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Earth observations reveal impacts of climate variability on maize cropping systems in sub-Saharan Africa

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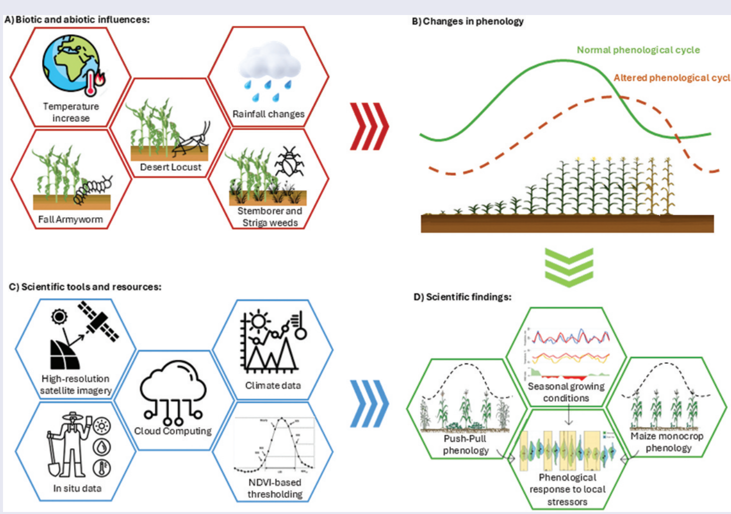
ABSTRACT

In Kenya, climate variability and change threaten smallholder, rainfed farms, with crop failures, yield reductions, and pest infestations. Efficient agroecological strategies, such as Push-Pull intercropping, offer documented benefits including pest control, improved soil fertility, and water conservation compared to traditional maize monocropping. To date, no studies exist comparing traditional maize monocropping and Push-Pull intercropping using earth observation tools over several growing seasons in East Africa. Our research addresses this by harmonizing Landsat 7, 8, 9 with Sentinel-2 remote sensing time series from 2016 to 2023. Phenological metrics of 15 growing seasons are extracted based on a threshold method using the Normalized Difference Vegetation Index (NDVI) as a vegetation proxy. Field data from 58 sites in southwestern Kenya provided training for this analysis, revealing detectable inter-class differences. Notably, Push-Pull intercrop fields showed greater resilience during biotic stress events, such as the locust outbreak in 2020 short rainy season and the fall armyworm infestation in combination with delayed and below-average rainfall during the short 2021 and the long 2022 growing seasons. Higher maximum NDVI and extended season duration indicated a higher resilience of Push-Pull farming under unfavorable agricultural conditions. Short growing seasons with unfavorable conditions showed earlier end of seasons in both systems, whereas long growing seasons with unfavorable conditions caused delayed onset and end of seasons. This study marks the first attempt to leverage earth observation data to compare traditional maize agriculture with agricultural systems featuring applied ecological management strategies, showcasing the potential of earth observation tools to monitor and evaluate agroecological resilience.



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1. Introduction

Climate change can be defined as significant long-term variations in meteorological conditions such as precipitation and temperature (Allen 2003; World Meteorological Organization 1992). The effects of changing climate are inevitable and felt globally (Adams et al. 1998; Aydinalp and Cresser 2008; Salvo, Begalli, and Signorello 2013). It is a cause of concern considering the importance of variations in meteorological parameters on agricultural production (Sharma et al. 2022; Torres, Howitt, and Rodrigues 2019). This becomes more alarming considering that, to meet the food demand of the projected global population of 9 billion by 2050, an increase in staple cereal production of +70% is required (Neupane et al. 2022).

The gravity of climate change impact on agricultural yield varies by crop type, geographical location and local climate (Challinor et al. 2014). The impact of climate change is distributed unevenly worldwide. The current climatic tendencies will lead to destructive changes to sub-Saharan Africa (Mubenga-Tshitaka et al. 2023; Schlenker and Lobell 2010). In East Africa, current trends indicate up to 20% increase in rainfall from December to February and a decrease in rainfall of up to 10% from June to August accompanied by higher projected temperatures of up to 1.9°C by the year 2050 (Gebrechorkos, Hülsmann, and Bernhofer 2019; Hulme et al. 2001; IPCC 2023). In addition, highly dynamic population growth (UN 2018) and a very dynamic urbanization trend (Taubenböck et al. 2024) predicted for sub-Saharan Africa will increase food insecurity.

East African countries are highly reliant on the agricultural sector. For Kenya, agriculture accounts for an estimated 21.2% of Gross Domestic Product (GDP) and employs over 70% of the rural population (The World Bank 2022). Moreover, smallholder farmers, most vulnerable demographic, account for more than 80% of total agricultural output of Kenya (Market Alliance 2022).

Changing climate results in nightly and daily warming as well as shifts in precipitation patterns in Kenya (Malhi, Kaur, and Kaushik 2021; Torres, Howitt, and Rodrigues 2019). Temperature and precipitation are direct inputs in agricultural production, hence any changes to these parameters will affect the agricultural output (Deschenes and Greenstone 2004), i.e. through abiotic stresses (Halford et al. 2015; Sánchez-Bermúdez et al. 2022). Based on Kenya's annual maize yield data from 1979 to 2012, significant increases in temperature and reduction in seasonal rainfall resulted in maize yield decreases of 0.07 tons/ha/decade (Mumo, Yu, and Fang 2018). More recent maize yield data from 2012 to 2022 have shown increases in maize yield during growing seasons with increased seasonal rainfall (Ondiek, Saber, and Abdel-Fattah 2024). Research using household surveys mirror the findings of numerical and statistical studies. Ochieng, Kirimi, and Mathenge (2016) found that long-term temperature increase has a larger impact on small-scale crop production than short-term precipitation fluctuations. Severe temperature during the vegetative state has also led to decreased cereal kernel quality and amounts (Hütsch, Jahn, and Schubert 2019). Timely rainfall can be a mitigating factor; however, severe fluctuations in precipitation can also lead to outstanding yield loss and crop failure (GEOGLAM 2019). To make matters worse, negative effects on agriculture through biotic stresses such as presence of weeds, pest outbreaks and soil fertility decrease have also been widely recognized (Jafari Jozani et al. 2022; Shahzad et al. 2021). Above-average rains in 2019 led to wet soil and vegetation conditions which subsequently created favorable settings for locust gregarization in East-Africa (Cressman 2013). The fall armyworm (FAW) invasion since 2016 has caused severe damage to maize yield and is a major threat to food security throughout East Africa (Sisay et al. 2019; Tambo et al. 2020). Other important constraints to maize production include the lepidopterous stemborers (Kfir et al. 2002; Midega et al. 2015) and parasitic Striga weed (David et al. 2022; Khan et al. 2002), which can cause measured maize yield losses of up to 88%.

Considering these challenges, agroecological management strategies for the control of stemborers and striga weeds in maize fields have been widely developed in providing a biological alternative to expensive and harmful pesticides. By 2016, Push-Pull intercropping have been employed by over 125.000 smallholder farmers in East Africa leading to substantial maize yield increases (Khan et al. 2016). Push-Pull is a stimulo-deterrent diversionary strategy that relies on behavioral manipulation using airborne volatile organic compound from companion plants to manage crop pests. To achieve this, the main cereal crop, such as maize, is intercropped with a repellent plant Desmodium sp., that pushes the stemborer and FAW pests from the main crop. The Desmodium root exudates are also known to suppress parasitic Striga weeds by triggering suicidal germination (Hooper et al. 2015). In addition, the leguminous Desmodium fixes nitrogen in the soil enhancing soil fertility and retaining soil moisture in dry conditions. Around the plot edges, a trap plant, Brachiaria sp., is planted that naturally attracts stemborer and acts as a pull for the egg-laying female stemborer (Khan et al. 2016; Khan et al. 2001; Midega et al. 2015). The push and pull plants are both valuable additives, as Desmodium is rich in protein and Brachiaria contains high levels of carbohydrates and are known to increase milk production in cattle. Acting together, these plants provide a push and pull effect which increases maize yield, maize resistivity to stemborer, FAW and striga weeds, enhances soil fertility and promotes water retention (Buleti et al. 2023). Ecological management such as Push-Pull intercropping has shown promise for the sustainable management of insect pests (Steffan-Dewenter, Kerr, and Rachel 2024). Yet, few studies have compared the response of Push-Pull intercrops to external forcings with that of traditional maize monocrop fields on a temporal scale using earth observation (EO) data.

The smallholder farms in Kenya are largely rainfed, making them highly dependent on timely seasonal rains (Richard et al. 2017). It is common to see the yearly total precipitation relatively unchanged, while the timing of the rainfall and its intensity become steadily more difficult to predict and adapt to (Otte et al. 2017; Torres, Howitt, and Rodrigues 2019). The onset of the seasonal rainfall is an important factor contributing to a successful growing season. The timing of the rains will determine the planning and preparation of the land as well as the sowing of the crop (Ojo, Temenu, and Ilunga 2019). Therefore, the temporal variations in rainfall and its intensity have a direct impact on food supply.

In this regard, capturing the seasonal phenology of agriculture is crucial to provide timely information on plant responses to external forcings. Despite the added value of EO already demonstrated in a range of agricultural applications (Gao and Zhang 2021; Worrall et al. 2023), many studies rely on traditional crop monitoring through household surveys, which leads to sparse information based on little to no integration of EO-based crop yield and condition models (Nakalembe et al. 2021, Qader et al. 2021). This approach suffers from several limitations: (i) it requires time and a high amount of human resources, (ii) the generated output provides only a local assessment preventing the results from being generalized across relevant regional scales, and (iii) the data collection at a single timestep prevents incorporation of a temporal element (Henrys and Jarvis 2019). In contrast, earth observation presents a significant potential to overcome such limitations by introducing remote sensing data at multiple temporal and spatial resolutions.

The present study focuses on demonstrating the response of varying management strategies of agriculture to external climatic forcings by using the multispectral-normalized difference vegetation index (NDVI) to estimate phenological metrics, such as start, peak and end of seasons on field-level. The method was applied on maize monocrop and maize Push-Pull intercrop fields in the Lake Victoria region of Kenya over several growing seasons by employing a harmonized dense time series of Landsat and Sentinel-2 observations and ground truth data with the aim of illustrating the ability of both systems to perform under varying climatic conditions. We specifically aim to: (i) synthesize available climatological knowledge to derive an accurate depiction of the climatic conditions and biotic stresses in the area from 2016 to 2023, (ii) extract the phenological metrics of maize monocrop and Push-Pull fields and (iii) examine the impact of climatic and biotic factors on the performance of these two agricultural systems.

