the smallest POD among the analyzed precipitation series. For TAMSAT, the relatively higher accuracy is related to a better probability of detecting rainfall events. Hence, we perform our analyses with the MSWEP precipitation product.

Product	Accuracy	FAR	POD	RMSE (mm/day)
MSWEP	80.34%	13.65%	57.72%	0.324
TAMSAT	78.97%	9.99%	41.69%	0.328
ERA5	79.59%	14.78%	57.62%	0.331
CHIRPS	77.87%	9.61%	37.5%	0.343
IMERG	79.09%	11.04%	46.83%	0.335

Table 1: Performance comparison of different precipitation products for events in years 2005–2020.

4.2. Vegetation and precipitation anomalies

4.2.1. Short-term rainfall events

From Table 2 it is possible to see that the SPI derived from MSWEP calculated at various short-term accumulations shows a positive correlation with vegetation condition. We selected the accumulation that exhibited the strongest correlation with the Normalized Difference Vegetation Index (NDVI). Based on the results in Table 2, the SPI-90 which is the accumulation that on

average showed the highest correlation with vegetation (about 33% correlation) whereas the 30-day accumulation was the least correlated with vegetation status. Given this result, we decided to restrict our analysis to SPI accumulations of at least 60 days. We depicted in Figure 1b the spatial variability of the correlation between the two indices and detected some interesting features. Interestingly, we do not find any significant correlation for the areas in northern Ethiopia, whereas the areas with the highest correlation are concentrated over the semi-arid areas in north Kenya and Somalia and the coastal areas in the South. Figure 1c summarizes the behavior of the median of the SPI-90 and NDVI for the chosen period, with the three gray shaded areas indicating respectively the long, mid (wet season for northern Ethiopia), and short rainy seasons in the HoA. From this chart, we observed how considerable positive anomalies in rainfall in 2006 or 2019 correlate with strong vegetation vigor in the main harvest season (e.g. October-December), whereas rainfall deficits in 2008, 2009, 2012, or 2016 correspond with notable vegetation stress. The most severe agricultural drought in our sample happens in correspondence with the 2010 harvest season (October-November). In Figure 2 we used the box plot (reporting both the mean value and the Inter Quartile Range –IQR) to summarize the daily rain rates, SPI values, and NDVI measurements for the whole area (i.e. Somalia, Kenya, Ethiopia, Djibouti) between 2009 and 2010. Upon examining the vegetation and precipitation indices during the antecedent year, we found contrasting patterns between the end of 2009 and the beginning of 2010. During the 2009 short rainy season, a 20-day precipitation deficit (03-24 November) in correspondence with the green-up phase of a considerable number of crops was anticipated and followed by strong precipitation events (days with IQR well outside the climatology IQR). The lack of rain at an important phase of the rainy season led to a harvest season (October-November) with vegetation vigor below the climatology. Additionally, it is important to add that the October intense rains generated a partial recovery in the vegetation status after a significant drought year for the HoA area. Before the intense rainfalls of October, the daily SPI median value was around or below -1 (corresponding to mild meteorological drought) also indicating a situation of meteorological drought. Notably, the alternation of precipitation events of opposite directions within a few days generated an overall positive value in the SPI-90 median between the end of 2009 and throughout 2010 (see Figure 2b where the average SPI-90 for the area is depicted) which did not suggest a condition of water stress. However, given the intense short-term rainfalls in October, the SPI-90 median in the short rain season was relatively high (around 1 with a short minimum of around

258 -0.4), despite the 20-day precipitation deficit. This caused the SPI-90 median to only briefly
 259 reach a negative peak of 0.4 negative deviations from the median by the end of 2009, which
 260 indicated a near-normal situation even though it subsequently stabilized around positive values.
 261 Subsequently, with new anomalous rains in the February-March period just before the long rainy
 262 season, the SPI median jumped up to positive values in February 2010 and this positive trend
 263 continued until the end of the rainy season (i.e. May 2010).

Accumulation (days)	Correlation ERA5	Correlation MSWEP
30	20.04%	22.30%
60	27.52%	30.10%
90	29.72%	32.97%
180	28.77%	31.80%

Table 2: Correlation between precipitation (SPI) and vegetation (NDVI) indices at different accumulation times.

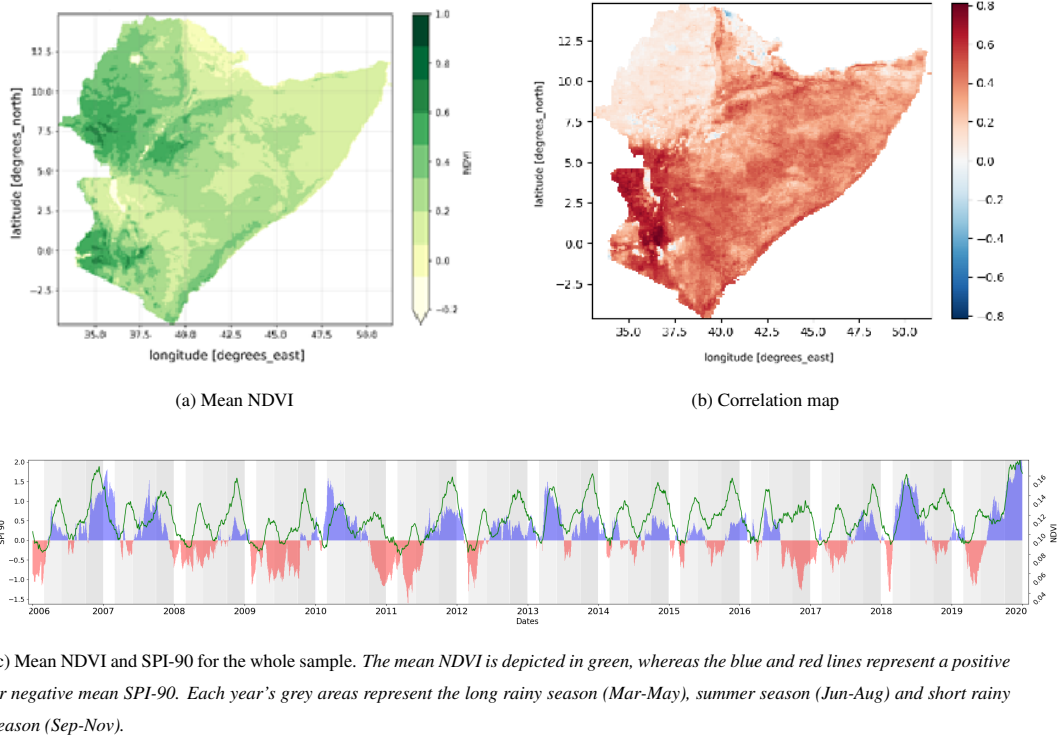
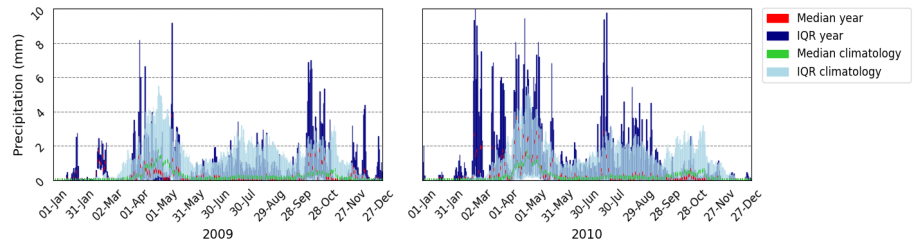
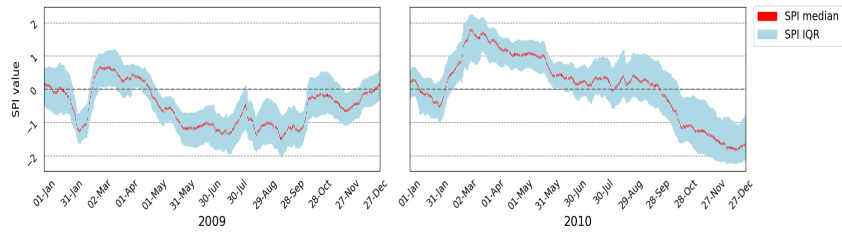


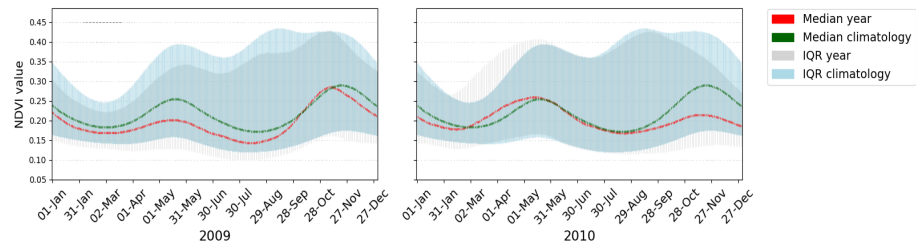
Figure 1: Top: (a) Mean NDVI derived from MSG SEVIRI daily dataset and (b) average spatial correlation between SPI-90 and NDVI for the Horn of Africa. Bottom: (c) Temporal evolution of NDVI and SPI-90 over the study period.



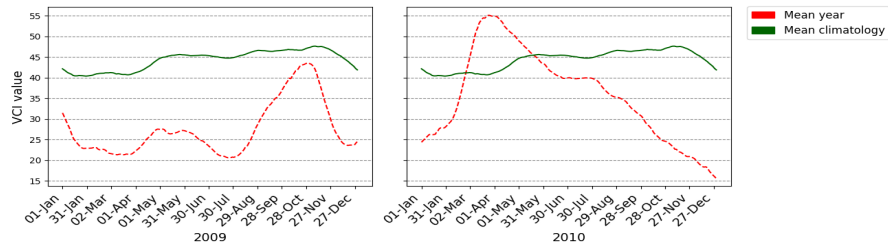
(a) Precipitation



(b) Standard Precipitation Index (SPI-90)



(c) Normalized Difference Vegetation Index



(d) Vegetation Condition Index

Figure 2: Box plots of precipitation, Standard Precipitation Index (SPI), vegetation (NDVI) and mean vegetation anomaly (VCI) for the years 2009-2010.

264 4.2.2. *Out-of-season precipitation anomalies*

265 Further, the analysis of the precipitation series at finer temporal resolution shows how the
266 SPI index tends to be exposed to anomalous fluctuations in precipitation regimes outside wet
267 seasons. For instance, anomalous rain events during the dry period make the precipitation index
268 easily converge to positive values, but these isolated rains have a small impact on the dormant
269 vegetation and, therefore, are likely not related to vegetative growth. As depicted in Figure
270 3a, a dry-wet pattern can be observed between the end of 2008, a year characterized by a mild
271 drought event during the long rainy season, and the beginning of 2009. Following substantial
272 precipitation events that marked the onset of the short rainy season in 2008, below-climatology
273 rainfalls for two months occurred in the middle of the harvest season. This was only signaled by
274 the SPI-90 at the end of January 2009 (see Figure 2b). However, a moderate agricultural drought
275 was already depicted in the vegetation indices between the end of 2008 and the first week of
276 January 2009 (Figures 3d, 2d). In this case, the water stress in the middle of the short rainy
277 season corresponds with a substantial decrease in vegetation greenness. On the other hand, we
278 only observed a drop in the SPI index after about 1-2 months. Another clear example of this
279 behavior is shown in Figures 3a and 3b, where some isolated rains in the first week of January
280 2008 make the SPI index easily reconverge to a median of 0, whereas the NDVI and VCI indices
281 still clearly depict below-average vegetation vigor due to a considerable shortage in precipitation
282 in the previous rainy season.

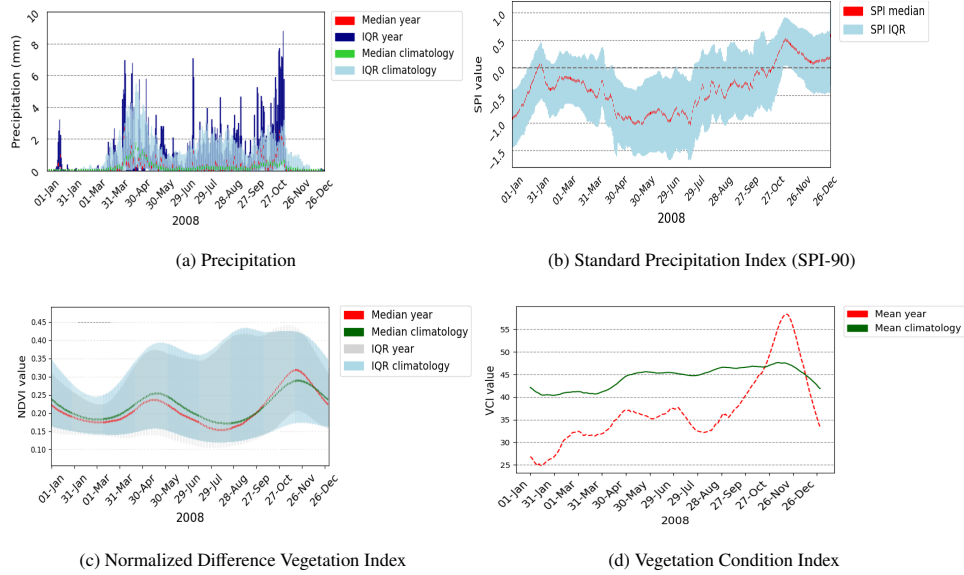
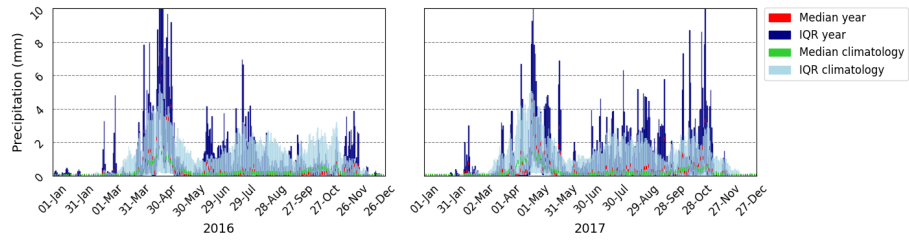


Figure 3: Box plot of precipitation, precipitation anomalies (SPI), vegetation (NDVI) and mean vegetation anomaly (VCI) for the year 2008.

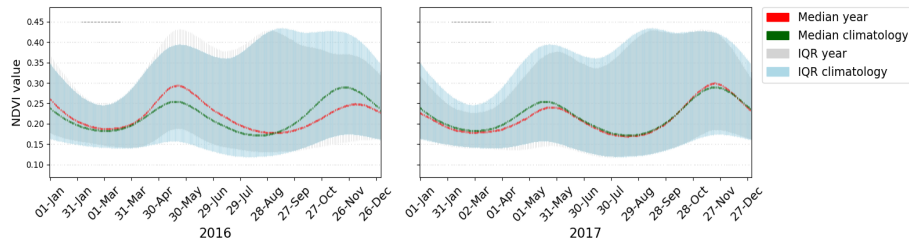
4.2.3. Selecting the proper time accumulation

We also tested the sensitivity of SPI indices at different accumulations in real settings. Towards the end of 2016, as depicted in the charts of the NDVI and VCI series (Figure 4b, 4c), we observed a severe agricultural drought during the harvest season (October-November) following three and a half years of successful precipitations and positive vegetative growth (see Figure 1c). As depicted in Figure 5, the SPI-60 and SPI-90 consistently deviate from the zero median, indicating a significant meteorological drought from the beginning of August 2016. Conversely, the SPI-180 accounts for this variation only at the beginning of October 2016, with the series median suddenly plunging to two negative deviations, indicating a severe drought by the end of the month. In the following year (2017), after a long rainy season with below-climatology rainfall, some intense precipitation events before and during the short rainy season led to the recovery of the SPI-60 index, as evident from the positive values for the SPI interquartile range and median. However, despite the positive trend on the precipitation series, the VCI median (see Figure 4c) exhibited a significant negative trend and the NDVI values remained below climatology, indicating a mild agricultural drought (i.e. mean VCI reaching the minimum of 35 at the end of January 2017). As opposed to the index at 60-day accumulation, the SPI-90 and SPI-180 depict

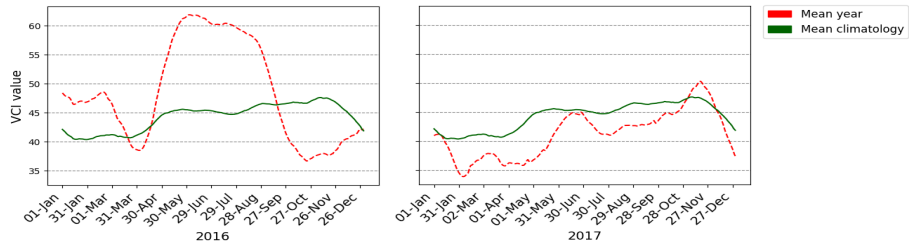
299 a moderately dry situation, with negative values for the median and 25th percentile, which align
300 better with the vegetation stress situation depicted in the VCI median. In this case, the SPI-180
301 effectively captures the information regarding the meteorological drought over the preceding six
302 months, making it less sensitive to intense short-term precipitation events. These two events
303 demonstrate the trade-off associated with using the index at larger time accumulations, balanc-
304 ing robustness to wet-dry occurrences with timeliness in responding to short-term precipitation
305 events. In general, the SPI-180 requires more time to detect a meteorological drought and to
306 revert to a normal hydrological state following the equilibrating effects of precipitation events.
307 Consequently, as expected, utilizing the index at longer accumulation is effective in detecting
308 longer-duration drought events but it is less likely to promptly detect short-term precipitation
309 deficits that could still have an impact on vegetation.



(a) Precipitation



(b) Normalized Difference Vegetation Index



(c) Vegetation Condition Index

Figure 4: Box plots of rain rate (mm/day) and of vegetation (NDVI) and mean vegetation anomaly (VCI) for the years 2016-2017.

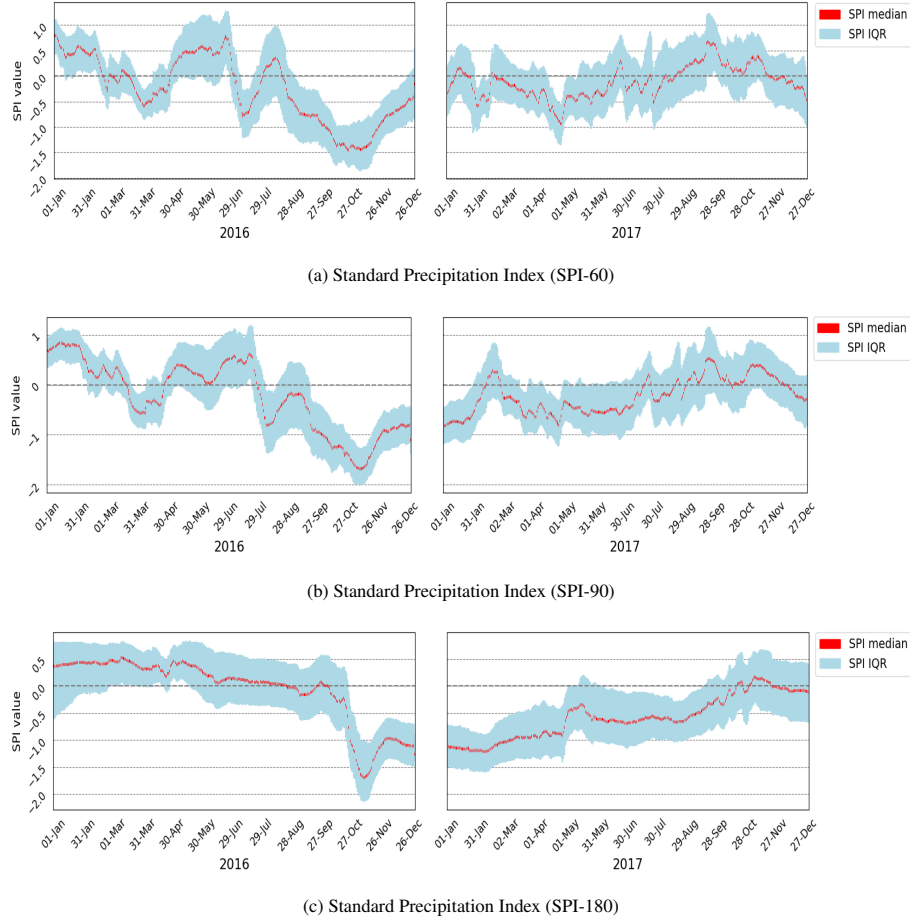


Figure 5: Box plot of SPI-60, SPI-90 and SPI-180 for the years 2016-2017.

4.3. Vegetation heterogeneous response to precipitation

As we established the severity of the 2010 agricultural drought, we decided to further decompose the NDVI series for this period of interest by soil variety to see the potential heterogeneous dynamics of vegetation response to water stress. Looking at the climatology by vegetation type, we can analyze the phenology of each soil type. Cropland, forest, and herbaceous wetlands exhibit a linear growth cycle with the highest green peak around October (See Figure 6f, 6e, 6d). Shrublands instead, which constitute the most dominant surface soil type for the analyzed area, present two growing seasons with a green peak at the end of each rainy season (Figure 6b). A similar pattern can be observed for herbaceous vegetation (Figure 6c). Instead, sparse vegetation presents less significant vegetation growth cycles, with a decrease in greenness in correspondence

320 with the summer (Figure 6a).

321 Upon examining Figure 6 it is evident how certain vegetation types displayed better resilience
322 to the 20-day rainfall deficit in the short rainy season compared to the early 2009 drought, while
323 others suffered both events. By observing the box plots representing the vegetation series (see
324 Figures 6a, b, c, d, e, f) and the precipitation in the long rainy season of 2009 (see Figures
325 6g, h, i, j, k, l), it is apparent that the second event had a more substantial impact on the soil
326 types that present a bi-model vegetation growth cycle. For instance, the shrublands and the
327 herbaceous vegetation types were particularly impacted by this fast event, which happened during
328 their second green-up phase, as shown by the climatology box plot (see Figures 6b, c). Therefore,
329 even if their vegetation was temporarily restored to climatology levels for one week at the end
330 of October after the short-term anomalous rainfalls (see Figures 6h, i), they were considerably
331 impacted by the short dry event. Also the sparse vegetation soil type was majorly impacted by
332 the event with rain rates considerably lower than the climatology levels (see Figures 6a-g).

333 On the contrary, looking at the rain rates for the forest and cropland soil types we can observe
334 that the meteorological drought event during the short rainy season lasted for about one week
335 (shown by the box plot with IQR close to 0 for the 75th percentile in early November - see
336 Figure 6k - l), and was followed by a few days with significantly high rains. In addition, for
337 these soil types the second dry event follows a short rainy season onset with regular rains. As
338 a consequence, the vegetation of these soil types seemed to suffer less the rainfall deficit (see
339 Figure 6e-f) in the short rainy season. On the contrary, for these two soil types the long rainy
340 season dry event had a major effect, as shown in the vegetation box plots. The strong impact of
341 the meteorological drought is confirmed in the SPI-90 box plot for cropland (Figure 7), with an
342 extreme meteorological drought signaled at the end of the short rainy season of 2009. On the
343 other hand, an overall good long rainy season for the croplands made the vegetation recover to
344 normal levels at the end of the year (see Figure 6f-l).

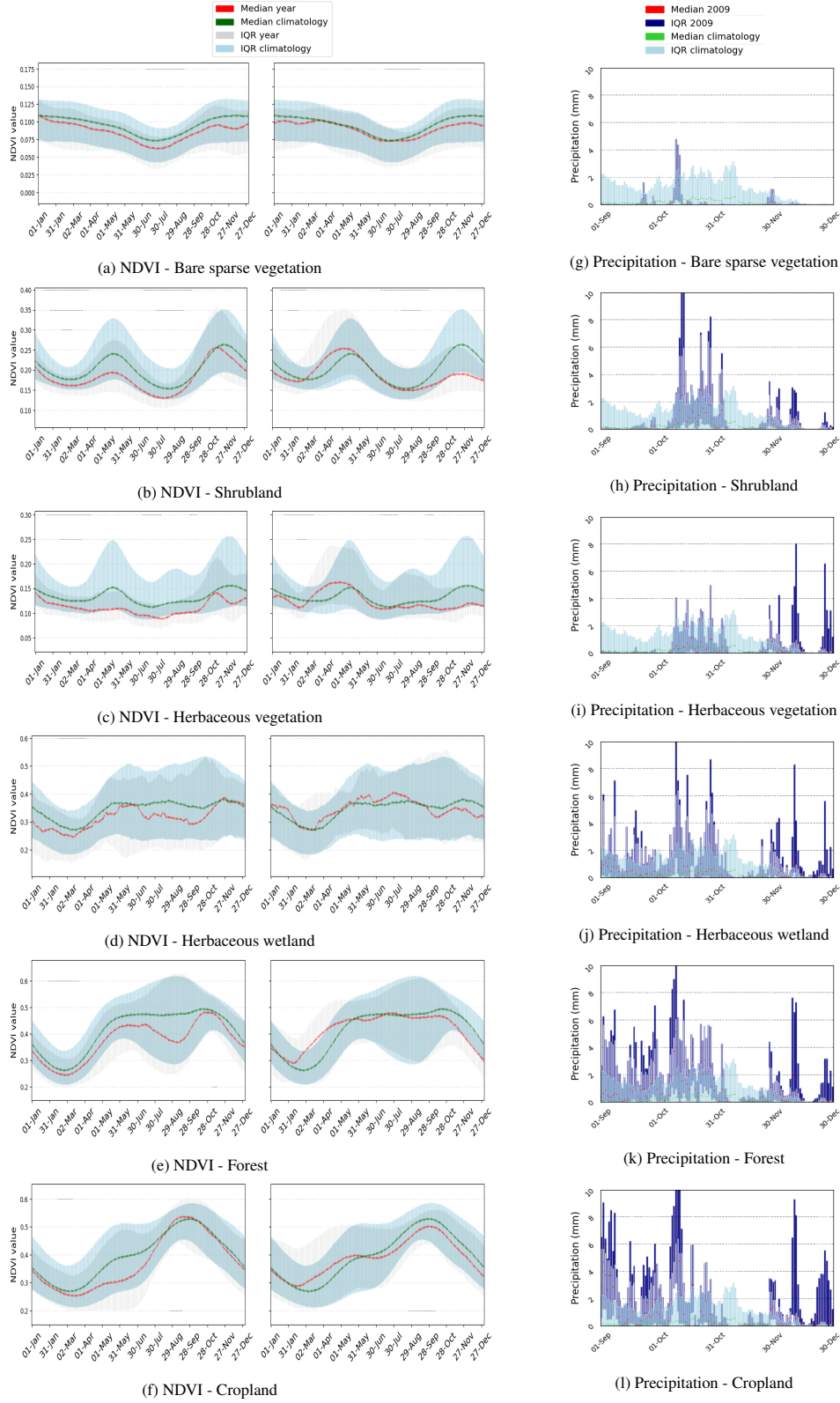


Figure 6: NDVI and precipitation for different land cover classes. NDVI boxplots for 2009-2010 (left column) and precipitation for the short rainy season in 2009 (right column) are shown for: Bare sparse vegetation, Shrubland, Herbaceous vegetation, Herbaceous wetland, Forest, and Cropland.