2. Materials and methods

2.1. Study area

The study area is located in southwestern Kenya (Figure 1). In terms of climate, the region is part of the tropical rainforest climate zone and is characterized by relatively constant high temperatures of 18°C or higher and generally high yearly rainfall with over 2.000 mm per year (Beck et al. 2018). The climate in the area is heavily influenced by the Inter Tropical Convergence Zone (ITCZ) (Palmer et al. 2023). The annual changes of the ITCZ result in two wet seasons: April to June known as the “long rainy season” and

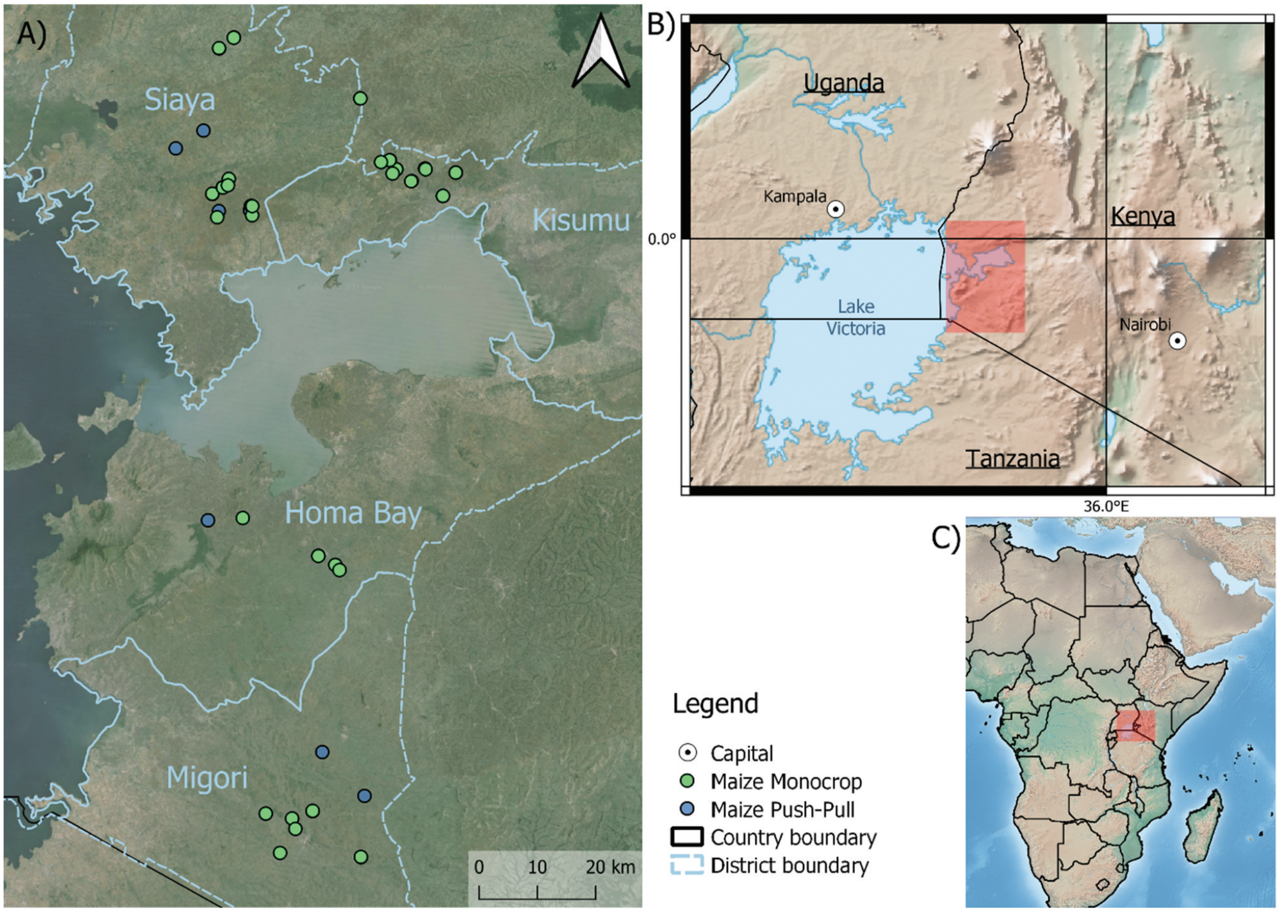

Figure 1. Overview of the study area. Spatial distribution of the in-situ data gathered during the field work is shown in A) where single points denote fields containing one or several sampled fields, regional extent of the study area in B), and continental extent of the regional map shown in C). Sentinel-2 cloud free composite is used as a background layer for A) and Natural Earth vector and raster map data available at naturalearthdata.com/ is used as background for B) and C).

October to December referred to as "short rainy season" (The World Bank 2020). This results in a bimodal growing season pattern with the growing seasons occurring in the periods of March to July and October to December.

The area is characterized by fertile agricultural land which is predominantly rainfed. As a result, the majority of the population performs small-scale farming, grazing, and fishing. A wide variety of staple and cash crops are cultivated in the area, most notably maize, cassava, sweet potato, beans, groundnuts, banana, sugarcane, sorghum, and coffee (Ekesa et al. 2015).

2.2. Data

2.2.1. Satellite data

For the temporal analysis, we used freely available high-spatial resolution products from USGS Landsat missions and Copernicus Sentinel-2 program (Table 2). We used the Landsat Level 2 products, which contain atmospherically corrected and orthorectified surface reflectance values. The Landsat products have a spatial resolution of 30 meters with a panchromatic band in 15-meter resolution and provide seven spectral bands of which red and near-infrared were used in this study to derive the vegetation index. The Landsat constellation is set up with an offset which allows a repeat coverage of 8 days, while the Sentinel-2 mission provides an image scene every 5–6 days. Sentinel-2 sensor provides 12 spectral bands in 10-to-20-meter spatial resolution. The Sentinel-2 Level 2 images are atmospherically corrected using ESA´s sen2cor algorithm (Main-Knorn et al. 2017).

2.2.2. Ground reference and in situ data

A data gathering campaign took place during the long growing season in May 2023. The campaign focused on surveying the four maize-producing regions in Kenya close to Lake Victoria: Siaya, Kisumu, Homa Bay and Migori (Figure 1). During the survey, corner and center coordinates of Push-Pull intercrop and maize monocrop fields were collected using GPS Coordinates App Version 4.71 (174). Afterwards the in-situ data was imported to the QGIS 3.22.6 and with the help of the satellite basemap, small field boundary adjustments were made. We used only fields containing the same crop type throughout the study period, relying on information provided by the farmers for pre-seasons. In total, 58 ground-referenced fields have been selected of which 26 were Push-Pull and 32 were maize monocrop fields. An example of Push-Pull intercrop and maize monocrop fields can be seen in Appendix B. A summary of the field dimensions for each group can be seen in Table 1. The farmers were kept in regular contact throughout the study duration. Field visits by the local agricultural scientists from International Centre of Insect Physiology and Ecology (icipe) took place at a regular basis ensuring continues in situ data validation. The data gathering campaign concluded with the interviews of farmers whose fields were sampled during which the crop type of previous seasons was confirmed. The farmer interviews added insights into agricultural tendencies in the area and individual perspectives on the conditions of the local climate and its agricultural impacts.

2.2.3. Climate and growing season condition data

Several systems and tools leveraging state of the art earth observation data are readily available and have been deployed in national agricultural monitoring programs. The GEOGLAM Crop Monitor for Early Warning (CM4EW) is a relatively recent crop monitoring tool with the focus of providing a reliable and vetted crop assessment for countries exposed to food insecurity (Becker-Reshef et al. 2020). CM4EW provides monthly crop condition assessments based on multi-source consensus data. The monthly reports are prepared at the end of the month, starting ten days before the publication date to ensure timely information. Partner organizations submit crop condition data which is then complimented with agrometeorological earth observation data at the sub-national level (Becker-Reshef et al. 2020). In addition to agricultural assessments, regional and global climatic conditions which are likely to affect the growing season and crop yield are projected and outlined. A total of 88 monthly crop condition reports and 6 special reports for the study area are available for the 2016–2023 period and were used in this study.

We used ERA5-Land reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) for calculation of precipitation and temperature in the research area (2019). Lastly, the multivariate ENSO index was included to highlight the evolution of El Niño and La Niña events which

Table 1. In-situ data statistics for push-pull and maize monocrop fields. Average length, width and area of each crop type are shown, together with the minimum and maximum dimensions within each crop type.

Cropping type	Length, m	Width, m	Area, m2
Push-Pull	25.5 (10–57)	13.9 (10–25)	363.9 (100–918)
Maize monocrop	21.3 (10–42)	13.7 (10–24)	295.6 (120–816)

Table 2. A summary of the collected datasets used in this study. The satellite data consists of sentinel-2, Landsat 7, Landsat 8 and Landsat 9 sensor data; the ground-truth vector data of the monocrop and push-pull fields were collected. Lastly, monthly climate assessment reports from GEOGLAM crop monitor spanning 2016–2023 period were used.

Data	Product Name	Resolution Spatial-Temporal	Source/references
Satellite data	Sentinel-2 A/B	10m 5–6 days	www.corpenicus.eu.
	Landsat 7	15m 16 days	www.usgs.gov.
	Landsat 8	15m 16 days	www.usgs.gov.
	Landsat 9	15m 16 days	www.usgs.gov.
Vector data	Monocrop and Push-Pull ground-truth data	field-level single time step	fieldwork
Climate data	CM4EW growing season condition assessment	district-level monthly	https://cropmonitor.org/.
	Multivariate ENSO index	no spatial resolution monthly	(NCAR 2022)
	ERA5-Land	9km daily	[C3S (2019)]

significantly influence the weather pattern in East Africa (NCAR 2022).

2.3. Methods

The study follows a 4-step methodological workflow: (i) growing season condition estimation: it focuses on synthesizing monthly regional climate and growing season assessment reports into a single, consistent growing season condition overview from 2016 to 2023; (ii) satellite data pre-processing: it is centered around satellite data pre-processing for phenological metrics extraction; (iii) phenological metrics extraction: it utilizes a dense harmonized NDVI timeseries to retrieve the phenological metrics of the maize monocrop and Push-Pull intercrop fields in the study area; and, (iv) statistical analysis of the impacts of climate conditions on crop phenology: the phenological outputs of sections 2 and 3 are compared with the reported growing season conditions from section 1.