Figure 7: SPI-90 for Cropland vegetation type during years 2009-2010

4.4. Analysis with precipitation products

To qualitatively assess the importance of selecting different precipitation products in our study, we substituted the MSWEP series with other types of products, including rain-gauge and satellite products, and analyzed their ability to describe the 2009-2010 drought events. Looking at Figure 8, the similarity between the rainfall patterns in the IMERG, MSWEP, and ERA5 products is evident, with MSWEP and IMERG displaying slightly more intense rain rates during strong wet events compared to ERA5. Both the summer 2009 decrease in rain rate and the November 2009 dry event are still visible in the two products. Also using the GPCC products provides a clear picture of the dry event, even though the product presents more isolated rain events throughout the year compared to the IMERG, ERA5, and MSWEP products. Further, the GPCC product exhibits a wet bias compared to all the other products in the case of extreme rainfall events, which is seen in the behavior of the 75th percentile for the days with intense rain rates. The picture is completely different when we use the CHIRPS or TAMSAT products, which present a dry bias compared to the other precipitation series analyzed in this work. If some deficits in rain rate for the climatology can be observed in September, no significant difference from the climatology is seen at the final stages of the short rainy season of 2009. On the contrary, a clear abundance of precipitation for the climatology is observed for the short rainy season of 2009 and in the long rainy season of 2010. The dry bias of these two products is clearly shown in the box plots. As a matter of fact, for a considerable number of days during the long rainy season the rain rate mean climatology and its IQR are very close to 0. Despite the considerable differences in raw precipitation. When describing the same event using the SPI index constructed with the other products the differences are negligible and we would always conclude for the absence of a meteorological drought condition during the short rainy season in 2009.

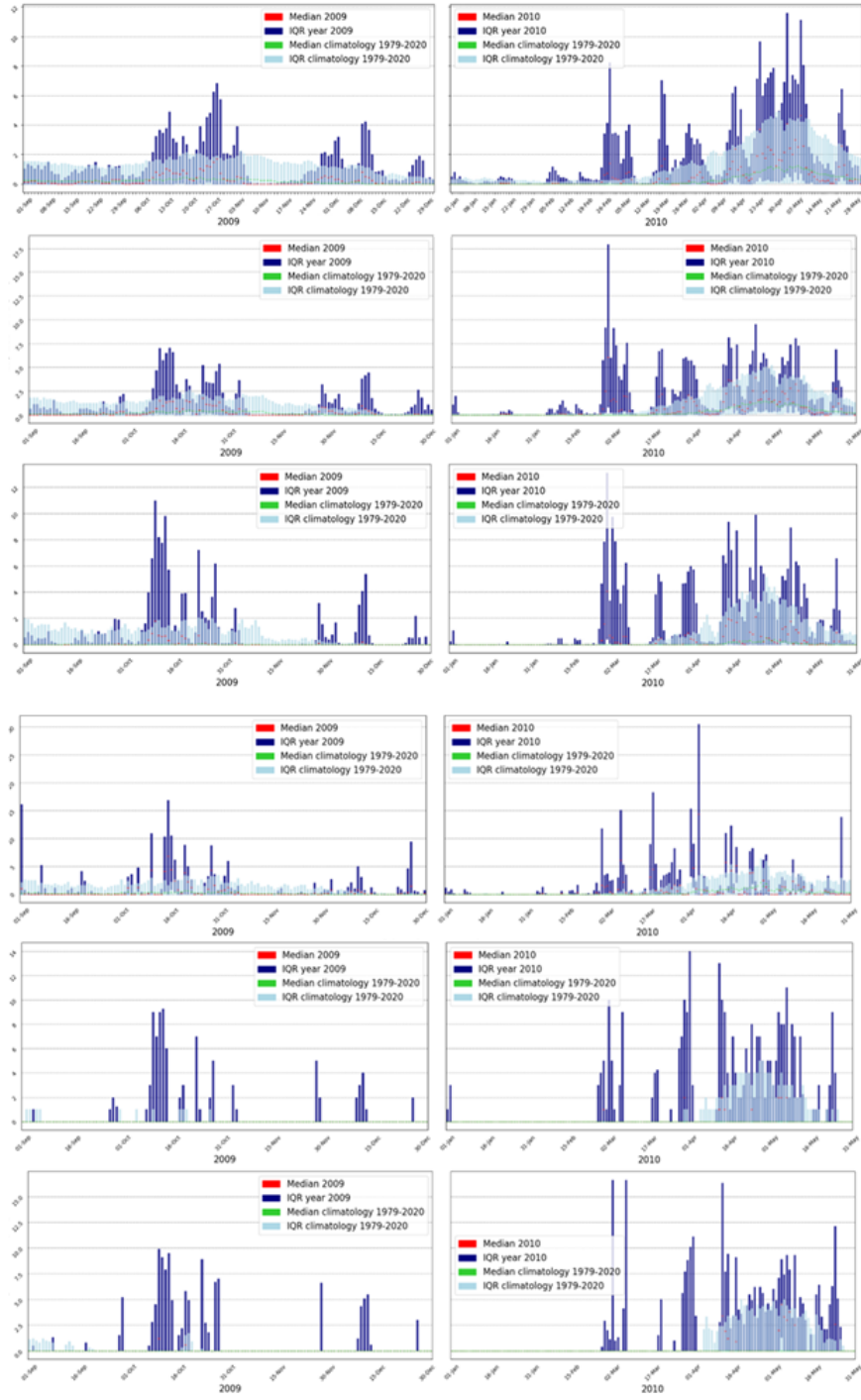


Figure 8: Raw precipitation boxplot for a) ERA5, b) MSWEP, c) IMERG, d) GPCC, e) CHIRPS, f) TAMSAT

5. Discussion

5.1. Alternative precipitation products

The application of daily global precipitation products to monitor the effect of precipitation on vegetation stress has so far been limited in the Horn of Africa. In our study, the usage of daily temporal resolution enabled the identification of sub-monthly precipitation events that cannot be detected with monthly temporal resolution and that can be of a strong indicator of future vegetation stress. Monitoring drought events at an improved temporal scale is important because dry events can develop rapidly when persistent atmospheric anomalies last for more weeks (Otkin et al. 2013). Extended periods of low precipitation, elevated surface temperatures, strong winds, and clear skies can lead to a rapid decline in vegetation health (Otkin et al. 2013), enhancing evapotranspiration and resulting in a swift depletion of root zone soil moisture (Mozny et al. 2012). Moreover, even short episodes of water stress during critical crop growth stages can severely impact crop development (Otkin et al. 2013); this is particularly relevant in parts of Southern and Eastern Africa, where precipitation largely determines leaf phenology (Buitenwerf, Rose, and Higgins 2015; Rishmawi, Prince, and Xue 2016). We have shown that using MSWEP or ERA5 precipitation datasets can provide an improved capability to detect precipitation events (1 mm of rain or higher) with respect to the GPCC baseline. Our findings align well with previous research in the area. The great skill of the MSWEP product is shown by a POD of 57.72% and the lowest RMSE in our sample (0.324 mm/day). The global study by Mekonnen et al. (2023) identifies the product as the best one for the monitoring precipitation at daily temporal resolution in the African continent. On the other hand, we found that CHIRPS data at daily temporal resolution are the least accurate, which is especially shown in a considerably inferior POD (37.75%) and the highest RMSE (0.343 mm/day). Dinku, Funk, et al. (2018), validating satellite products with rain gauges in the HoA demonstrate that CHIRPS performs better than regional satellite products (ARC2, TAMSAT) at a monthly scale, but at a daily scale its performance is relatively poorer. Belay et al. (2019) demonstrate in the Beles Basin of Ethiopia it underestimates the occurrence of rainfall compared to rain gauges, with a larger bias for lowlands compared to highlands. Mekonnen et al. (2023) argue that the CHIRPS product at daily temporal resolution shows a dry bias in many African regions and therefore suggest it for drought applications. In our qualitative experiment we showed that adopting the CHIRPS product would provide a completely different picture than the other products (MSWEP, ERA5, IMERG), with the box plot for the entire HoA

area consistently showing a mean and 25th percentile of 0 rain rate outside wet seasons whereas overestimating days with intense precipitation events. Belay et al. (2019) attribute possible reasons for the tendency of CHIRPS on a daily scale to underestimate rainfall to mismatches in satellite and rain gauge products, and especially to the CHIRPS algorithm to retrieve daily data from pentadal rainfall or the shallow convection in the case of a warm cloud-top temperature. Additionally, they argue that the last issue causes the CHIRPS algorithm to fail whenever the cloud top temperature is lower than thermal infrared thresholds. Overall, we remark the previous findings of global validation studies in the African continent and reiterate that the suitable precipitation product needs to be carefully selected for different areas and applications (Le Coz and Van De Giesen 2020; Mekonnen et al. 2023).

5.2. *Dry-wet events*

We found that according to our NDVI index derived from a geostationary satellite, the 2010 vegetative drought event was the most severe in the 2005-2020 period. Examining the relationship between vegetation and precipitation, we established how the Standard Precipitation Index (SPI) calculated from MSWEP at various short-term accumulations can provide an important signal of potential changes in vegetation condition Henricksen and Durkin (1986), Tucker and Choudhury (1987), Tucker (1989), Gutman (1990), Dutta, Kundu, and Patel (2013), and Barbosa et al. (2019). Hydrologists concur that one of the major limitations of the SPI index is the requirement to specify a time frame for accumulating precipitation. We investigate the sensitivity of SPI at different daily accumulations (e.g. 30, 60, 90, and 180 days) to model dry or wet events and to anticipate changes in vegetation status. Our results align with the findings of Ji and Peters (2003) and Dutta, Kundu, and Patel (2013), who concluded that shorter SPI monthly accumulations (1 month using monthly temporal resolution) are the least correlated with vegetation, as opposed to the SPI-90 (3 months). Previous research has shown that shorter SPI accumulations (1-2 months) effectively represent soil moisture content (Ji and Peters 2003), 3-4 months accumulations better represent seasonal patterns, whereas longer accumulations (12-24 months) correlate with hydrological long-term cycles or inter-year teleconnection patterns such as El Nino cycles (Penalba and Rivera 2016). This motivated the recent development of alternative drought indices (e.g. Standardized weighted average precipitation - SWAP, Standardized Antecedent Precipitation Evapotranspiration Index - SAPEI) (Lu 2009; Li et al. 2020) that do not restrict the analysis to a specific time interval and better represent the physical interpreta-

tion of precipitation. Alternative avenues might involve the usage of Machine Learning models that are able to model the non-linear effects of precipitation on vegetation (Kraft et al., 2019). Moreover, our findings indicate that the SPI index can be highly sensitive to the alternation of quick wet-dry events. On the other hand, choosing the right time accumulation of SPI can be crucial to promptly anticipate vegetation changes. Overall, longer precipitation accumulations demonstrating better robustness to dry-wet alternation events at the cost of a decreased reaction time.

5.3. *Heterogeneous effect on soil type*

We decomposed the effects of the 2009–2010 drought by soil type to assess the heterogeneous responses of vegetation to water stress. This analysis is crucial, as a decline in cropland NDVI greenness serves as a key indicator of food security. For instance, previous studies (Brown and Beurs 2008) have shown a positive correlation between NDVI and crop yields. The decomposition by soil type revealed variations in vegetation resilience and coping mechanisms during the agricultural drought. Our analysis indicated that the water deficit during the 2009 long rainy season had a more pronounced negative impact on crop growth. In contrast, the precipitation deficit during the 2009 short rainy season primarily affected soil categories not typically associated with crop cultivation. According to the U.S. Department of Agriculture Foreign Agricultural Service, the first event coincides with the harvest season for approximately 60% of Somalia’s and 20% of Kenya’s sorghum, as well as a significant share of both countries’ corn. This likely resulted in a failed harvest season for these crops. Additionally, this period overlapped with the planting phase for a substantial portion of Kenyan croplands (April–May) and later Ethiopian croplands (May–July), potentially impairing vegetation growth at a crucial stage in their cycle. The finding that forested areas exhibited greater resilience to short-term precipitation deficits, with vegetation quickly recovering to climatological levels by early 2010, is unsurprising given that they exhibit growth patterns that are less sensitive to short-term anomalies in precipitation. Instead, for herbaceous vegetation, sparse vegetation, and shrublands, the November precipitation deficit coincided with the second green-up phase, significantly affecting these soil types. Unlike forests, these vegetation types rely more heavily on surface soil moisture and exhibit stronger seasonal dependencies in their growth cycles. As a result, even short-term precipitation anomalies can disrupt their phenological development, leading to delayed or reduced vegetation greening (Vicente-Serrano et al., 2013). These areas are generally not associated with crop cultivation but can serve

461 as pastoral rangelands and grasslands. As a result, the precipitation shortage during the long rainy
462 season potentially had a more profound impact on livestock-dependent communities. The degra-
463 dation of these rangelands due to drought implies reduced forage availability can potentially lead
464 to livestock increased mortality rates. Such adverse effects can further exacerbate food insecurity
465 and economic hardship, particularly for pastoralist groups whose livelihoods are intricately tied
466 to the health of their grazing ecosystems (Barrett et al. 2020). Previous studies highlighted the
467 hardship of the 2008-2010 drought event and its role in causing food security emergencies and
468 wider socio-economic disruptions. Muller (2014) concluded that the event affected roughly 13
469 million people. Particularly, the 2010-2011 drought event had a devastating impact on Somalia,
470 resulting in 250,000 estimated fatalities (Hillbruner and Moloney 2012; Lyon and Vigaud 2017).

471 **6. Conclusion**

472 In this paper, we examined the progression of meteorological droughts into agricultural
473 droughts in the Horn of Africa at an improved temporal resolution for the period 2005–2020.
474 Using images from the geostationary satellite MSG SEVIRI, we constructed a novel vegeta-
475 tion time series and employed different precipitation products to analyze changes in vegetation
476 health. Our findings demonstrate the importance of monitoring drought phenomena at improved
477 temporal resolution. We demonstrate that certain daily precipitation products, which have yet
478 to be widely adopted for studying the HoA, offer improved accuracy and a higher probability of
479 detecting rainfall events—albeit at the cost of an increased false alarm ratio. Furthermore, our
480 comparison of precipitation datasets revealed substantial discrepancies in raw precipitation esti-
481 mates. TAMSAT and CHIRPS exhibited an underestimation of rainfall events relative to other
482 products, as confirmed by validation statistics. In most cases, the Standardized Precipitation
483 Index at different short-term accumulations (30 to 180 days) effectively anticipated changes in
484 vegetation status. Given its strong correlation with vegetation indices, we selected the 90-day
485 SPI accumulation to represent the region’s hydrological conditions. However, qualitative as-
486 sessments of the index behavior during key rainfall events indicated performance degradation
487 when wet and dry events alternated abruptly or when anomalous events occurred outside wet
488 or dry seasons. Additionally, we explored the impact of SPI accumulation periods, finding that
489 longer accumulation windows provided greater robustness to wet-dry fluctuations but introduced
490 a trade-off between precision and timeliness in detecting drought events. Through a detailed

491 analysis of drought events, we assessed their effects across different soil types. Our results indi-
492 cate that cropland and forest soils exhibited greater resilience to water stress compared to other
493 soil types. However, the response to drought varied depending on the severity of rainfall deficits
494 in the short or long rainy seasons characteristic of each soil type. In summary, the use of daily
495 temporal resolution allowed us to identify drought events at a sub-monthly scale—an advan-
496 tage over coarser temporal resolutions, such as monthly data, which may not reveal shorter-term
497 events that can have lasting impacts on vegetation.