2.3.1. Growing season condition estimation

The reports gathered from the GEOGLAM Crop Monitor for Early Warning database were synthesized to get an accurate depiction of the crop conditions during the timeframe of this study. A special focus was given on the identification and timing of extreme hot, dry, or wet conditions, desert locust, FAW, and delayed onset of the season. Growing seasons which contained these conditions during the majority of the season were categorized having *stress-induced growing conditions*, while growing seasons with reportedly good conditions were categorized as having *favourable growing conditions*. The timing and cause of stress-induced growing conditions were cross-referenced with additional scientific publications where available.

2.3.2. Satellite data pre-processing

The pre-processing of satellite data followed the methodological workflow presented in Liepa et al. (2024). Several pre-processing steps were performed to obtain a dense cloud-free and cloud shadow-free time series data set spanning the years 2016 to 2023. The image collections of Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 and 9 Operational Land Imager (OLI), and Sentinel-2 Multispectral Instrument (MSI) were filtered for our study area and the study duration using general spatial and temporal filtering methods in Google Earth Engine (GEE) (Gorelick et al. 2017). Top-of-Atmosphere (TOA) data collections were selected, and the Sensor Invariant Atmospheric Correction (SIAC) was applied (Yin, Lewis, and Gómez-Dans 2022). Utilizing the same atmospheric correction method on imagery from different sensors allowed us to minimize the discrepancies in atmospheric effects exerted on the satellite imagery. Masking cloud and cloud shadow was performed subsequently. Quality Assessment (QA) bands generated from the CFMASK algorithm (Qiu, Zhu, and He 2019; Zhu, Wang, and Woodcock 2015) were used to remove pixels containing cloud contamination in the Landsat sensors. Cloudy pixels in Sentinel-2 were masked using the cloud probability band with the probability value set to less than 25%. Pre-processing was concluded by addressing the different solar and view angles associated with satellite sensors, by applying a Bi-directional Reflectance Distribution Function (BRDF) correction (Claverie et al. 2018; Roy et al. 2016, 2017). This allowed us to adjust the viewing and illumination angles of the satellite imagery. The BRDF correction was executed in the GEE cloud computing environment (Nguyen et al. 2020; Poortinga et al. 2019).

2.3.3. Phenological metrics extraction

The dense NDVI time series was generated by harmonizing Sentinel-2 A/B, Landsat 7, Landsat 8 and Landsat 9 satellite imagery (Liepa et al. 2024). A harmonic curve was fitted on the NDVI time series to smoothen the observed data and cubic interpolation was applied for gap filling purposes as proposed and implemented in Google Earth Engine (GEE) by Descals et al. (2020). A thresholding method was used to estimate the key growing season parameters; start of season (SoS), end of season (EoS) and duration of the season (DoS) (Descals et al. 2021; Standfuß et al. 2022; Vrieling, Leeuw, and Said 2013). The NDVI ratio was used for setting the threshold value (White, Thornton, and Running 1997). The ratio was calculated using the absolute maximum and minimum values of the NDVI during each growing season. The start of season (SoS) and end of season (EoS) are denoted as the first and last days when the NDVI time series of a pixel exceeds the local 50%-threshold (White et al. 2009). The duration of season is calculated by subtracting the date of the EoS by the date of the SoS. In addition to the before mentioned phenological metrics, the maximum vegetation was captured by extracting the maximum NDVI value during each growing season. The phenological extraction was applied on a pixel-by-pixel basis and aggregated for each agricultural field.

2.3.4. Statistical analysis of the impacts of climate conditions on crop phenology

We investigated the significance of the impacts of climate conditions on crop phenology by applying the Welch Two Sample t-test (Welch 1947). This method allowed us to determine whether the crop phonologies derived for the two agricultural systems have significant differences. This test maintains nominal type 1 error rates for groups with unequal sample sizes and should thus produce a more robust statistical analysis. For the t-test, we rejected the null hypothesis of no significant difference at an error probability of 0.1.

3. Results

3.1. Growing season conditions

A graphical summary of the crop conditions from 2016 to 2023 is shown in Figure 2. Southwestern Kenya where the study region is situated experiences more favorable agricultural conditions in contrast to other parts of Kenya. The proximity to Lake Victoria makes the area more resilient to prolonged dry spells and extensive heat episodes. Nevertheless, this area is not immune to adverse climate and periodically experiences poor, climate-driven agricultural periods. The short growing season in 2016 was affected by delayed onset of rainfall leading to dry conditions in October and November (GEOGLAM Crop Monitor 2017a). Additionally, first instances of non-native fall armyworm in the research area were reported (GEOGLAM Crop Monitor 2017b). Delayed rainfall conditions were documented in the subsequent short growing season of 2017 as well (GEOGLAM Crop Monitor 2017c). Following mostly favorable short and long growing seasons in 2018, the substantial rainfall deficits returned in 2019. February and March of 2019 registered up to 75% below-average cumulative rainfall which drastically delayed crop planting in the area (GEOGLAM Crop Monitor 2019). These significantly drier and hotter conditions were driven primarily by the weak El Niño-Southern Oscillation (ENSO) conditions. A year later, the Indian Ocean Dipole (IOD) reversal enhanced rainfall in East Africa, causing flooding in several counties in southwestern Kenya (GEOGLAM Crop Monitor 2020). Above-average rainfall caused an increase in vegetation even in areas with previously sparse vegetation providing favorable conditions for desert locust breeding (Wang et al. 2021). Ultimately, this led to the worst Desert Locust outbreak in East Africa in 25 years.

The most recent challenge came at the end of the year 2021 when delayed rainfall and below-average cumulative precipitation resulted in diminished yields in the 2021 short rainy season. The unfavorable conditions persisted during the subsequent long growing season at the beginning of 2022, which suffered greatly from unpredictable rains and extensive dry spells (GEOGLAM Crop Monitor 2021). To make matters worse, an African armyworm invasion in late April 2022 caused extensive damage to crop fields and added additional stress to an already vulnerable agricultural region (GEOGLAM Crop Monitor 2022).

3.2. Phenological metrics of the in-situ fields

The growing season durations of maize monocrop and Push-Pull classes through the period of the study are shown in Figure 3. Maize monocrop and Push-Pull have very similar growing season duration averages with a few exceptions being the 2018 long growing season, the 2018 short growing season, the 2020 short growing season and the 2021 short growing season. Here, the growing seasons are longer in the Push-Pull fields by about a week. The growing seasons appear to be slightly longer for both agricultural systems during the weak positive ENSO condition between mid-2018 and 2020 (Figure 2). Mean and standard deviation values of growing season duration and maximum NDVI are shown in Appendix C.

Push-Pull fields recorded the highest maximum NDVI averages on 11 of the total 15seasons (Figure 4). During the long growing seasons of 2016 and 2017 as well as during the short growing season of 2017 and 2018 the monocrop class showed the highest NDVI averages. However, the biggest difference between monocrop and Push-Pull intercrop in

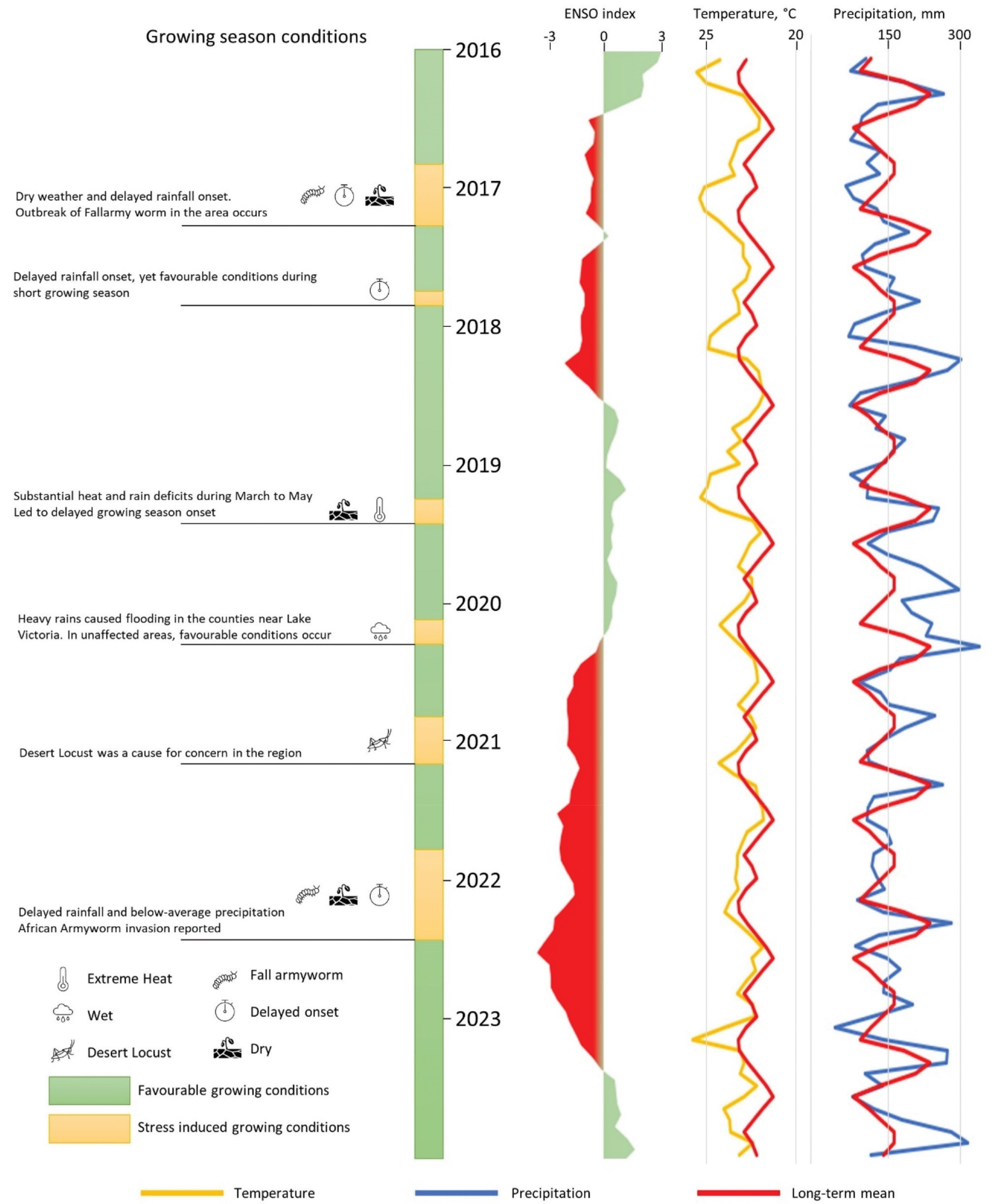

Figure 2. Graphical depiction of the growing season conditions between 2016 and mid-2023 for the study area based on monthly GEOGLAM Crop Monitor assessments. Multivariate ENSO index (NCAR 2022) is depicted with negative (red) and positive (green) phases indicating El Niño and La Niña events respectively. Monthly temperature and precipitation data acquired from ERA5-land dataset (2019) together with the long-term mean in red.