498 **CRedit authorship contribution statement**

499 Riccardo D’Ercole: Writing – original draft, Visualization, Software, Methodology, Investiga-
500 tion, Formal analysis, Data curation. Daniele Casella: Writing – review & editing, Supervision,
501 Methodology. Paolo Sanò: Writing – review & editing, Supervision, Resources, Conceptualiza-
502 tion.

503 **Data Availability**

504 The NDVI dataset can be downloaded from the Zenodo public repository [https://doi.org/](https://doi.org/10.5281/zenodo.14001095)
505 10.5281/zenodo.14001095.

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1 Deep Learning models for short-term Drought Prediction in the 2 Horn of Africa

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4 Abstract

This study evaluates a series of Deep Learning (DL) architectures tailored to spatio-temporal data for the task of short-term agricultural drought forecasting. Leveraging a daily NDVI dataset derived from MSG SEVIRI, in combination with meteorological and soil moisture data, we constructed a data cube to predict vegetation status across the Horn of Africa region. We evaluated multiple DL models and found that a probabilistic diffusion model outperformed deterministic counterparts (e.g., ConvLSTM, WaveNet), especially under extreme drought conditions. The diffusion model effectively captures the stochastic nature of vegetation dynamics. Our findings highlight that while recurrent models perform well under normal conditions and short lead times, they tend to smooth out extreme values or fail during unprecedented drought events. Additionally, it is evident that our probabilistic approach based on a diffusion process, which reduces the dimensionality of the NDVI time series via a custom autoencoder, offers improved predictive accuracy and computational efficiency. The integration of prior vegetation history with meteorological predictors was shown to enhance forecast reliability at all lead times.

5 **Keywords:** Machine learning, drought prediction, NDVI, agricultural drought, Diffusion model,
6 Graph Neural Networks, Variational Autoencoder

7 1. Introduction

8 To reduce the devastating impact of droughts and enable a rapid humanitarian response, in-
9 tegrating advances in next-generation remote sensing products and Artificial Intelligence into

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existing Early Warning Systems can be highly beneficial, especially in regions where ground-based data is sparse. Furthermore, monitoring environmental hazards at a sub-monthly temporal resolution can enable the early detection of sudden extreme events that may be difficult to anticipate with coarse temporal resolution data. In the context of droughts, few researchers have explored the potential of high-temporal-resolution instruments, as the benefits of frequent monitoring are less immediately evident compared to other weather phenomena such as floods or wildfires. On the other hand, drought prediction on short-term scales remains challenging due to the complexity of understanding hydrological processes (Park et al. 2020). As a result, short-term forecasts are less refined and accurate than seasonal ones (Park et al. 2020). Improving the temporal resolution of drought monitoring could help policymakers anticipate crises, allocate resources efficiently, issue timely warnings, and ultimately save lives (Fensholt, Anyamba, et al. 2011; West, Quinn, and Horswell 2019; Barrett et al. 2020; Salakpi et al. 2022; WMO et al. 2023).

Previous studies have demonstrated that high-frequency data can be valuable for a wide range of mesoscale earth system applications, including drought finance and insurance (Jensen et al. 2019), monitoring of vegetation phenology (García-Haro et al. 2019; Lu et al. 2024), monitoring of regional and national crops (Fritz et al. 2019; Hu et al. 2020), food security prediction (Foini et al. 2023), and regional hydrological modeling (Bhattacharya et al. 2010). A recent technical report by the WMO highlights the potential of geostationary satellites for nowcasting applications in the African continent, especially given its vulnerability to rapidly changing weather, exacerbated by climate change (WMO et al. 2023).

Deep Learning (DL) models can play an important role in leveraging the dense information content of high-frequency data. Thanks to recent technological innovations, researchers have increasingly focused on the exploitation of higher spatial or temporal resolution data for Earth surface forecasting. Early studies in the Horn of Africa have demonstrated the validity of ML approaches in predicting regional-level drought events in Kenya (Adede et al. 2019; Lees et al. 2022; Salakpi et al. 2022), leveraging the Vegetation Condition Index (VCI) used by the Kenyan National Drought Management Authority (NDMA) to monitor agricultural drought events (Barrett et al. 2020; Lees et al. 2022; Salakpi et al. 2022). Adede et al. (2019) used monthly lagged values of vegetation and precipitation data to predict future vegetation anomalies in four Kenyan counties using an Artificial Neural Network approach. Barrett et al. (2020) presented a pipeline

41 to predict the 3-months average of the Vegetation Condition Index (VCI3M) over pastoral liveli-
 42 hood zones in the country. If on the one hand in their work they used daily MODIS and 16-day
 43 Landsat data, they subsequently employed compositing techniques for the former dataset and
 44 brought the data to weekly temporal resolution (7 days). Moreover, the authors framed the prob-
 45 lem as a time-series regression, predicting future observations of the index based on the previous
 46 observations. A major drawback of their work is the usage of a random subset of pixels per
 47 region and the computation of a regional-level mean of the VCI. Building on top of this work,
 48 Salakpi et al. (2022) used weekly composites of vegetation status from a daily MODIS product,
 49 of daily ESA-CCI Soil Moisture and CHIRPS daily precipitation to predict the VCI3M with a
 50 Bayesian auto-regressive distributed lag (BARDL) approach. Even though they still focused on
 51 regional-level prediction (counties), they achieved a considerable improvement in the forecast-
 52 ing range by approximately two weeks compared to the previous work (Salakpi et al. 2022). The
 53 authors also demonstrated the relative importance of precipitation and soil moisture anomalies
 54 in their predictions at different ranges. The parallel work by Lees et al. (2022) used an improved
 55 output spatial resolution at the cost of the output temporal resolution, as the authors resampled
 56 daily data to monthly. They customized a Long Short Term Memory (LSTM) DL model for the
 57 task, an ideal choice given its recurrent structure, and used the previous three months of the VCI
 58 to predict the index in the next step. Compared to the previous literature, where scholars trained
 59 Machine Learning models at either coarse temporal or spatial resolution (Barrett et al. 2020; Lees
 60 et al. 2022), the work by Park et al. (2020) was one of the first efforts to exploit Deep Learning
 61 models (a ConvLSTM architecture) to predict drought incidence at short-term scale with the aid
 62 of high temporal resolution data. A recent work by Requena-Mesa et al. (2021) published the
 63 EarthNet2021 dataset, which uses daily meteorological weather outputs or static variables (e.g.
 64 Digital Elevation Model - DEM) to predict fine-scale (20 m) vegetation conditions every 5 days
 65 in the European region. This work enabled other researchers to test the performance of spatio-
 66 temporal Deep Learning applications to the task, exploiting deterministic-type models like the
 67 ConvLSTM (Benson et al. 2024) or probabilistic ones like diffusion models (Zhao et al. 2024).
 68 However, as the dataset used the output of a numerical weather model which is only available
 69 for Europe (E-OBS), it was not possible to train models with global validity. A subsequent work
 70 from Robin et al. (2022) extended the dataset for the African continent, using the global ERA5
 71 reanalysis dataset as meteorological input, although at an output temporal resolution of 10 days.

The very recent work by Ji et al. (2025) published a 5-days temporal resolution dataset to globally monitor compound drought and heat events at mesoscale (2.5 km).

If on the one hand the efforts of monitoring droughts at finer spatial resolution are an important step towards the understanding of the phenomenon, on the other hand there remains unexploited potential in the utilization of high temporal resolution instruments. As most of these applications exploited Low Orbit Satellites (LEO) instruments that in general offer higher spatial resolution at the cost of lower temporal revisits, drought monitoring rarely exploited daily or sub-daily temporal resolution (Fensholt, Anyamba, et al. 2011; Miura et al. 2019) data. On the other hand, previous research (Fensholt, Sandholt, et al. 2006; Fensholt, Anyamba, et al. 2011) has demonstrated the benefits of generating high temporal resolution vegetation series due to their ability to offset the effect of cloud cover (Fensholt, Sandholt, et al. 2006; Fensholt, Anyamba, et al. 2011) or to produce more consistent vegetation series due to constant viewing angles. As a consequence, this allows better describing short-term variations in phenology (García-Haro et al. 2019; Lu et al. 2024), and, in turn, an improved detection of drought phenomena (Fensholt, Anyamba, et al. 2011). To demonstrate the validity of enhanced temporal resolution datasets in the task of Earth surface prediction, we used a vegetation status dataset derived from geostationary satellite (D’Ercole et al. 2024) and combined it with features derived from ERA5. The contributions of our work are multiple. We derived a coarse spatial but high temporal resolution Earth surface prediction dataset for the Horn of Africa (Ethiopia, Somalia, Kenya, Djibouti), which is more robust to cloud cover contamination. We tested the ability of data-driven methods to predict vegetative status and evaluated the performance of the recent Deep Learning architectures at different steps in the future. We used innovative architectures based on a graph structure or a diffusion process and evaluated their performance and computational efficiency. With the aim to unveil the role of different features for the prediction of vegetation, we performed an experiment to understand the importance of single features.

2. Related work

2.1. Remote sensing data

Despite the important role of the EarthNet2021 dataset (Requena-Mesa et al. 2021) in democratizing the task of Earth surface prediction, there are a few considerations to be made when assessing the inference power of the derived vegetation status dataset. As the authors point out,

the dataset is biased towards the Spring-Summer months, which on the other hand are also the months when cloud cover is mostly present. Additionally, given the fact that the vegetation status dataset is derived from Sentinel-2 multispectral images, even if the authors select tiles with the lowest off-nadir angle, as a correction for the observation angle and Sun Zenith Angle are not provided, the quality of the inferences from the vegetation indices derived from those images is reduced. These problems can be attenuated by the creation of vegetation status dataset derived from geostationary satellite (GEO), as GEO data can provide increased ability to attenuate of the effect of cloud cover (Fensholt, Sandholt, et al. 2006; Fensholt, Anyamba, et al. 2011; Miura et al. 2019). Moreover, vegetation series derived from a geostationary satellite maintain a constant viewing angle for a certain region, and the observation time can be selected in order to reduce the variability of the Sun Zenith Angle.

In order to understand the various aspects of droughts, a key component to monitor the hydrological process is Soil Moisture (SM). As a matter of facts, SM can represent deficits in the water content and anticipate the information contained in the NDVI (Enenkel et al. 2015) and it plays an important role in the carbon cycle by controlling the terrestrial carbon uptake (Tiexi Chen et al. 2016). However, despite their strong spatiotemporal continuity, SM data derived from reanalysis have shown high uncertainty in the Horn of Africa region (Agutu et al. 2021), prompting the use of alternative products from active or passive microwave sensors. These sensors have shown a high sensitivity to soil moisture dynamics and offer reliable all-weather monitoring capabilities (Babaeian et al. 2019).

2.2. Deep Learning architectures

Diaconu et al. (2022) proposed to solve the task with a ConvLSTM architecture, which is an ideal choice given the model ability to exploit the spatiotemporal components of the input features. Lately, graph-based structures are emerging as a meaningful alternative to tabular data to solve forecasting problems. The European Centre for Medium-Range Weather Forecast (ECMWF) produces medium-range weather forecast with a Graph Neural Network (GNN) model denominated Artificial Intelligence Forecasting System (AIFS) (Lang et al. 2024). An adaptation of a GNN to the task of NDVI forecasting was proposed by Beyer et al. (2023). In their work, the authors included a precipitation input and the previous observations of the NDVI and used a WaveNet (Wu et al. 2019) architecture. They demonstrate that modeling the NDVI forecasting task using a graph structure provides considerable computational and performance

133 advantages over a ConvLSTM architecture when the operator is not focused on monitoring a
134 physical phenomenon over the entire image or in the case pictures are not complete. More re-
135 cently, Zhao et al. (2024) proposed to solve the problem with a probabilistic approach based
136 on a diffusion process. The authors designed a diffusion Transformer (DiT) architecture with
137 a pre-trained variational autoencoder (VAE) used to condition the model with climatological
138 information.

139 **3. Methodology**

140 *3.1. Study Region*

141 The Horn of Africa (HOA) is an area characterized by a wide range of climates and terrains,
142 spanning from humid highlands to arid lowlands and coastal regions (Dinku, Ceccato, and Con-
143 nor 2011). Ethiopia and Kenya are home to the region’s main highland areas, while the land-
144 scapes of Somalia and Djibouti are largely arid (Dinku, Ceccato, and Connor 2011). The region
145 experiences three distinct rainy seasons, with Somalia, Djibouti, Kenya, and southern Ethiopia
146 following a bimodal rainfall pattern, where the long rains occur from March to May and the
147 short rains from October to December (Liebmann et al. 2014). In contrast, northern Ethiopia
148 receives most of its rainfall during the July to September period. The annual rainfall varies sig-
149 nificantly across the region, ranging from less than 300 mm in the lowlands to over 1,200 mm in
150 the highland areas (Fenta et al. 2017).

151 *3.2. Data*

152 We used as output dataset an NDVI dataset as described in D’Ercole et al. (2024). The vegeta-
153 tion status dataset was derived from SEVIRI top-of-atmosphere (TOA) reflectances, then cleaned
154 with the SEVIRI Cloud Mask product and smoothed with a Whittaker filter with a V-curve (Eil-
155 ers, Pesendorfer, and Bonifacio 2017) and an ex-post bias correction using MODIS vegetation
156 status dataset, which is deemed to account for the remaining effect of atmospheric factors. As
157 stated in Benson et al. (2024) one of the major drawbacks of the EarthNet2021 dataset is the lack
158 of modeling of vegetation dynamics, which makes the prediction task more challenging. This is
159 the reason why we use 90 days of the previous vegetation observations as input to our model in
160 order to provide information on recent vegetation dynamics.

161 To model SM, we decided to use a global daily SM product derived from the Active Mi-
 162 crowwave Instrument - Scatterometer (AMI-SCAT) on board the European Remote-sensing Satel-
 163 lites (ERS) and the Advanced SCATterometer (ASCAT) on board the series of Meteorological
 164 Operational (Metop) satellites. We used the climate record ASCAT RZSM DR v3 10km (H145)
 165 (H SAF 2020), developed from ECMWF within the EUMETSAT Satellite Application Facility in
 166 Support to Operational Hydrology (H SAF). The SM data record consists of liquid soil wetness
 167 index for four different soil layers (0 - 3m depth), it covers the years 1992-2022 with a resolution
 168 of 10 km.

169 Additionally, we use climatological data from ERA5, the fifth generation ECMWF atmo-
 170 spheric reanalysis global product. The product provides hourly precipitation data which have
 171 been aggregated to daily. We include variables that account for additional components of the
 172 hydrological process: minimum and maximum daily temperature, potential evaporation, evapo-
 173 ration and total daily precipitation.

174 3.3. Models

175 We defined the vegetation prediction task as learning to forecast the vegetation state time t
 176 using the function F :

$$X_{t+S} = F(X_{t-K:t}, Z_{t-K:t}) \quad (1)$$

177 where S represents the steps of daily observations in the future, whereas K are the lags of the
 178 variable used for the prediction. X is the vector of the past lags of the instance, whereas Z is
 179 the vector of the ancillary dynamic variables. We performed a series of experiments to test the
 180 model ability to predict different future vegetation status at steps s by using different input lags
 181 K .

182 3.3.1. Deterministic

183 In line with previous studies (Diaconu et al. 2022; Robin et al. 2022) we employed a ConvL-
 184 STM model (Shi, Gao, et al. 2017) as a baseline for the vegetation forecasting task. This model
 185 integrates the recurrent architecture of Long Short-Term Memory (LSTM) networks, known for
 186 capturing long-term dependencies in data, with the Convolutional Neural Networks (CNNs),
 187 which have become a baseline in Computer Vision due to their ability to extract meaningful
 188 features from images.

189 Alternatively, it is possible to define the image forecasting task using a graph structure (Wu
 190 et al. 2019) where the graph is represented as $G = (V, E)$, where V and E are respectively the
 191 nodes and the edges of an undirected graph and A refers to the derived adjacency matrix. In
 192 our setting, the nodes are single pixels and the edges are the connections between them. The
 193 WaveNet architecture (Wu et al. 2019) consist of a graph convolutional layer (GCN), which
 194 gathers nodes' neighbor relation information, and a temporal convolution layer (TCN), modeled
 195 from a dilated causal convolution layer (Yu 2015). As the graph convolutional layer needs the
 196 knowledge over an adjacency matrix, the authors (Yu 2015) demonstrated that when its structure
 197 is unknown, it is possible to learn it with a self-adaptive structure during training.

$$Z = \sum_{k=0}^K \tilde{A}_{apl}^k X W_k \quad (2)$$

198 In equation 2, X denotes the input features, W is the matrix of the model parameters, and Z
 199 is the output of the convolutional layer. This operation can help discover hidden spatial depen-
 200 dencies in different places; as an example, it can identify a relationship between locations along
 201 a water body. Instead, the TCN is able to capture temporal patterns of a single node, which
 202 offers advantages over traditional RNN-based methods for handling long-range sequences, as it
 203 processes the data in a non-recursive manner, thus enabling parallel computation and reducing
 204 the risk of gradient explosion. We use a structure with 32 channels in the residual and skip con-
 205 nections, 6 stacks of residual blocks and 6 blocks with 4 dilated causal convolution layers. In
 206 our case, formulating the model with a graph structure makes it possible to avoid including in
 207 the task water surfaces (e.g., lakes, sea), which constitute about 34% of the pixels in our images.

208 3.3.2. Probabilistic

209 The advantage of employing a probabilistic model to predict vegetation status stands in the
 210 fact that these models are able to capture well the uncertain evolutions of vegetation (Zhao et al.
 211 2024). Recent works (Asperti et al. 2023; Leinonen et al. 2023; Gao et al. 2024) have used
 212 diffusion models to Earth Science for the task of nowcasting precipitation, as these models have

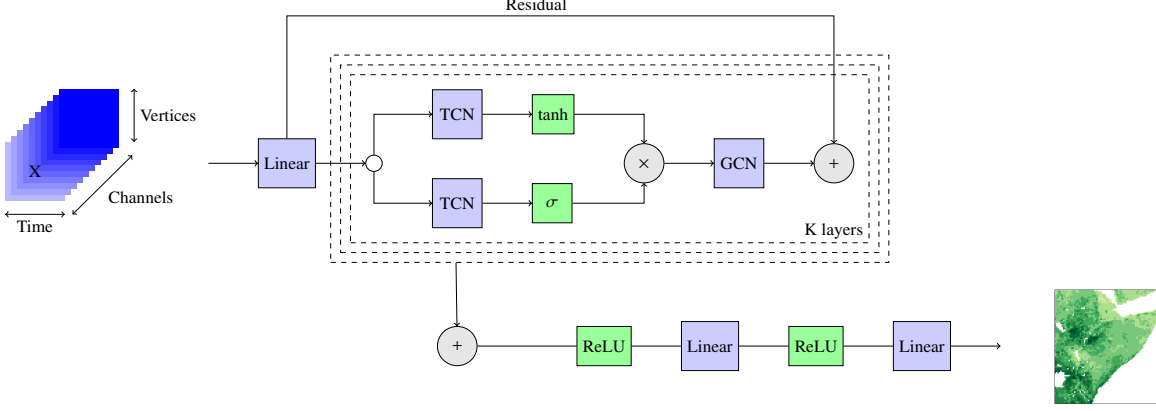


Figure 1: WaveNet pipeline

the ability to generate images with high accuracy. Diffusion models generate new samples from the prior data distribution by gradually transforming random noise into images from the target data distribution. The model acquires this ability during the training phase, when the original training data is gradually converted into noise (forward diffusion) and, subsequently, a neural network helps reconstruct the original images through a series of incremental steps (i.e. reverse diffusion process).

In recent works (Pinaya et al. 2022; Takagi and Nishimoto 2023; Yang et al. 2023), the introduction of Latent diffusion Models (LDMs) has improved the performance of these models, as they are able to operate in a latent space instead of the pixel space, and therefore can learn a superior representation of the data. In our work, we use the standard denoising diffusion implicit model formulation (DDIM) (Song, Meng, and Ermon 2020), which consists of a non-Markovian diffusion process. This is a simplification of the denoising diffusion probabilistic model (DDPM) (Ho, Jain, and Abbeel 2020), which considers the forward and reverse diffusion process as two standard Markov chains. We assume that given a data distribution $x_0 \sim q(x_0)$, the forward Markov process entails a sequence of random variables $x_1, x_2, \dots, x_T$ with transition kernel $q(x_t | x_{t-1})$. Given a time horizon of $T > 0$, it is possible to factorize the joint distribution of the random variables and define the reverse process starting as a multivariate Gaussian distribution with zero mean and identity matrix covariance at $p(x_T) = \mathcal{N}(x_T; 0, I)$ defined as:

$$p_\theta(x_0, \dots, x_T) = p_\theta(x_T) \prod_{t=1}^T p_\theta(x_{t-1} | x_t), \quad (3)$$

231 The forward process is a Markov chain in the form:

$$q(x_1, \dots, x_T | x_0) = \prod_{t=1}^T q(x_t | x_{t-1}). \quad (4)$$

232 In the forward process it is gradually added Gaussian noise to the data following a variance
233 schedule $\beta_1, \beta_2, \dots, \beta_T$, so each transition kernel becomes:

$$q(x_t | x_{t-1}) = \mathcal{N}(x_t; \sqrt{1 - \beta_t} x_{t-1}, \beta_t I). \quad (5)$$

234 And by sampling x_t at an arbitrary timestep t and using the notation $\alpha_t = 1 - \beta_t$ where $\bar{\alpha}_t =$
235 $\prod_{s=1}^t \alpha_s$, we obtain:

$$q(x_t | x_0) = \mathcal{N}(x_t; \sqrt{\bar{\alpha}_t} x_0, (1 - \bar{\alpha}_t) I). \quad (6)$$

236 Unlike DDPMs, which use a predefined variance schedule in the reverse process, DDIMs
237 leverage a deterministic non-Markovian process to improve efficiency while maintaining high-
238 quality sample generation. The process is defined as:

$$q(x_1, \dots, x_T | x_0) = q(x_T | x_0) \prod_{t=2}^T q(x_{t-1} | x_t, x_0) \quad (7)$$

239 Instead of treating the reverse step as a standard Gaussian transition, and using the marginal
240 distribution 5 we can express x_t as a linear combination of x_0 and a noise variable $\epsilon_t \sim \mathcal{N}(\epsilon_t; 0, I)$
241 we define a parameterized reverse process as:

$$x_{t-1} = \sqrt{\bar{\alpha}_{t-1}} \cdot \hat{x}_0(x_t) + \sqrt{1 - \bar{\alpha}_{t-1} - \sigma_t^2} \cdot \epsilon_\theta(x_t, \alpha_t) + \sigma_t z_t, \quad (8)$$

242 where $\hat{x}_0(x_t)$ is the predicted denoised sample at timestep t , $\epsilon_\theta(x_t, t)$ is the estimated noise term,
243 $z_t \sim \mathcal{N}(0, I)$ is standard Gaussian noise, and σ_t controls the level of stochasticity. By setting
244 $\sigma_t = 0$, we recover a fully deterministic process, ensuring that a single latent code uniquely
245 determines the generated sample.

246 In practice, the denoising process is modeled by a neural network that learns to forecast the
247 noise added at each step t , finally recovering the original data at the end of the process. We select

248 a U-Net architecture which differs from the original implementation (Ronneberger, Fischer, and
 249 Brox 2015) and use a sigmoid diffusion schedule, which has been shown to work well in the
 250 case of images with 64 x 64 pixels (Ting Chen 2023). We use a U-Net network with a ConvNet
 251 backbone (Liu et al. 2022), which uses layer normalization, depth-wise separable convolutions,
 252 residual connections within the block (inspired from ResNet). The ConvNet block is designed to
 253 be more computationally efficient while maintaining or improving accuracy and uses a larger ker-
 254 nel (e.g., 7x7) compared to the 3x3 convolutions typically used in a U-Net. ConvNet architecture
 255 should offer stronger generalization capabilities (Liu et al. 2022). We also use ancillary features
 256 as conditioning information for our denoising task. The usage of conditioning information (the
 257 so-called "guided diffusion") allows for controlling how the model generates new samples. This
 258 is simply achieved by including conditioning information z at each diffusion step, reformulating
 259 equation (3) to:

$$p_{\theta}(x_0, \dots, x_T | z) = p_{\theta}(x_T) \prod_{t=1}^T p_{\theta}(x_{t-1} | x_t, z), \quad (9)$$

260 where the estimated noise at timestep t will represent a weighted combination of both the
 261 conditioning and unconditioning information.

262 Zhao et al. (2024) proposed a LDM diffusion model with a DiT (Peebles and Xie 2023) archi-
 263 tecture and a pre-trained variational autoencoder (VAE) to solve the vegetation status forecasting
 264 task. We also used a VAE in our analysis, but as our objective was not to predict a series of im-
 265 ages, we separately trained a VAE from our daily vegetation status dataset derived from SEVIRI
 266 and used it to provide background information on the evolution of vegetation in the previous 180
 267 days. We used the VAE to extract temporal features to be included as input to our denoising
 268 model as conditioning information. We adapted a VAE architecture which has been previously
 269 tested for vegetation remote sensing images (Di Martino et al. 2023). The model is made of an
 270 encoder-decoder structure with six consecutive stacks of 1D Convolutions over the time dimen-
 271 sion, max-pooling, a batch normalization layer, and an exponential linear unit (ELU) activation
 272 layer. The pixel-wise convolutions over the time dimension allow for the extraction of temporal
 273 features from the single NDVI series. To avoid spillover of information from the training to the
 274 validation set, we trained our VAE with time series from the first 8 years. The VAE takes a time
 275 series of the previous 180 days for a single pixel at time t and is trained to reconstruct the time
 276 series after compression. The encoder compresses it into 36 variables, whereas the decoder re-

constructs the original features with very high correlation (99.7%). The latent vector z equation can be expressed as:

$$z = \mu(x) + \sigma(x) \odot \epsilon \quad (10)$$

Where μ and σ are respectively the mean and the variance of the latent distribution.