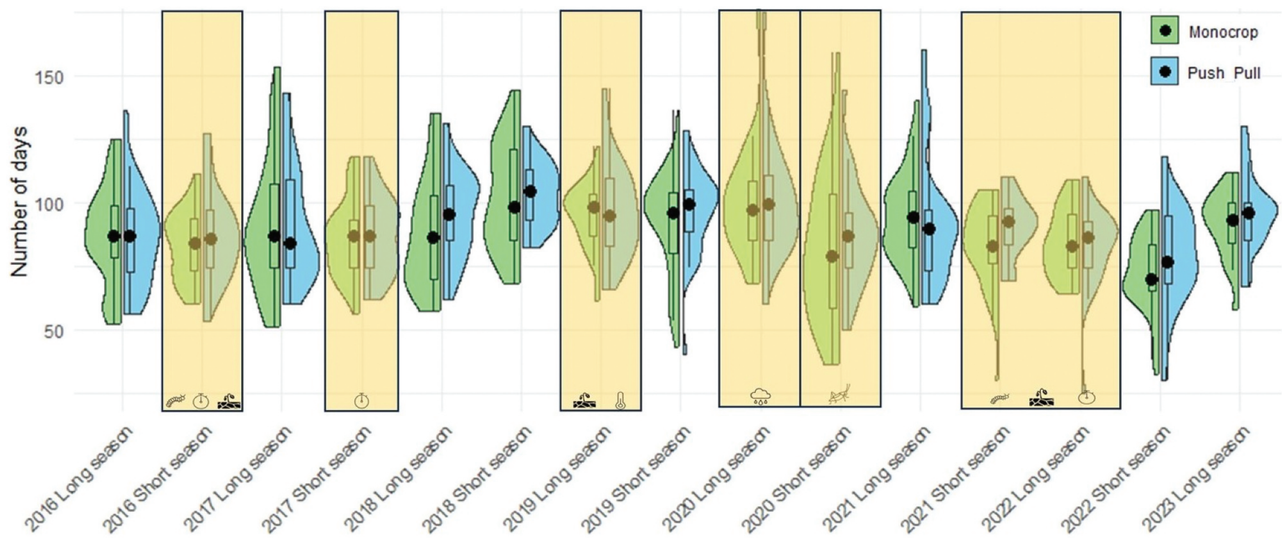

Figure 3. Growing season duration violin plots for maize monocrop and push-pull intercrop classes derived using the harmonized sentinel-2 and Landsat product. Maize monocrop class is depicted in green and the push-pull intercrop is visible in blue. Black dot indicates the mean value of each class. Seasons with stress-induced growing conditions are depicted by yellow boxes and are based on Figure 2.

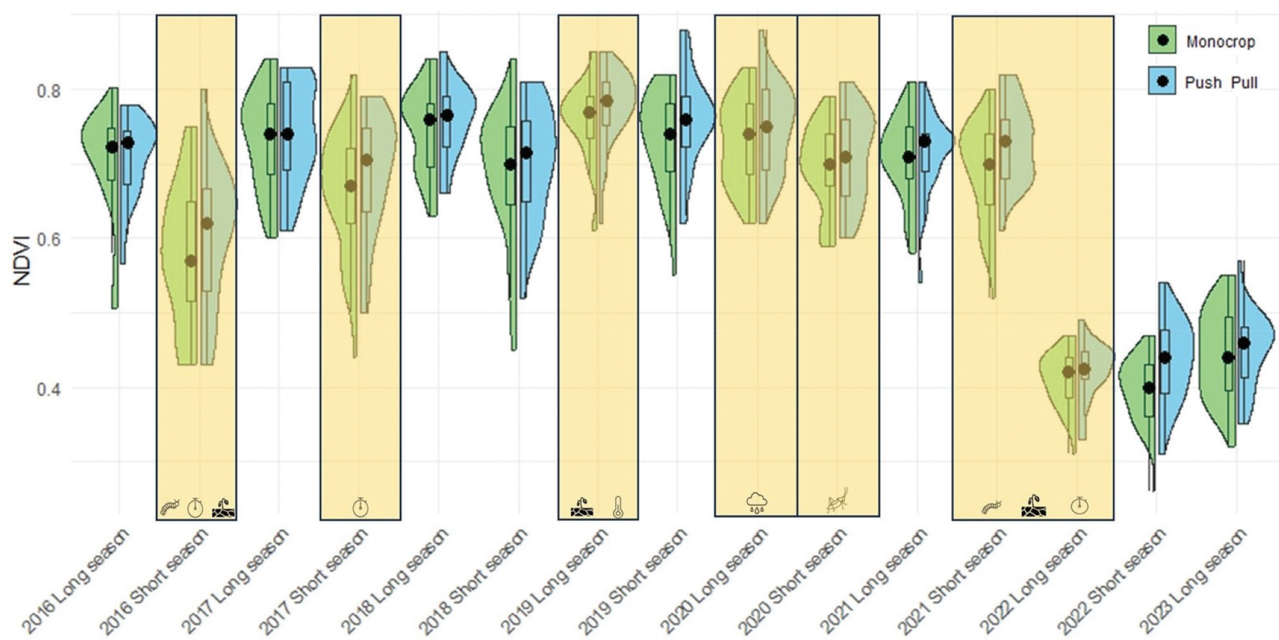

Figure 4. Growing season maximum NDVI violin plots for each growing season derived using the harmonized sentinel-2 and Landsat product. Maize monocrop class is depicted in green and the push-pull intercrop is visible in blue. Black dot indicates the mean value of each class. Seasons with stress-induced growing conditions are depicted by yellow boxes and are based on Figure 2.

the context of maximum NDVI does not appear during these seasons. The biggest discrepancy is observed during the short growing seasons of 2016 and 2022 where Push-Pull intercrop showed higher maximum NDVI values by 0.5 and 0.4, respectively. Interestingly, the biggest discrepancies occur during the short growing seasons which are known to experience less predictive and more sporadic rains.

The growing seasons since 2022 have shown consistently low maximum NDVI values for all classes. The same is partially reflected in the duration of the seasons as both maize monocrop and Push-Pull have recorded short growing season durations since 2022 (Figure 3).

3.3. *Effects of climatic forcings on push-pull and monocrop fields*

The growing conditions were unfavorable in two of the four seasons with the most difference in seasonal duration (Figure 5). This was due to the desert locust outbreak (2020 short season) in combination with the fall armyworm and delayed rainfall, and below-average precipitation (2021 short season). Here, Push-Pull fields recorded longer growing season duration than its monocrop counterparts. During the growing seasons with favorable environment, Push-Pull and maize monocrop fields had very even growing season lengths with one exception being 2018 long where Push-Pull agricultural cycle lasted 97 days in contrast to 88 days of maize monocrop.

In four periods where monocrop fields had longer growing seasons, two of the periods had unfavorable climatic conditions caused by delayed rainfall (2017 short season) and drought (2019 long season). The average day difference recorded was 1 and 3 days, respectively. Favorable growing conditions were registered during the season with the largest negative day difference between Push-Pull and Monocrop (2021 long season). This is also the only season with statistical analysis indicating a significant difference in duration of season with a p-value of 0.034. The p-values of the Welch Two Sample t-test for all growing seasons and phenological metrics are presented in the Appendix D.

Highest maximum NDVI differences were recorded during the short growing seasons coinciding with unfavorable growing conditions (Figure 6). The 2016 short and 2021 short growing seasons featured unfavorable growing conditions caused by fall armyworm outbreaks, the pest against which the Push-Pull agricultural concept was developed to combat. The p-values of 0.034 and 0.013, respectively, support the significant difference in maximum NDVI difference for the short growing seasons of 2016 and 2021. The short growing season of 2017 featured delayed rainfall. With the p-value of 0.367, the maxNDVI difference for this season is not supported by the statistical analysis. Among the seasons with the highest maxNDVI differences, the short season of 2022 (p-value of 0.005) appears to be the only one occurring during favorable growing conditions.

Both agriculture types show some degree of effect by climatic forcings in terms of start and end of growing season (Figure 7). During the short rain seasons of 2016, 2017, 2020 and 2021 which featured stress-induced growing conditions, the end of season occurred considerably earlier in both agricultural systems. The same is not apparent during the long rainy seasons where the seasons with stress-induced conditions (years 2019, 2020 and 2022) show later onset and end of the season. Long growing seasons of 2019 and 2022 recorded substantially late onsets for both cropping systems with seasonal onsets starting at the end of April to beginning of May. These recordings correspond with documented considerable rain deficits and delayed onset of seasonal rains.

Inter-class comparison shows that the start of season for maize monocrop and Push-Pull show significant differences during the 2017 and 2020 short rainy seasons, and the long rainy seasons of 2019 and 2020. These seasons feature stress-induced growing conditions. Weather induced unfavorable growing conditions produced significant seasonal onset difference between maize monocrop and Push-Pull agriculture. The difference in the end of seasons between the two agricultural classes is significant during the 2016 and 2022 short rainy seasons, and the long rainy seasons of 2016 and 2023. Of these four seasons, only the short rainy seasons possessed stress-induced growing conditions. This indicates that the end of the growing season is influenced by fall armyworm and delayed rainfall.

Stable conditions with little to no difference between start and end of growing seasons are registered in favorable growing settings as well. Push-Pull fields in general show a later end of season, however the difference is not significant.