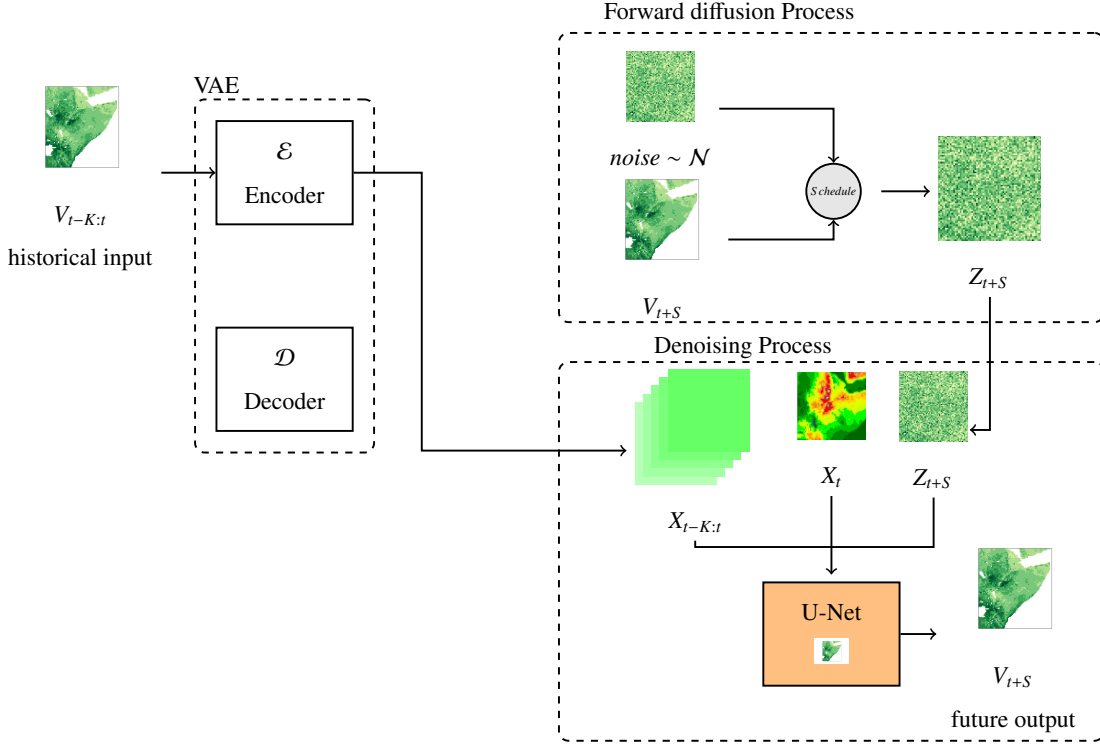


Figure 2: Diffusion pipeline

280 3.4. Experimental Setup

281 Our data cube contains daily data for the period 2005-2022. The application of the Whittaker
282 smoother in the vegetation status series and the choice of two meteorological products that are
283 created for climatological analysis (e.g. the ERA5 reanalysis and the H145 soil moisture climate
284 data record) ensures we have consistent and independent time series. Given the fact that the Horn
285 of Africa experienced a historical drought in the period 2020-2022, with five consecutive failed
286 rainy seasons and unprecedented dry conditions, we left these years for a separate evaluation. We
287 used the years 2005-2018 for training (2005-2016 training and 2017-2018 validation), whereas
288 the period 2019-2020 was used for independent testing. We used a non-overlapping (between
289 different datasets) learning window of 90 days in all our deterministic models. The tensor at time
290 t includes the previous 90 days of meteorological (precipitation, temperature, evaporation, and
291 potential evaporation) and Earth surface condition (soil moisture, vegetation status) information
292 and we predict a single instance which represent the future NDVI status. We used a bilinear
293 interpolation to regrid all our datasets to the spatial resolution of the coarser dataset (ERA5),
294 with a resolution of 0.25 (30 km²), and after selecting the area of interest, we obtained a series of
295 images with 64 x 64 pixels. Finally, we trained all our models using a Mean Squared Error (MSE)
296 loss function, excluding from its computation lakes or water bodies, and a learning rate schedule
297 with a reduction on the plateau. In contrast with the EarthNet2021 literature (Requena-Mesa
298 et al. 2021; Robin et al. 2022; Zhao et al. 2024), we train separate models for each prediction
299 step.

300 We trained our probabilistic models using the same data splitting strategy, while slightly mod-
301 ifying the input feature configuration. After training a Variational Autoencoder (VAE) designed
302 to compress a 180-day time series of vegetation values at the pixel level, we used the encoder to
303 generate a 36-dimensional latent representation that summarizes the vegetation dynamics over
304 the previous six months. These latent features are then concatenated along the channel axis with
305 the most recent (time t) meteorological and soil moisture variables, serving as conditioning inputs
306 for the diffusion model. During inference, each probabilistic model is evaluated by averaging 10
307 distinct realizations.

308 We opted for two separate modeling settings—probabilistic and deterministic—based on both
309 computational constraints and performance considerations. Prior work suggests that diffusion
310 models may be hindered by overly complex or high-dimensional conditioning inputs, which can

destabilize the denoising process. Consequently, we employed a 180-day input window for the autoencoder to capture long-term vegetation status in a compact form, and a 90-day learning window for the deterministic models, which represented the maximum feasible input size given our available computational resources. Further justification for these choices is provided in the discussion section.

3.5. Evaluation metrics

We used the Root Mean Squared Error (RMSE) metric to evaluate the performance of different models, as the metric is a baseline in the Earth Surface prediction tasks (Requena-Mesa et al. 2021; Zhao et al. 2024). The RMSE is sensitive to large pixel differences, making it useful for capturing overall fidelity and mismatches in the forecasts but does not take into consideration image structural information (e.g. patterns, textures). Similar to previous works (Requena-Mesa et al. 2021; Zhao et al. 2024) on the task of vegetation status prediction, we use a Structural Similarity Index Measure (SSIM), which can describe the visual perceived quality of images by considering structural information, luminance, and contrast. To compute this metric, we deviated from the implementation in the EarthNet dataset which uses input values scaled between 0 and 1 and instead use the NDVI in the range from -1 to 1. This allows a better representation of the original NDVI images from SEVIRI, which can present negative values in the case of water surfaces, bare soil, and rock or urban landscapes. We used a kernel size of 11 to evaluate neighboring information of single pixels:

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (11)$$

Where μ e σ represent the mean and the variance or covariance, $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$, the parameters are defined as by default $k_1 = 0.01$ $k_2 = 0.03$ and using a dynamic range parameter of $L = 2$.

We use a mask that exclude water bodies and locations with more than 180 consecutive days of clouds in order to provide a fair comparison for the evaluation metrics.

3.5.1. Extreme event prediction

Further, we performed another test to check our model prediction ability in the case of extreme events. As stated in a recent report by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) (2023), the Horn of Africa experienced a series of five failed rainy seasons

339 starting from the short rainy season in October-December 2020 to October-December 2022, with
340 about 32 million people in vulnerable conditions. Particularly, the March-May 2022 season was
341 the most severe drought recorded in the past 70 years. To understand how the model would have
342 performed in this setting, we take our model predictions and separately evaluate the model error
343 over the years 2021-2022. As using a model that performs well in the case of strong drought
344 events is an important objective of this study, we provide a separate analysis of the models’ per-
345 formance. It is important to note, however, that our model would require further tuning to be
346 used in an operational setting. Currently, it relies on meteorological inputs from a reanalysis
347 product with a latency of 3 months. However, a near-real-time version of this product (ERA5-T)
348 is available with a latency of only 5 days. Similarly, we use a demonstrational version of a soil
349 moisture data record, which also has a near-real-time counterpart with a latency of 12 hours.

350 3.5.2. *Ablation study*

351 To understand the importance of conditioning information in our probabilistic models, we
352 performed a series of experiments. We computed new models using different combinations of
353 meteorological and Earth surface condition variables and we measure variations in the best model
354 prediction skill.

355 3.6. *Computational resources*

356 The Deep Learning experiments for the deterministic models and the VAE were conducted
357 on a machine equipped with dual AMD EPYC 7313 processors (16 cores) and 256 GB of
358 RAM. Model training utilized six NVIDIA Quadro RTX A6000 GPUs (48GB GDDR6 each)
359 with NVLink bridges for faster inter-GPU communication.

360 The WaveNet model took approximately 30 minutes per epoch to train, whereas the ConvL-
361 STM instead required about 1 hour per epoch. The diffusion model instead was much lighter
362 and took about 1 minute per epoch and was trained using a much lighter machine, with Intel I7
363 Pro CPU (10 cores), 32 GB of RAM and equipped with a single Nvidia RTX 5000 GPU. On the
364 other hand, the generation process of the diffusion model is quite resource-expensive, requiring
365 about 1 hour to generate samples for the test dataset.

4. Results

4.1. Independent validation

When looking at the validation metrics on the test set covering the years 2019-2020 (see Table 1), it is clear that the deterministic models WaveNet and ConvLSTM models do a great job in predicting short-term evolution of vegetation (e.g. prediction at 10 to 30 days), with a very small RMSE and a SSIM metric close to 1. The high forecasting ability of the WaveNet is visually confirmed by the predicted maps at short latencies (10 to 30 days) in Figure 3. Instead, the error is relatively higher for the diffusion model at small prediction steps. Interestingly, we noted a considerable decrease in performance for the ConvLSTM model since step 45, which is suggested by higher RMSE and SSIM near to 0.81. Instead, the drop in performance is less pronounced for the WaveNet model, with a RMSE of 0.04 and a SSIM of about 0.9 for predictions at 60 days. On the other hand, the diffusion model performance decreases at a slower rate as shown from the results on the test set at steps from 30 to 60 days (see Figure 4) and the prediction error seems to be related to an overestimation of the future vegetation status, as it can be observed in Figure 3. These results are visually confirmed by the predicted maps in Figure 3, where it is apparent that the diffusion model at short prediction steps slightly underestimates the future vegetation condition in some green areas in Kenya and southern Ethiopia for a day at the end of the rainy season (1st of May 2020), which correspond to the first green-up phase of some crops in the HOA. A similar feature is observed for the predictions of the ConvLSTM, but, on the other hand, the model does a better job of predicting the condition of some semi-arid areas in Somalia. When we visually take a look at the model predictions at 45 and 60 days, we note that the ConvLSTM tends to deliver predictions around the median for the whole area, underestimating green areas and overestimating arid and semiarid areas. Overall, given the great prediction skill of the diffusion model for longer prediction (45, 60 days) steps, as visually confirmed in the example in Figure 3, we selected this model and narrowed our analyses.

Model	10 Days		15 Days		30 Days		45 Days		60 Days	
	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM
ConvLSTM	0.013	0.980	0.027	0.930	0.033	0.912	0.063	0.810	0.060	0.802
WaveNet	0.008	0.992	0.010	0.988	0.020	0.965	0.032	0.916	0.039	0.890
Diffusion	0.020	0.964	0.023	0.954	0.032	0.919	0.037	0.891	0.040	0.878

Table 1: RMSE and SSIM Metrics for Models at different prediction steps

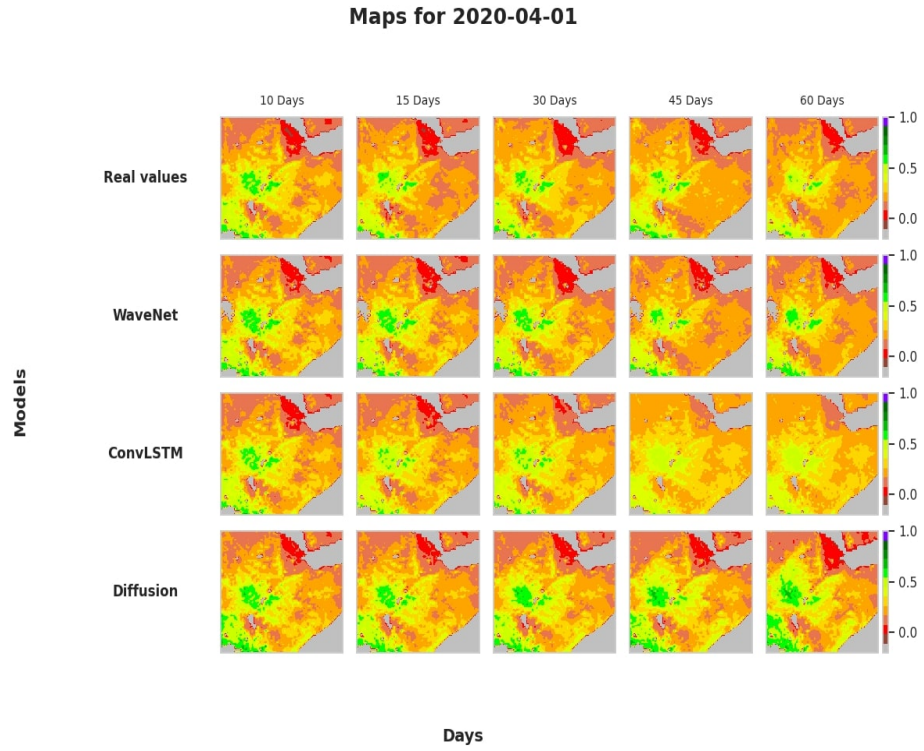


Figure 3: Model maps for a selected day at different time steps in a normal year

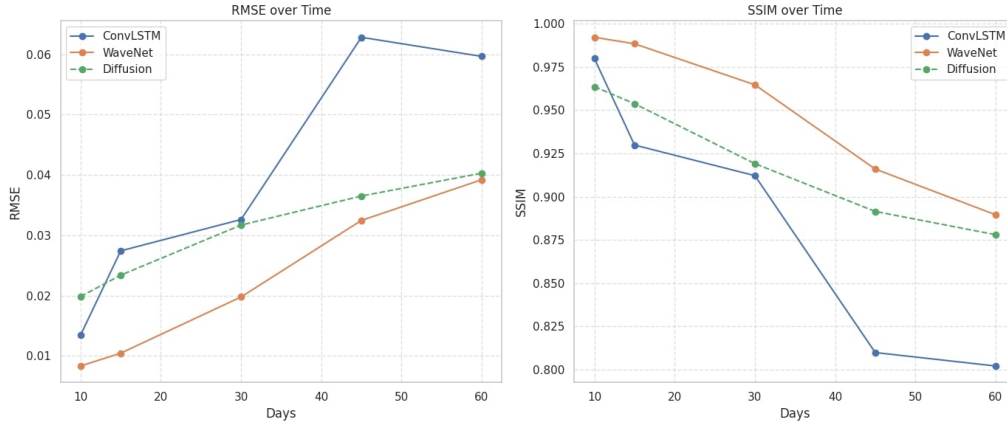


Figure 4: Models performance at different time steps

4.2. Model performance during drought years

The picture dramatically changes when testing the results on independent data from the two drought years (2021-2022). For instance, from Figure 5 it is clear that the WaveNet model prediction skill is greatly compromised during the dry event. This is well described by the RMSE errors at different prediction steps that range from 0.09-0.22 in 2021 and 0.1-0.28 in 2022 (Figure 6) and the plunge in the SSIM metric during the years 2021-2022 (see Figure 7). The large error is mostly attributed to an overestimation of the actual NDVI realization, as demonstrated by the bias statistics in Table 2 and in the scatterplot in Figure 8. The ConvLSTM instead is quite robust for the drought years, actually achieving better performances in 2021 compared to the previous years. This is depicted in Figures 6 and 7 where we present the errors and the SSIM at different forecast steps over the four years. Instead, the performance of the diffusion model slightly decreases during drought years, with a larger error in 2022, the second consecutive drought year. The model bias slightly increases at longer prediction steps, with a tendency to overestimate the vegetation status realization (see Table 2). The tendency of the model to skew predictions towards the mean is shown in the scatterplot of the real values compared to the predicted ones in both testing datasets (years 2019-2022) in Figure 8, where it is shown a deviation of the slope of the cloud of points compared to the diagonal line. In 2022 the error statistic for the ConvLSTM and diffusion model at 60 days are similar, although the SSIM metric demonstrates the superiority of the latter. Overall, the significant performance of the diffusion model especially during such a severe drought event makes it an ideal candidate for our analyses. We plot in Figure 9 the

411 median and interquartile range of the actual realization of NDVI against those of the real values
 412 at different prediction steps. This figure demonstrates that the prediction at longer time steps
 413 (60 days), although with some overestimation that increases with lead times, follows the actual
 414 values well.

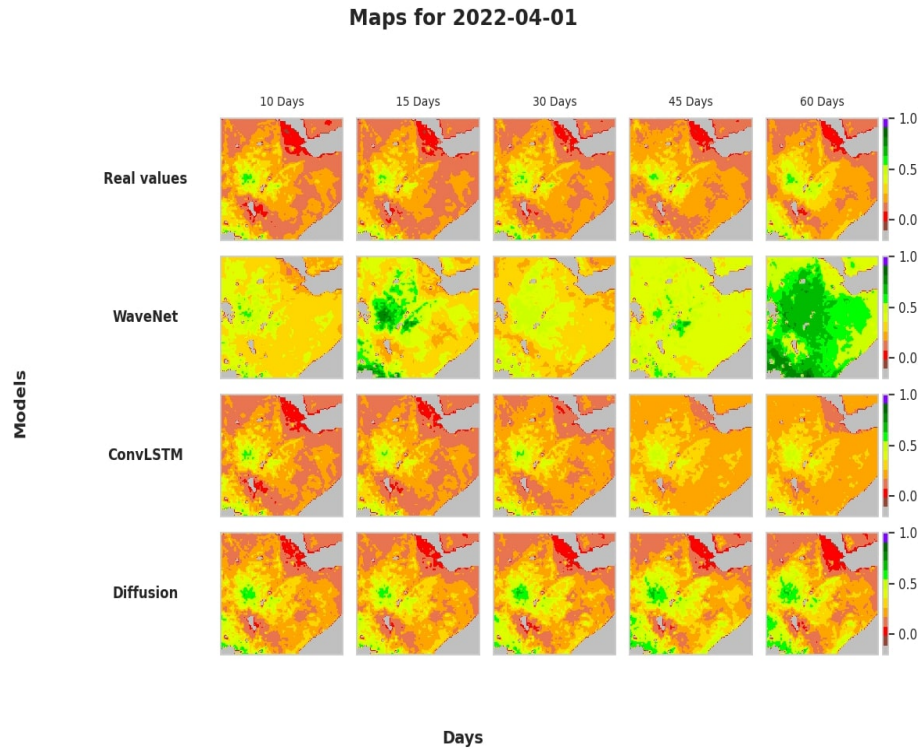


Figure 5: Model maps for a selected day at different time steps in a drought year

Model	10 Days	15 Days	30 Days	45 Days	60 Days
ConvLSTM	-0.01	0.00	0.00	0.01	0.01
WaveNet	0.05	0.11	0.04	0.06	0.17
Diffusion	0.00	0.00	-0.01	-0.01	-0.02

Table 2: Bias metrics for models at different prediction steps for drought test dataset (years 2021-2022)

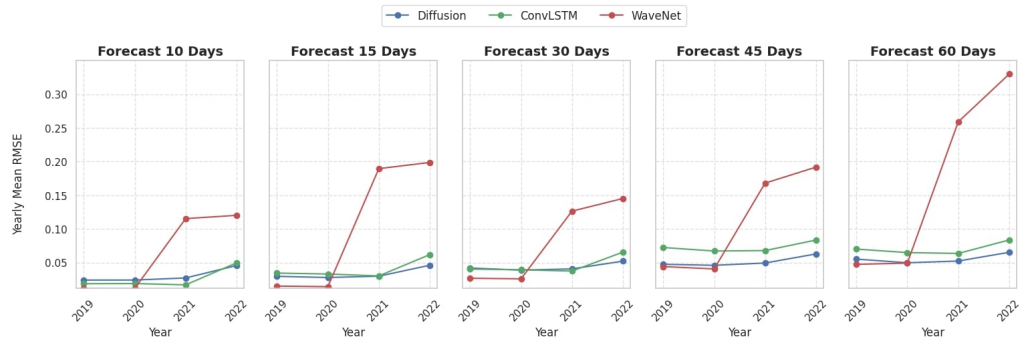


Figure 6: Average error (RMSE) by year (2019-2022)

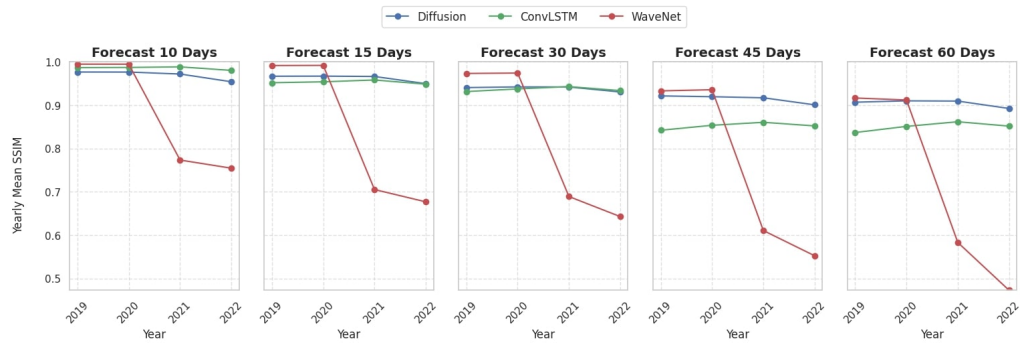


Figure 7: Average structural similarity index metric (SSIM) by year (2019-2022)

Model Predictions Over All Dates - Hexbin Plots

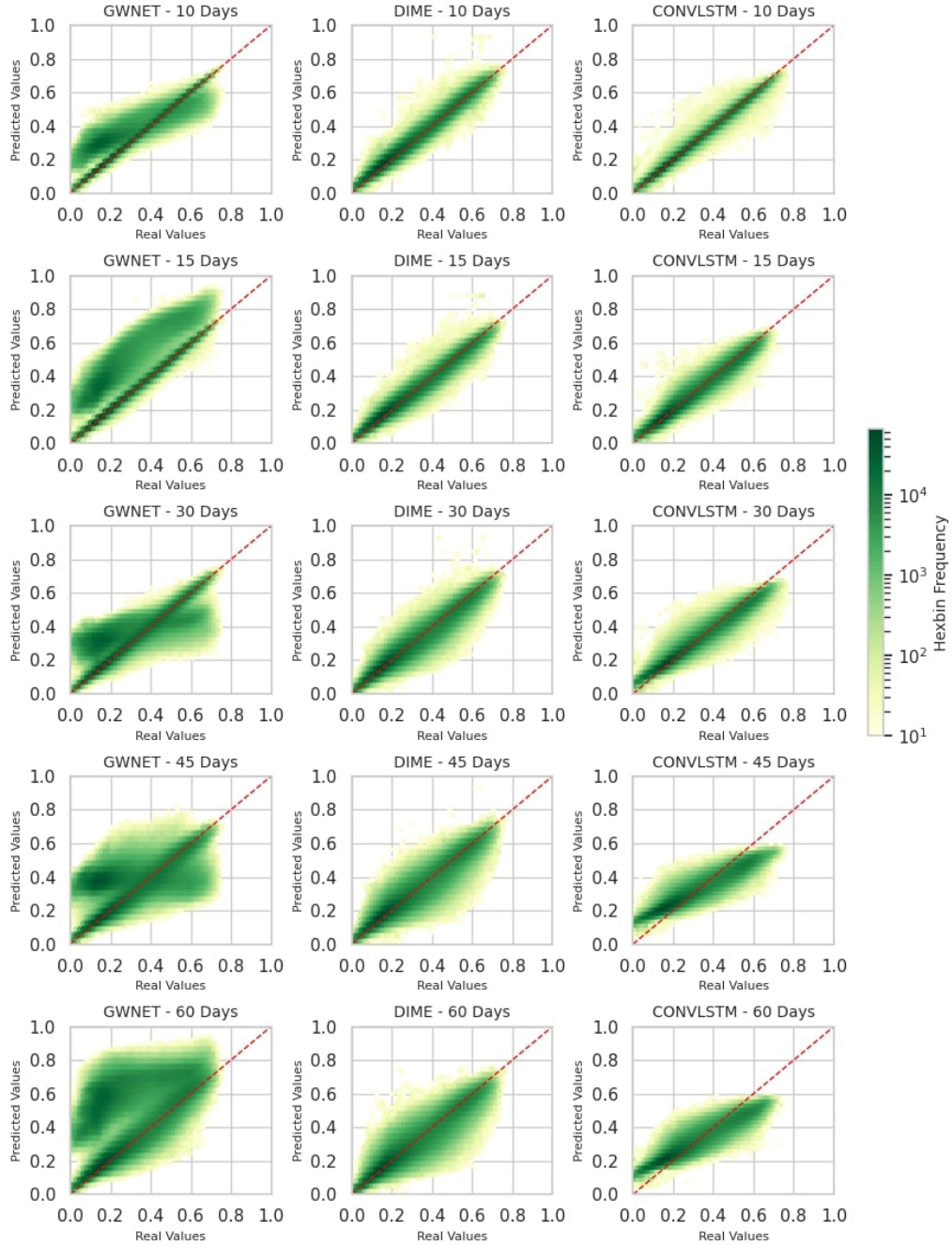


Figure 8: Scatterplot predicted vs real at different time steps (years 2019-2022).

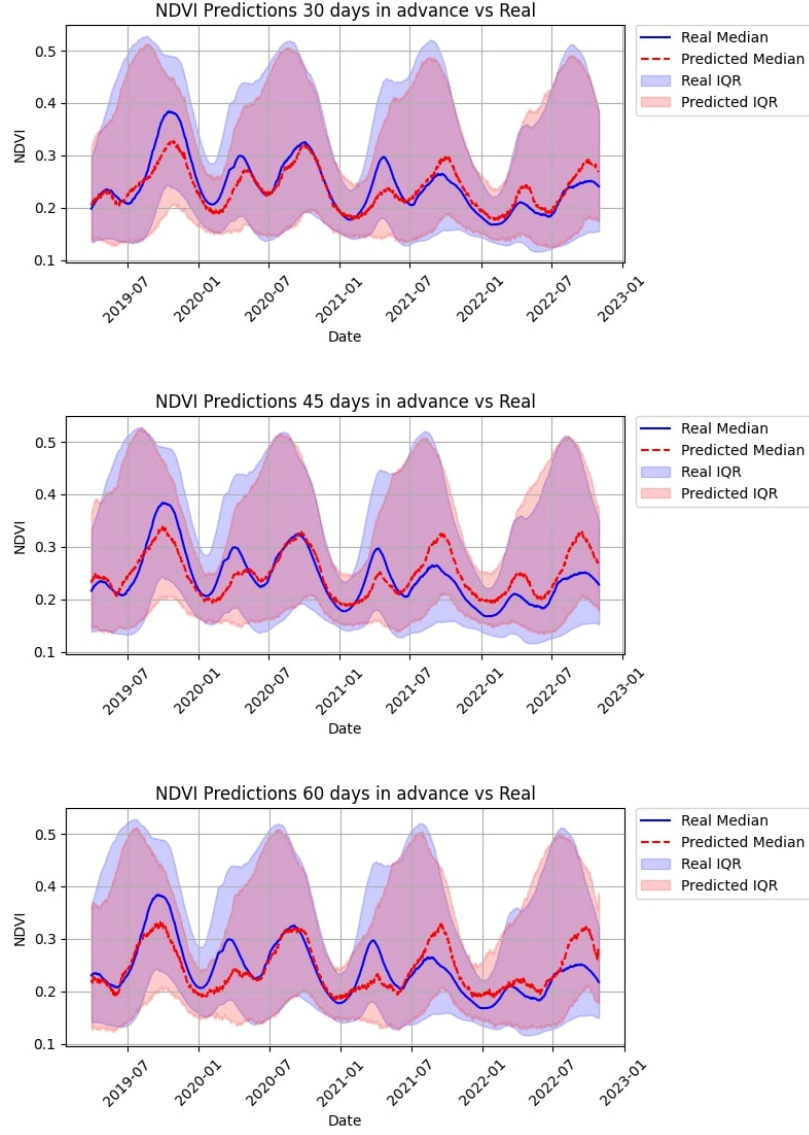


Figure 9: Predicted vs Real for diffusion models at 30, 45 and 60 days

4.3. Ablation study

After training diffusion models with different prediction steps and varying combinations of input features, we observe a few interesting findings. Table 3 shows the results of the ablation study on the diffusion model, we compared the diffusion model statistics on the full test dataset (years 2019-2022) with the ones obtained by training the diffusion model using only vegetation

data as input (second row in Table 3) or using only meteorological and soil moisture data (last row of the table). The diffusion model with all features generally outperforms the other models at all prediction steps, with slight exceptions for 15 and 30 days where the difference is negligible. In contrast, models trained only on climatological and soil moisture features from the previous step exhibit significantly larger errors at all time steps, as reflected by the error metrics, and much larger uncertainty as reflected by the performance oscillations at increasing time steps.