4. Discussion

4.1. *Climatic condition assessment*

The synthesis of the climatological assessment reports from GEOGLAM provided an overview of weather conditions in the research area. This allowed us to determine whether the growing conditions were favorable or stress-induced in terms of rain

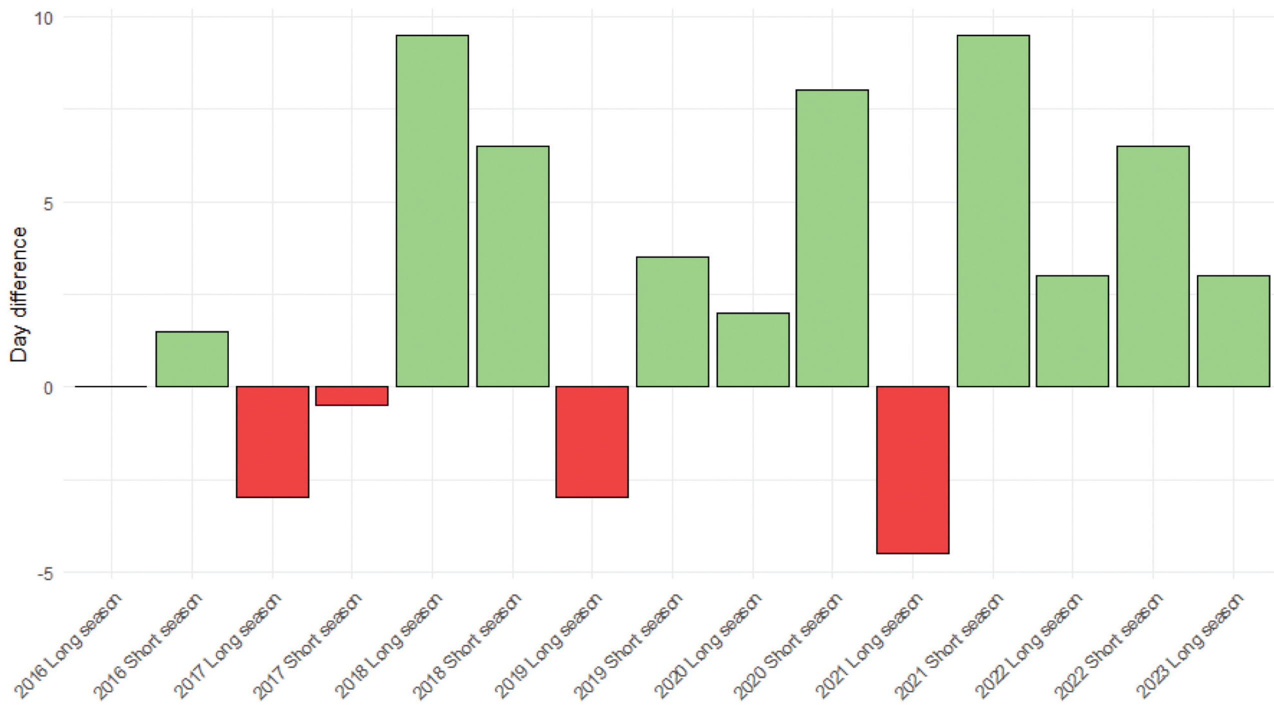

Figure 5. Difference in seasonal durations between push-pull and monocrop classes. The positive values in green indicate seasons during which the push-pull crop type observed longer seasonal duration average. The negative values in red indicate the seasons where push-pull showed shorter seasonal duration average.

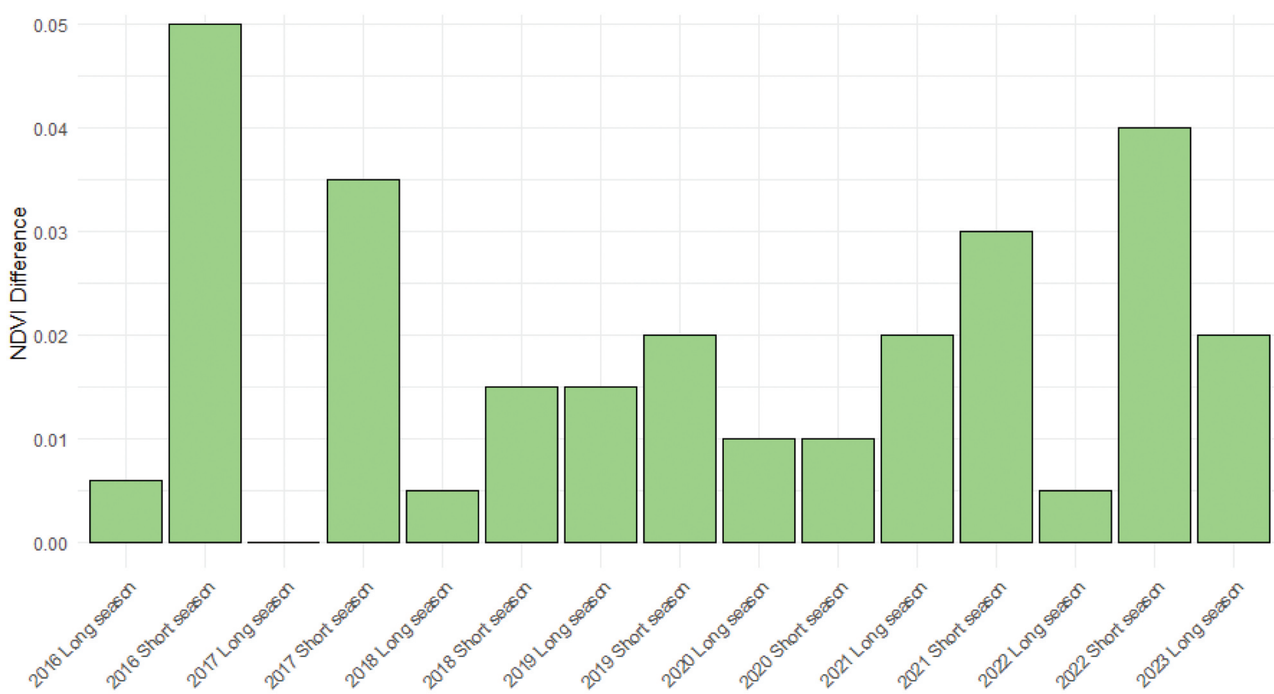

Figure 6. Difference in seasonal maximum NDVI between push-pull and monocrop classes. The positive values in green indicate seasons where push-pull class observed on average higher maxNDVI values. Higher NDVI values have been observed during all growing seasons except 2017 long season where NDVI values were equal.

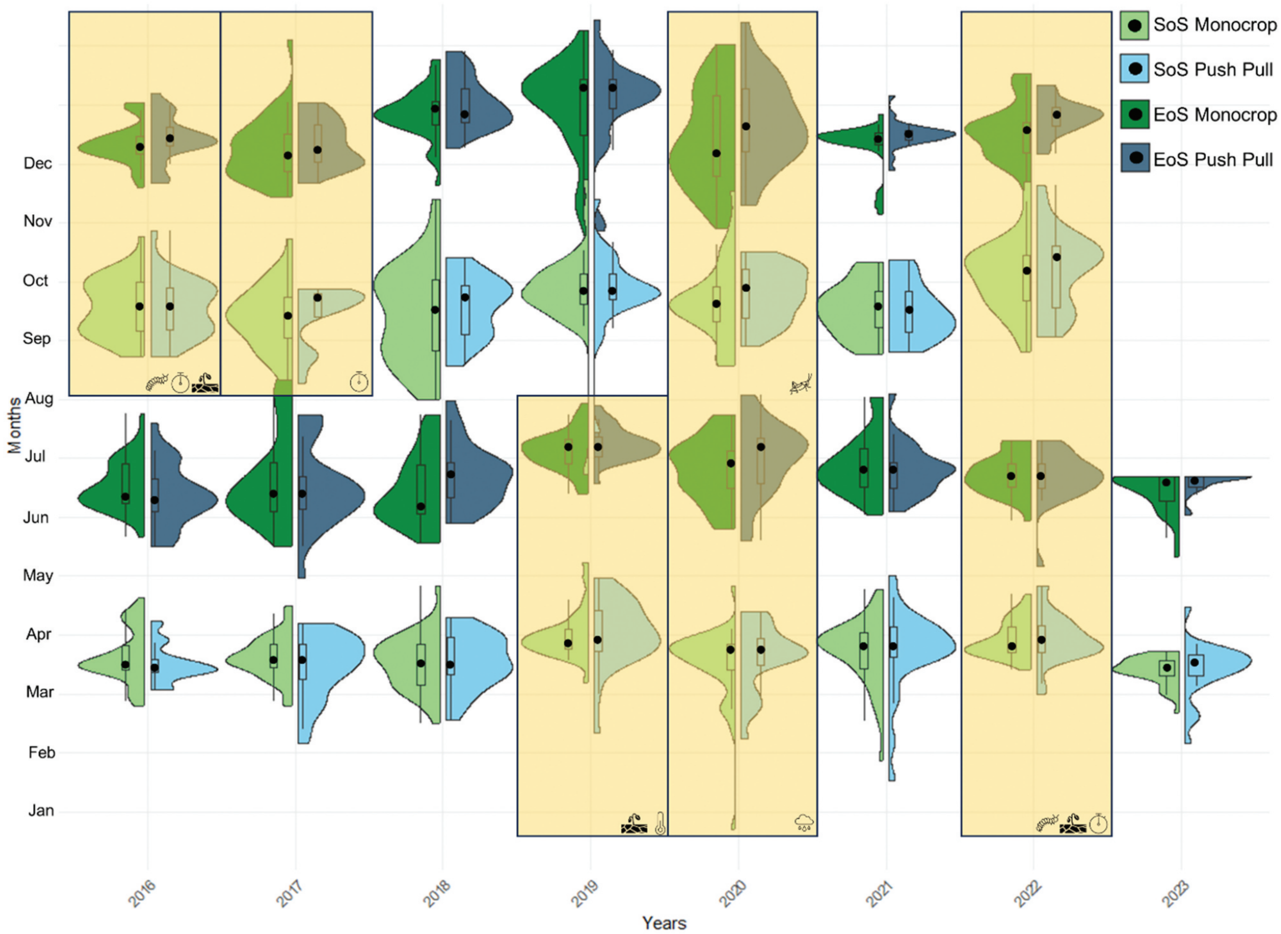

Figure 7. Start of season (SoS) in brighter colors and end of season (EoS) in darker colors for each class during the study period derived using the harmonized sentinel-2 and Landsat product. Maize monocrop class is depicted in green, push-pull intercrop is visible in blue. Black dot indicates the mean value of each class and seasons with stress-induced growing conditions are depicted by yellow boxes and are based on Figure 2.

timing and intensity as well as temperature and biotic stresses. The literature review revealed that 7 out of the total 15 growing seasons had stress-induced growing conditions which may have exerted unfavorable conditions on the crops in the research area. The outputs of GEOGLAM reports in the area are consistent with other assessments. The rainfall anomalies of October to December 2016 and first outbreaks of fall armyworm were highlighted by Uhe et al. (2018) and Groote et al. (2020) respectively. Rain deficits of the 2019 and the 2022 long growing seasons and delayed onset of the 2017 short season were also reported (Funk et al. 2022; Han et al. 2022; Harrison and Way-Henthorne 2019). Excessive rainfall which caused flooding and subsequent crop failures of 2020 were mentioned in a large meteorological study by Wainwright et al. (2021). A desert locust outbreak exerted additional stress to crops in the end of 2020 (Kimathi et al. 2020; Mullié et al. 2023). Lastly, the most recent event of 2021/2022 resulting in adverse effects on agriculture inflicted by reappearance of the fall armyworm, delay in rainfall and below-average rain totals were documented in several studies (Funk et al. 2022; Kansiime, Rwomushana, and Mugambi 2023; Mutyambai et al. 2022). Overall, these studies confirm the climate conditions assumed here on the basis of GEOGLAM reports.