Model	10 Days		15 Days		30 Days		45 Days		60 Days	
	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM
Diffusion with all features	0.023	0.957	0.025	0.949	0.031	0.916	0.038	0.886	0.041	0.875
Diffusion with autoencoder	0.029	0.950	0.025	0.953	0.033	0.918	0.044	0.877	0.043	0.873
Diffusion with meteorological	0.065	0.785	0.064	0.803	0.062	0.787	0.094	0.682	0.057	0.821

Table 3: RMSE and SSIM Metrics ablation study

5. Discussion

5.1. Short term drought prediction with Deep Learning

The added value of our research is the successful adaptation of a series of DL architectures that exploit spatio-temporal features in the task of vegetation status forecasting over large areas, delivering very accurate predictions described by the low RMSE error and high SSIM. We demonstrated that it is possible to apply different DL models to predict the short-term evolution of vegetation and, consequently, to monitor the outbreak of vegetation anomalies at different sub-seasonal lead times. We showed that spatio-temporal deterministic models are stable under regular climatological conditions (e.g. ConvLSTM, WaveNet) and at shorter steps. We have shown that, similar to the original ConvLSTM paper (Shi, Z. Chen, et al. 2015), the predictions of the ConvLSTM model tend to converge around the mean as the lead time increases, whereas the WaveNet failed in the case of a historically severe drought event. Overall, we concluded that the diffusion model is more robust to strong drought events and delivers better predictions at longer time steps. The probabilistic nature of the denoising steps allows to accurately model the uncertain evolution of vegetation and to reconstruct the stochastic nature of vegetation dynamics (Zhao et al. 2024). Through the series of iterative steps performed in the denoising process, the model was able to transform an initial noise into output maps that represent the forecasted future

status of vegetation. Through the usage of an ensemble method, our approach also allows for a quantification of the uncertainty associated with the predictions. Similarly to Salakpi et al. (2022), the use of a probabilistic approach to predict drought in the Horn of Africa generated more accurate outputs and was robust to drought events that occur during the short rainy season, which corresponds to the green-up phase of a considerable share of crops in the area. Our diffusion pipeline is affine to Zhao et al. (2024) even though our works are not directly comparable as the source datasets are derived from different areas (the Horn of Africa Area as opposed to Europe) and at different resolutions (ours at finer temporal but coarser spatial resolution) and utilized different sensors (ours is derived from MSG SEVIRI). Furthermore, we did not use a pre-trained autoencoder to derive final predictions, but used a custom autoencoder to reduce the dimensionality of the input time series, deriving features that contain information on the vegetation evolution in the previous half year.

As previous studies have shown (Park et al. 2020; Requena-Mesa et al. 2021; Salakpi et al. 2022; Zhao et al. 2024), the inclusion of meteorological variables to predict the future status of vegetation is a crucial factor to improve forecast capability. In contrast with previous works (Requena-Mesa et al. 2021; Robin et al. 2022; Zhao et al. 2024) which used DL models to directly predict multispectral images, we used the NDVI index as an instance, making our output easily interpretable. On the other hand our approach makes it difficult to produce different indices that can deliver other information, as in the case of Zhao et al. (2024) who are able to generate indices such as the Enhanced Vegetation Index, used to detect high biomass regions or the Structure Insensitive Pigment Index, employed to study the structure and condition of vegetation canopies. A potential drawback of our approach compared to similar works (Zhao et al. 2024) is that by barely concatenating the conditioning information and noisy images on the channel dimension might not help the model discern the impact of the meteorological or the Earth surface features. This is why Zhao et al. (2024) proposed a diffusion Transformer custom architecture. Another potential shortcoming of our work is that we resampled all the input features to a coarser grid, whereas adopting other approaches could have leveraged the original spatial dimension of the input images. Moreover, as many other authors, we informed our models only with meteorological variables (including soil moisture), not accounting for non-meteorological factors, such as plant diseases or human interventions (e.g., fires, water storage and irrigation). Despite overlooking these factors, our models demonstrate unprecedented prediction skills. An interesting

topic for future research would be to analyze if these factors are inferred by the models through the NDVI time series, or if they constitute a major contribution to the residual errors. Lastly, while the NDVI is widely used to assess vegetation health and monitor ecological responses to droughts, it provides an incomplete picture of drought impacts and vegetation health, reflecting solely vegetation greenness.

5.2. High temporal resolution

The increased temporal resolution combined with a temporal filter designed to reconstruct the upper-envelope (Whittaker smoother) of the vegetation series allowed to derive a vegetation status dataset that better reconstructs the vegetation phenology by interpolating between an increased number of data points (D’Ercole et al. 2024). Additionally, the usage of daily temporal resolution and employment of a temporal filter enabled the generation of stable vegetation series that are easier to learn with DL models. This preliminary step before the modeling phase considerably decreases fluctuations between consecutive vegetation status images by removing the residual effect of clouds (i.e. after applying the cloud mask) and makes our vegetation status index more stable for inferences. Conversely, we have previously shown that this does not compromise the ability of the index to detect drought phenomena (D’Ercole et al. 2024), and that the increased temporal resolution allows for a quicker detection of drought events compared to the information derived from 10-days vegetation composites from Polar-orbiting satellites like MODIS. If our model is an improvement in terms of spatial resolution compared to previous approaches (Lees et al. 2022), our dataset does not have an equally fine-grained spatial resolution as the EarthNet dataset (Requena-Mesa et al. 2021; Zhao et al. 2024) and therefore it was not possible to draw inferences on the status of local phenomena such as agriculture, but we were only able to describe vegetation dynamics over larger areas. Our model is therefore more suitable to be used as a decision-support system for problems that encompass larger areas (e.g. Early Warning Systems, drought-insurance). Further, our approach can be easily extended to monitor locations that are part of the SEVIRI full-disk. Compared to the previous study by Robin et al. (2022) we did not perform a forecast over the whole African continent, but on the other hand we used imagery at higher temporal resolution (daily instead of 10 days). With some modifications, the model can be adapted to other geostationary datasets such as GEOS, Himawari, and in the future MTG Flexible Combined Imager (FCI).

504 5.3. Models trade-offs and computational needs

505 Another added value of our study is the demonstration that it is possible to achieve better
506 performance compared to very sophisticated DL models, while at the same time reducing com-
507 putational requirements. As demonstrated in Beyer et al. (2023), selecting a WaveNet model
508 offers some considerable computational gains compared to the ConvLSTM architecture thanks
509 to the ability to discard pixels that are not of interest (e.g. water bodies, null pixels). The model
510 is very skilled at predicting vegetation in the short and medium term, but performs poorly in
511 the case of extreme events unseen in the training data. Given the unprecedented nature of the
512 drought events in the region in 2020-2022, retraining our model on this new data would make
513 it more robust to similar events. However, the analysis clearly demonstrates the generalization
514 capabilities of single models. On the other hand, given the foreseen increase in the frequency,
515 severity and intensity of dry phenomena, a probabilistic approach remains more advisable. In
516 our case study we showed that employing a probabilistic approach based on the diffusion model
517 demands much less training time and resources compared to sophisticated deterministic models
518 like the ConvLSTM or the WaveNet. The model indeed requires an expensive generation process
519 but this can be reduced using a Denoising diffusion Implicit Models approach.

520 The decision to employ two distinct input configurations — one for the diffusion-based proba-
521 bilistic models and another for the deterministic models — introduces complexity when attempt-
522 ing to isolate performance differences that emerge from architectural choices. This distinction
523 makes it more challenging to directly attribute performance gains or losses to either the model-
524 ing choices or the nature of the input data. Nonetheless, we adopted this approach based on both
525 theoretical and practical considerations. Prior research has established that diffusion models,
526 which generate outputs by gradually refining noisy predictions through a denoising process, are
527 not necessarily well-suited to large, channel-stacked inputs (Ho, Jain, and Abbeel 2020; Zhao
528 et al. 2024). Especially when paired with latent space encodings, diffusion models are more
529 adapt at capturing distributional uncertainty and learning from compressed but semantically rich
530 summaries of long-term trends. Our approach reduces the dimensionality of the conditioning
531 input while preserving essential information over longer temporal windows. In contrast, deter-
532 ministic models such as WaveNet and ConvLSTM are specifically designed to model temporal
533 dependencies across sequential inputs. These architectures benefit from longer context windows
534 and rely on structured time-series input to learn temporal trends and dependencies. For this rea-

son, we used a 90-day input sequence of meteorological and Earth surface condition features for the deterministic models, which was the upper limit we could accommodate given memory constraints.

6. Conclusion

In this study, we constructed a novel data cube for vegetation drought forecasting at a daily temporal resolution, leveraging a recently developed NDVI dataset (D’Ercole et al. 2024) based on the geostationary MSG SEVIRI. This dataset enables stable vegetation time series thanks to the high frequency of the sensor (approximately every 15 minutes). We combined this data with meteorological quantities derived from the ERA5 reanalysis model and a soil moisture product from ASCAT. Through a series of experiments, we tested different spatio-temporal Deep Learning architectures to the task of sub-seasonal vegetation status forecasting over large areas and found that a probabilistic model based on a diffusion process provides robust forecasting skills up to 60 days into the future. Furthermore, we also demonstrated that the model performs particularly well in the case of the 2021–2022 drought event, which has been recorded as the most severe dry event for the region. This is in contrast to the graph-based deterministic model (WaveNet), which showed very large errors for extreme events not present in the training dataset. Furthermore, the tested diffusion model preserves the spectral characteristics of the forecasts, while the recurrent convolutional model (ConvLSTM) shows important smoothing effects for the longer forecast times. An in-depth analysis of the probabilistic model performance was conducted to ascertain the significance of the predictor variables in forecasting outcomes. The primary conclusions of this analysis emphasize the critical role of vegetation status data from the prior 180 days, while the meteorological parameters generally offer a slight performance improvement. Finally, we demonstrated that the performance improvement of the diffusion pipeline can bring along a significant reduction in computational costs associated with model training.

CRedit authorship contribution statement

Riccardo D’Ercole: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. Daniele Casella: Writing – review & editing, Supervision, Methodology. Paolo Sanò: Writing – review & editing, Supervision, Resources, Conceptualization.

564 **Data Availability**

565 The NDVI dataset can be downloaded from the Zenodo public repository [https://doi.org/](https://doi.org/10.5281/zenodo.14001095)
566 10.5281/zenodo.14001095.

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3. Conclusions

This thesis presents a comprehensive investigation into the use of high-temporal-resolution Earth Observation (EO) data and advanced Machine Learning methods to improve drought monitoring and vegetation forecasting in the Horn of Africa. Across three complementary studies, a novel framework was developed that leverages the unique capabilities of geostationary sensors, coupled with data fusion techniques and probabilistic modeling, to advance our understanding and predictive capability of vegetation dynamics under climate stress.

At the foundation of this work lies the construction of a new NDVI dataset from the SEVIRI sensor onboard MSG, designed specifically to overcome the limitations of cloud contamination and exploit the sensor's exceptional temporal resolution (15-minute revisit time). A targeted cloud-masking and smoothing strategy enabled the derivation of stable, daily vegetation time series, which demonstrated strong agreement with established polar-orbiting products, both in terms of climatological trends and event-level anomalies. The validation of this dataset, named HRSEVIRI-1D-NDVI, proved its capacity to identify the intensity, timing, and spatial extent of key drought episodes, with accuracy comparable to established early warning systems such as ASAP.

Building upon this foundational dataset, the second part of the thesis explored the translation of meteorological drought into vegetation stress across multiple soil types and rainfall regimes. Using high-resolution precipitation data and standardized precipitation indices (SPIs), the analysis demonstrated that daily precipitation products, though often underutilized, substantially enhance the ability to capture short-term drought signals. In general, the choice between different accumulations of precipitation to derive the SPI index implied a trade-off between timeliness and detection skill. The 90-day SPI, in particular, was shown to effectively reflect vegetation stress patterns, although its performance diminished under conditions of rapidly alternating rainfall extremes. These findings emphasize the value of daily temporal resolution in characterizing the nuanced progression of droughts and their diverse impacts on different ecosystems. The third and most advanced component of this research focuses on the development of a forecasting system capable of predicting vegetation condition at sub-seasonal lead times. To this end, a multi-source data cube was created, integrating HRSEVIRI-1D-NDVI with ERA5 meteorological reanalysis variables and ASCAT soil moisture estimates. This comprehensive dataset served as the input for testing a suite of spatio-temporal Deep Learning models. Among these, a diffusion-based prob-

abilistic model emerged as the most effective, demonstrating robust forecasting performance up to 60 days ahead, including during the unprecedented 2021–2022 drought event. Crucially, this model retained the spectral integrity of the vegetation signal and avoided the smoothing artifacts observed in more conventional models such as ConvLSTM.

An in-depth feature importance analysis confirmed that the model’s skill is primarily driven by vegetation time series from the preceding 180 days, while the inclusion of meteorological predictors offered consistent but secondary benefits. This underscores the importance of vegetation memory and reinforces the potential of EO-based time series as leading indicators in ecological forecasting. Furthermore, the diffusion model offers considerable computational advantages, requiring significantly less training time compared to other Deep Learning architectures, thereby supporting its scalability for operational deployment.

Collectively, this thesis contributes a novel EO-based framework that bridges the gap between near-real-time drought monitoring and anticipatory forecasting. By integrating dense temporal EO data, statistical smoothing techniques, and state-of-the-art Deep Learning architectures, it provides a reproducible and scalable approach for enhancing climate resilience in vulnerable regions. The outcomes not only demonstrate clear improvements in monitoring and forecasting accuracy but also offer practical implications for the design of early warning systems and the implementation of proactive adaptation strategies.

Future work may extend this framework in several directions: incorporating finer-scale Earth Surface prediction models, exploring additional conditioning variables such as irrigation, plant diseases, land degradation metrics, and testing real-time implementation with operational forecasts. The methodological insights developed here, especially the combination of geostationary observations with diffusion-based learning, hold great promise for global applications in environmental risk assessment, food security planning, and climate adaptation.

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