4.2. *Seasonal phenological metrics estimation*

Using the harmonized dataset of Landsat 7, 8, 9, and Sentinel-2 together with the NDVI-based thresholding method allowed us to extract phenological metrics of maize monocrop and Push-Pull intercrop fields. This marks the first attempt in comparing traditional agriculture with agricultural systems featuring applied ecological management strategies based on earth observation data. For reference on the seasonal timing, we planned the ground truth data gathering campaign during the early stage of 2023 long growing season. Field observations gave us a clear timing on the start of the growing season. Farmer interviews added further knowledge on the growing status and anticipated harvest. The monthly assessments from GEOGLAM CM4EW were additional sources used for the seasonal timing reference. Based on these sources, our phenology extraction method could be fine-tuned.

The phenology extraction method allowed us to retrieve the start, peak, duration and end of each growing season. The descriptive ability of the phenological metrics is not uniform. In terms of capturing the changes in phenology driven by climatic forcings between the monocrop and Push-Pull agricultural classes, maximum NDVI provided most descriptive value (Liepa et al. 2024). This is not surprising as maximum NDVI targets the detection of vegetation productivity in turn shedding light on the health of plants in a field. In contrast, the duration of season showed minimal difference between monocrop and Push-Pull agriculture. This can be attributed to the farming practices, as the farmers tend to clear the fields toward the end of the season regardless of the crop yield. Even in crop failure during the early stages of the season, the plants remain in the fields as removal of them can lead to soil degradation and less moisture retention. This impacts the descriptive ability of the end of season metric as well (Liepa et al. 2024). Little change was detected between classes in terms of start of the season since both agricultural types exhibited similar onsets of the season throughout the study period.

The harmonization performance was analyzed on 10-m resolution by resampling the Landsat imagery. By following the pre-processing steps outlined in Liepa et al. (2024), the rescaling prevented loss of data quality. The combined use of Landsat and Sentinel-2 provided a cloud-free image for each pixel every three to four days. The use of the Sentinel-2 constellation alone would provide a revisit time of five days prior to cloud and cloud shadow masking. Thus, inclusion of the Landsat sensors greatly increases the temporal coverage of the target areas.

A noteworthy constraint of the methodology is the relatively small sample size. While the Push-Pull intercrop is now a widely employed cropping practice in Kenya, there are very few fields that have been cultivated throughout the duration of the study. This renders the comparison of the climatic impacts on Push-Pull intercrop and conventional maize monocrop. The sample size also has an effect on the results of statistical significance. A small sample size decreases the power of the statistical tests by increasing the risk of Type II errors, making the true effects difficult to detect. This might explain the misalignment between observed notable differences in phenological metrics and the statistical significance outlined in section 3.3

4.3. Relationship between the phenological metrics and seasonal climatic forcings

Differences between maize monocrop and Push-Pull intercrop fields were at their peak during periods of biotic stresses in the area. These were caused by desert locust (2020 short season) and fall armyworm (2016 short, 2021 short and 2022 long seasons). The FAW outbreaks were accompanied by delayed and below-average rainfall in all three seasons. Interestingly, the first outbreak of the fall armyworm recorded in the 2016 short season showed similar difference in maximum NDVI values, but the duration of the season difference was less profound. This shows that the response of these two agricultural systems to biotic stresses is not always the same from a remote sensing perspective. Such behavior can have several explanations, including transient on-farm farmer mitigative interventions and model performance. As the 2016 short season saw the first recorded outbreak of FAW in the area, farmer intervention via pesticide or fertilizer use could have deviated from later outbreaks. From the modeling perspective, less EO data further back in time might have impacted the harmonization efforts leading to diminished phenology extraction accuracy.

The biggest discrepancies between the two agricultural systems occurred mainly during the short growing season between the October and December months. Unlike the rains during the long growing season, rainfall in the period of October to December is more unpredictable which can cause issues with crop planting for farmers. Having Push-Pull outperforming maize monocrop during short growing seasons may indicate a higher adaptive capability of Push-Pull intercropping. This is further supported by a study based on household surveys in the research area by Ndayisaba et al. (2023). The research found that under rainfall-deficit periods Push-Pull agriculture yielded more maize than its non-push-pull counterpart. Higher climate resilience was also recorded in Ethiopia by Gugissa, Abro, and Tefera (2022) highlighting that the findings are not site-specific.

4.4. Future research and outlooks

The current study emphasizes changes in precipitation and temperature as direct effects of climate change on agriculture. In the context of the performance of Push-Pull and non-Push-Pull agriculture under future climate, it is important to note additional influences such as below-ground processes (Rosenzweig et al. 2001; Ziska and McConnell 2016), soil nutrients and organic matter (Chen et al. 2020; Lu et al. 2013) and soil microbial biomass (Classen et al. 2015). Our research demonstrates the added value of earth observation tools in agricultural monitoring of small-scale agriculture in East Africa. Because of this, adaptation strategies should consider the combined scientific outputs spanning several research disciplines including earth observation. Such future ecological management strategies should also seek to meet various farmer needs and priorities including dietary diversity and address other constraints to ensure value addition and scaling (Chidawanyika et al. 2023). For the Push-Pull, the innovative approach has evolved over the years from the conventional to climate smart and later the 3rd generation Push-Pull technology to address both biotic and abiotic constraints (Cheruiyot et al. 2021). This has ensured wider adoption of the Push-Pull, even to much more arid regions based on context-specific companion cropping. More recently, the Push-Pull has been further intensified by integration with vegetables and edible legumes (Chidawanyika et al. 2023). This approach not only helps in building resilience, but also support scaling through bundled benefits that address various needs.

The study also shows that an area-wide EO-based monitoring system has the potential to systematically monitor and evaluate the acute situation of agricultural production. To fully understand the capabilities of such methodologies, future research should focus on transferability of the method to other regions featuring different pest and climate profiles.

5. Conclusion

This study marks the first attempt in comparing traditional maize cropping with agricultural systems featuring applied ecological management strategies based on earth observation and in situ data. Our study concludes with the following findings:

(i) Climate assessment of the area based on available climatological resources shows that 7 out of 15 growing seasons experienced unfavorable growing conditions between the years 2016 and 2023. These were caused by climatic factors, pest outbreaks or a combination of both.

(ii) Our research introduces a temporal element in agricultural monitoring by harmonizing Landsat 7, 8, 9 with Sentinel-2 spanning the duration of the study. In doing so, phenological metrics of the growing seasons are extracted based on a threshold method using the NDVI as a vegetation proxy. The comparison reveals that inter-class differences exist and are detectable using earth observation tools.

(iii) The impact of regional climatic forcings on the two agricultural systems was most severe during periods of biotic stresses caused by desert locust outbreak and fall armyworm. Higher values in both duration of the season and maximum NDVI indicated a higher resilience by Push-Pull agriculture in times of unfavorable agricultural conditions. Start and end of growing seasons for both cropping systems show similar responses to weather. Short rainy seasons with unfavorable growing conditions resulted in an earlier end of season. Long growing seasons with unfavorable conditions brought about delayed growing season start and ends.

Our research demonstrates the potential of earth observation tools in agricultural monitoring. Unpredictability in the future climate and forecasted increase in abrupt temperature and rainfall variations will influence the planting patterns and growing conditions of crops. Future management strategies should consider the combined scientific outputs spanning several research disciplines including earth observation to enhance the adaptive capacity and resilience of cropping systems.

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Data availability statement

Data will be made available on request.

References

Adams, R. M., B. H. Hurd, S. Lenhart, and N. Leary. 1998. "Effects of Global Climate Change on World Agriculture: An Interpretive Review." *Climate Research* 11 (1): 19–30. https://doi.org/10.3354/cr011019.

Allen, M. 2003. "Liability for Climate Change." *Nature* 421 (6926): 891–892. https://doi.org/10.1038/421891a.

Aydinalp, C., and M. S. Cresser. 2008. "The Effects of Global Climate Change on Agriculture." *American-Eurasian Journal of Agriculture & Environmental Science*.3 (5) :672–676 https://www.researchgate.net/profile/malcolm-cresser/publication/238091112_the_effects_of_global_climate_change_on_agriculture/links/02e7e532ca03f62d72000000/the-effects-of-global-climate-change-on-agriculture.pdf.

Beck, H. E., N. E. Zimmermann, T. R. McVicar, N. Vergopolan, A. Berg, and E. F. Wood. 2018. "Present and Future Köppen-Geiger Climate Classification Maps at 1-Km Resolution." *Scientific Data* 5 (1): 180214. https://doi.org/10.1038/sdata.2018.214.

Becker-Reshef, I., C. Justice, B. Barker, M. Humber, F. Rembold, R. Bonifacio, M. Zappacosta, et al. 2020. "Strengthening Agricultural Decisions in Countries at Risk of Food Insecurity: The GEOGLAM Crop Monitor for Early Warning." *Remote Sensing of Environment* 237:111553. https://doi.org/10.1016/j.rse.2019.111553.

Buleti, S. I., S. Kuyah, A. Olagoke, M. Gichua, S. Were, F. Chidawanyika, and E. A. Martin. 2023. "Farmers' Perceived Pathways for Further Intensification of Push-Pull Systems in Western Kenya." *Frontiers in Sustainable Food Systems*. 7, Article 1191038. 7. https://doi.org/10.3389/fsufs.2023.1191038.

C3S. 2019. *ERA5-Land Monthly Averaged Data from 1950 to Present*. Accessed March 25, 2024. https://doi.org/10.24381/cds.68d2bb30

Challinor, A. J., J. Watson, D. B. Lobell, S. M. Howden, D. R. Smith, and N. Chhetri. 2014. "A Meta-Analysis of Crop Yield Under Climate Change and Adaptation." *Nature Climate Change* 4 (4): 287–291. https://doi.org/10.1038/nclimate2153.

Chen, J., L. Elsgaard, van Groenigen, J. E. Olesen, K. Jan, J. E. Olesen, Z. Liang, et al. 2020. "Soil Carbon Loss with Warming: New Evidence from Carbon-Degrading Enzymes." *Global Change Biology* 26 (4): 1944–1952. https://doi.org/10.1111/gcb.14986.

Cheruiyot, D., F. Chidawanyika, C. A. O. Midega, J. O. Pittchar, J. A. Pickett, and Z. R. Khan. 2021. "Field Evaluation of a New Third Generation Push-Pull Technology for Control of Striga

Weed, Stemborers, and Fall Armyworm in Western Kenya." *Experimental Agriculture* 57 (5–6): 301–315. https://doi.org/10.1017/S0014479721000260.

Chidawanyika, F., B. Muriithi, S. Niassy, F. O. Ouya, J. O. Pittchar, M. Kassie, and Z. R. Khan. 2023. "Sustainable Intensification of Vegetable Production Using the Cereal 'Push-Pull technology': Benefits and One Health Implications." *Environmental Sustainability* 6 (1): 25–34. https://doi.org/10.1007/s42398-023-00260-1.

Classen, A. T., M. K. Sundqvist, J. A. Henning, G. S. Newman, J. A. M. Moore, M. A. Cregger, L. C. Moorhead, and C. M. Patterson. 2015. "Direct and Indirect Effects of Climate Change on Soil Microbial and Soil Microbial-Plant Interactions: What Lies Ahead?" *Ecosphere* 6 (8): 1–21. https://doi.org/10.1890/ES15-00217.1.

Claverie, M., J. Ju, J. G. Masek, J. L. Dungan, E. F. Vermote, J.-C. Roger, S. V. Skakun, and C. Justice. 2018. "The Harmonized Landsat and Sentinel-2 Surface Reflectance Data Set." *Remote Sensing of Environment* 219:145–161. https://doi.org/10.1016/j.rse.2018.09.002.

Cressman, K. 2013. "Role of Remote Sensing in Desert Locust Early Warning." *Journal of Applied Remote Sensing* 7 (1): 75098. https://doi.org/10.1117/1.JRS.7.075098.

David, O. G., A. S. Ayangbenro, J. J. O. Odhiambo, and O. O. Babalola. 2022. "Striga Hermonthica: A Highly Destructive Pathogen in Maize Production." *Environmental Challenges* 8:100590. https://doi.org/10.1016/j.envc.2022.100590.

Descals, A., A. Verger, G. Yin, and J. Penuelas. 2021. "A Threshold Method for Robust and Fast Estimation of Land-Surface Phenology Using Google Earth Engine." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 14:601–606. https://doi.org/10.1109/JSTARS.2020.3039554.

Descals, A., A. Verger, G. Yin, and J. Peñuelas. 2020. "Improved Estimates of Arctic Land Surface Phenology Using Sentinel-2 Time Series." *Remote Sensing* 12 (22): 3738. https://doi.org/10.3390/rs12223738.

Deschenes, O., and M. Greenstone. 2004 The Economic Impacts of Climate Change: Evidence from Agricultural Profits and Random. *American Economic Review* 97 (1): 354–385 doi:10.1257/aer.97.1.354

Ekesa, B., J. Rao, J.-J. Cadilhon, P. Ayebare, B. Bashaasha, C. Muyanja. 2015. A Situational Analysis of Agricultural Production and Marketing, and Natural Resource Management Systems in the Central Region of Uganda. doi:10.13140/RG.2.1.3559.8962.

Funk, C., G. Galu, D. Korecha, L. Harrison, W. Anderson, A. Hoell. 2022. "Forecast Update – East Africa Likely to Experience Six Droughts in a Row. University of California, Santa Barbara's Climate Hazards Center (CHC). Accessed January 15, 2024. https://blog.chc.ucsb.edu/?p=1240.

Gao, F., and X. Zhang. 2021. "Mapping Crop Phenology in Near Real-Time Using Satellite Remote Sensing: Challenges and Opportunities." *Journal of Remote Sensing* 2021, Article 2021/8379391. https://doi.org/10.34133/2021/8379391.

Gebrechorkos, S. H., S. Hülsmann, and C. Bernhofer. 2019. "Long-Term Trends in Rainfall and Temperature Using High-Resolution Climate Datasets in East Africa." *Scientific Reports* 9 (1): 11376. https://doi.org/10.1038/s41598-019-47933-8.

GEOGLAM. 2019. "Special Report: Kenya Long Rains Rapid Crop Assessment. GEOGLAM Crop Monitor. Accessed October 26, 2023 https://cropmonitor.org/index.php/2019/09/24/special-update-kenya/.

GEOGLAM Crop Monitor. 2017a. Early Warning Crop Monitor No. 13. GEOGLAM (13). Accessed March 11, 2023. https://cropmonitor.org/documents/EWCM/reports/EarlyWarning_CropMonitor_201702.pdf.

GEOGLAM Crop Monitor. 2017b. "Early Warning Crop Monitor No. 16." GEOGLAM (16). Accessed March 11, 2023. https://cropmonitor.org/documents/EWCM/reports/EarlyWarning_CropMonitor_201705.pdf.

GEOGLAM Crop Monitor. 2017c. "Early Warning Crop Monitor No. 23." GEOGLAM (23). Accessed March 11, 2023. https://cropmonitor.org/documents/EWCM/reports/EarlyWarning_CropMonitor_201712.pdf.

GEOGLAM Crop Monitor. 2019. "Early Warning Crop Monitor No. 37." GEOGLAM (37). Accessed March 11, 2023. https://cropmonitor.org/documents/EWCM/reports/EarlyWarning_CropMonitor_201904.pdf.

GEOGLAM Crop Monitor. 2020. Early Warning Crop Monitor No. 46. GEOGLAM (46). Accessed March 11, 2023. https://cropmonitor.org/documents/EWCM/reports/EarlyWarning_CropMonitor_202002.pdf.

GEOGLAM Crop Monitor. 2021. "Earl Warning Crop Monitor No. 66." GEOGLAM (66). Accessed March 11, 2023. https://cropmonitor.org/documents/EWCM/reports/EarlyWarning_CropMonitor_202111.pdf.

GEOGLAM Crop Monitor. 2022. "Early Warning Crop Monitor No. 71." GEOGLAM (71). Accessed March 11, 2023. https://cropmonitor.org/documents/EWCM/reports/EarlyWarning_CropMonitor_202205.pdf.

Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore. 2017. "Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone." *Remote Sensing of Environment* 202:18–27. https://doi.org/10.1016/j.rse.2017.06.031.

Groote, H. D., S. C. Kimenju, B. Munyua, S. Palmas, M. Kassie, and A. Bruce. 2020. "Spread and Impact of Fall Armyworm (Spodoptera Frugiperda J.E. Smith) in Maize Production Areas of Kenya." *Agriculture, Ecosystems & Environment* 292:106804. https://doi.org/10.1016/j.agee.2019.106804.

Gugissa, D. A., Z. Abro, and T. Tefera. 2022. "Achieving a Climate-Change Resilient Farming System Through Push–Pull Technology: Evidence from Maize Farming Systems in Ethiopia." *Sustainability* 14 (5): 2648. https://doi.org/10.3390/su14052648.

Halford, N. G., T. Y. Curtis, Z. Chen, and J. Huang. 2015. "Effects of Abiotic Stress and Crop Management on Cereal Grain Composition: Implications for Food Quality and Safety." *Journal of Experimental Botany* 66 (5): 1145–1156. https://doi.org/10.1093/jxb/eru473.

Han, X., Y. Li, W. Yu, and L. Feng. 2022. "Attribution of the Extreme Drought in the Horn of Africa During Short-Rains of 2016 and Long-Rains of 2017." *Water* 14 (3): 409. https://doi.org/10.3390/w14030409.

Harrison, L., and J. Way-Henthorne. 2019. "Kenya's March-To-May Season: An Examination of April 2019 Predictions, May 2019 Outcomes, and the Implications of a Poor Start to the Season." *University of California, Santa Barbara's Climate Hazards Center (CHC)*. Accessed January 15, 2019. https://agrilinks.org/post/kenyas-march-may-season-examination-april-2019-predictions-may-2019-outcomes-and-implications.

Henrys, P. A., and S. G. Jarvis. 2019. "Integration of Ground Survey and Remote Sensing Derived Data: Producing Robust Indicators of Habitat Extent and Condition." *Ecology and Evolution* 9 (14): 8104–8112. https://doi.org/10.1002/ece3.5376.

Hooper, A. M., J. C. Caulfield, B. Hao, J. A. Pickett, C. A. O. Midega, and Z. R. Khan. 2015. "Isolation and Identification of Desmodium Root Exudates from Drought Tolerant Species Used as Intercrops Against Striga Hermonthica." *Phytochemistry* 117:380–387. https://doi.org/10.1016/j.phytochem.2015.06.026.

Hulme, M., R. Doherty, T. Ngara, M. New, and D. Lister. 2001. "African Climate Change: 1900-2100." *Climate Research* 17:145–168. https://doi.org/10.3354/cr017145.

Hütsch, B. W., D. Jahn, and S. Schubert. 2019. "Grain Yield of Wheat (Triticum Aestivum L.) Under Long-Term Heat Stress is Sink-Limited with Stronger Inhibition of Kernel Setting Than Grain Filling." *Journal of Agronomy and Crop Science* 205 (1): 22–32. https://doi.org/10.1111/jac.12298.

IPCC. 2023. *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (Eds.)]*. Geneva, Switzerland: IPCC.

Jafari Jozani, H., M. Thiel, E. M. Abdel-Rahman, K. Richard, T. Landmann, S. Subramanian, and M. Hahn. 2022. "Investigation of Maize Lethal Necrosis (MLN) Severity and Cropping Systems Mapping in Agro-Ecological Maize Systems in Bomet, Kenya Utilizing RapidEye and Landsat-8 Imagery." *Geology, Ecology, and Landscapes* 6 (2): 125–140. https://doi.org/10.1080/24749508.2020.1761195.

Kansiime, M. K., I. Rwomushana, and I. Mugambi. 2023. "Fall Armyworm Invasion in Sub-Saharan Africa and Impacts on Community Sustainability in the Wake of Coronavirus Disease 2019: Reviewing the Evidence." *Current Opinion in Environmental Sustainability* 62:101279. https://doi.org/10.1016/j.cosust.2023.101279.

Kfir, R., W. A. Overholt, Z. R. Khan, and A. Polaszek. 2002. "Biology and Management of Economically Important Lepidopteran Cereal Stem Borers in Africa." *Annual Review of Entomology* 47 (1): 701–731. https://doi.org/10.1146/annurev.ento.47.091201.145254.

Khan, Z., C. A. O. Midega, A. Hooper, and J. Pickett. 2016. "Push-Pull: Chemical Ecology-Based Integrated Pest Management Technology." *Journal of Chemical Ecology* 42 (7): 689–697. https://doi.org/10.1007/s10886-016-0730-y.

Khan, Z. R., A. Hassanali, W. Overholt, T. M. Khamis, A. M. Hooper, J. A. Pickett, L. J. Wadhams, and C. M. Woodcock. 2002. "Control of Witchweed Striga Hermonthica by Intercropping with Desmodium Spp. and the Mechanism Defined as Allelopathic." *Journal of Chemical Ecology* 28 (9): 1871–1885. https://doi.org/10.1023/A:1020525521180.

Khan, Z. R., J. A. Pickett, L. Wadhams, and F. Muyekho. 2001. "Habitat Management Strategies for the Control of Cereal Stemborers and Striga in Maize in Kenya." *International Journal of Tropical Insect Science* 21 (4): 375–380. https://doi.org/10.1017/S1742758400008481.

Kimathi, E., H. E. Z. Tonnang, S. Subramanian, K. Cressman, E. M. Abdel-Rahman, M. Tesfayohannes, S. Niassy, et al. 2020. "Prediction of Breeding Regions for the Desert Locust Schistocerca Gregaria in East Africa." *Scientific Reports* 10 (1): 11937. https://doi.org/10.1038/s41598-020-68895-2.

Liepa, A., M. Thiel, H. Taubenböck, I. Steffan-Dewenter, I.-O. Abu, S. Dhillon, Otte, et al. 2024. "Harmonized NDVI Time-Series from Landsat and Sentinel-2 Reveal Phenological Patterns of Diverse, Small-Scale Cropping Systems in East Africa." *Remote Sensing Applications: Society & Environment* 35:101230. https://doi.org/10.1016/j.rsase.2024.101230.

Lu, M., X. Zhou, Q. Yang, H. Li, Y. Luo, C. Fang, J. Chen, X. Yang, and B. Li. 2013. "Responses of Ecosystem Carbon Cycle to Experimental Warming: A Meta-Analysis." *Ecology* 94 (3): 726–738. https://doi.org/10.1890/12-0279.1.

Main-Knorn, M., B. Pflug, J. Louis, V. Debaecker, U. Müller-Wilm, and F. Gascon. 2017. "Sen2Cor for Sentinel-2." *Proceedings of the SPIE* 10427 (10427). Accessed October, 2017. https://www.spiedigitallibrary.org/conference-proceedings-of-spie/10427/2278218/Sen2Cor-for-Sentinel-2/10.1117/12.2278218.full.

Malhi, G. S., M. Kaur, and P. Kaushik. 2021. "Impact of Climate Change on Agriculture and Its Mitigation Strategies: A Review." *Sustainability* 13 (3): 1318. https://doi.org/10.3390/su13031318.

Market Aliance. 2022. "Kenya Country Brief. Farm to Market Alliance. Accessed October 27, 2023. https://ftma.org/wp-content/uploads/2022/02/FtMA_Kenya_CountryBrief_Dec-2022.pdf.

Midega, C. A. O., T. J. A. Bruce, J. A. Pickett, and Z. R. Khan. 2015. "Ecological Management of Cereal Stemborers in African Smallholder Agriculture Through Behavioural Manipulation." *Ecological Entomology* 40 (Suppl 1): 70–81. https://doi.org/10.1111/een.12216.

Mubenga-Tshitaka, J.-L., J. Dikgang, M. Mwamba, W. John, and D. Gelo. 2023. "Climate Variability Impacts on Agricultural Output in East Africa." *Cogent Economics and Finance* 11 (1), Article 2181281. https://doi.org/10.1080/23322039.2023.2181281.

Mullié, W. C., A. Prakash, A. Müller, and E. Lazutkaite. 2023. "Insecticide Use Against Desert Locust in the Horn of Africa 2019–2021 Reveals a Pressing Need for Change." *Agronomy* 13 (3): 819. https://doi.org/10.3390/agronomy13030819.

Mumo, L., J. Yu, and K. Fang. 2018. “Assessing Impacts of Seasonal Climate Variability on Maize Yield in Kenya.” *International Journal of Plant Production* 12 (4): 297–307. https://doi.org/10.1007/s42106-018-0027-x.

Mutyambai, D. M., S. Niassy, P.-A. Calatayud, and S. Subramanian. 2022. “Agronomic Factors Influencing Fall Armyworm (Spodoptera frugiperda) Infestation and Damage and Its Co-Occurrence with Stemborers in Maize Cropping Systems in Kenya.” *Insects* 13 (3): 266. https://doi.org/10.3390/insects13030266.

Nakalembe, C., I. Becker-Reshef, R. Bonifacio, G. Hu, M. L. Humber, C. J. Justice, J. Keniston, et al. 2021. “A Review of Satellite-Based Global Agricultural Monitoring Systems Available for Africa.” *Global Food Security* 29:100543. https://doi.org/10.1016/j.gfs.2021.100543.

NCAR. 2022. “The Climate Data Guide: Multivariate ENSO Index. Last Modified 2022-11-07.” *National Center for Atmospheric Research*. Accessed May, 2024. https://climatedataguide.ucar.edu/climate-data/multivariate-enso-index.

Ndayisaba, P. C., S. Kuyah, C. A. O. Midega, P. N. Mwangi, and Z. R. Khan. 2023. “Push-Pull Technology Enhances Resilience to Climate Change and Prevents Land Degradation: Perceptions of Adopters in Western Kenya.” *Farming System* 1 (2): 100020. https://doi.org/10.1016/j.farsys.2023.100020.

Neupane, D., P. Adhikari, D. Bhattarai, B. Rana, Z. Ahmed, U. Sharma, and D. Adhikari. 2022. “Does Climate Change Affect the Yield of the Top Three Cereals and Food Security in the World?” *Earth* 3 (1): 45–71. https://doi.org/10.3390/earth3010004.

Nguyen, M., O. Baez-Villanueva, D. Bui, P. Nguyen, and L. Ribbe. 2020. “Harmonization of Landsat and Sentinel 2 for Crop Monitoring in Drought Prone Areas: Case Studies of Ninh Thuan (Vietnam) and Bekaa (Lebanon).” *Remote Sensing* 12 (2): 281. https://doi.org/10.3390/rs12020281.

Ochieng, J., L. Kirimi, and M. Mathenge. 2016. “Effects of Climate Variability and Change on Agricultural Production: The Case of Small Scale Farmers in Kenya.” *NJAS: Wageningen Journal of Life Sciences* 77 (1): 71–78. https://doi.org/10.1016/j.njas.2016.03.005.

Ojo, O. I., C. Temenu, and M. F. Ilunga. 2019. “Analysis of Length of Growing Season in Some Agro-Ecological Zones Using Non-Parametric Trend Test.” *Notulae Scientia Biologicae* 11 (2): 241–248. https://doi.org/10.15835/nsb11210314.

Ondiek, R. A., M. Saber, and M. Abdel-Fattah. 2024. “Spatial–Temporal Analysis of Impacts of Climate Variability on Maize Yield in Kenya.” *Agriculture* 14 (8): 1415. https://doi.org/10.3390/agriculture14081415.

Otte, I., F. Detsch, E. Mwangomo, A. Hemp, T. Appelhans, and T. Nauss. 2017. “Multidecadal Trends and Interannual Variability of Rainfall as Observed from Five Lowland Stations at Mt. Kilimanjaro, Tanzania.” *Journal of Hydrometeorology* 18 (2): 349–361. https://doi.org/10.1175/JHM-D-16-0062.1.

Palmer, P. I., C. M. Wainwright, B. Dong, R. I. Maidment, K. G. Wheeler, N. Gedney, J. E. Hickman, et al. 2023. “Drivers and Impacts of Eastern African Rainfall Variability.” *Nature Reviews Earth and Environment* 4 (4): 254–270. https://doi.org/10.1038/s43017-023-00397-x.

Poortinga, A., K. Tenneson, A. Shapiro, Q. Nquyen, K. San Aung, F. Chishtie, and D. Saah. 2019. “Mapping Plantations in Myanmar by Fusing Landsat-8, Sentinel-2 and Sentinel-1 Data Along with Systematic Error Quantification.” *Remote Sensing* 11 (7): 831. https://doi.org/10.3390/rs11070831.

Qader, S. H., J. Dash, V. A. Alegana, N. R. Khwarahm, A. J. Tatem, and P. M. Atkinson. 2021. “The Role of Earth Observation in Achieving Sustainable Agricultural Production in Arid and Semi-Arid Regions of the World.” *Remote Sensing* 13 (17): 3382. https://doi.org/10.3390/rs13173382.

Qiu, S., Z. Zhu, and B. He. 2019. “Fmask 4.0: Improved Cloud and Cloud Shadow Detection in Landsats 4–8 and Sentinel-2 Imagery.” *Remote Sensing of Environment* 231:111205. https://doi.org/10.1016/j.rse.2019.05.024.

Richard, K., E. M. Abdel-Rahman, S. Subramanian, J. O. Nyasani, M. Thiel, H. Jozani, C. Borgemeister, and T. Landmann. 2017. “Maize Cropping Systems Mapping Using RapidEye Observations in Agro-Ecological Landscapes in Kenya.” *Sensors (Basel, Switzerland)* 17 (11): 2537. https://doi.org/10.3390/s17112537.

Rosenzweig, C., A. Iglesius, X. B. Yang, P. Epstein, and E. Chivian. 2001. “Climate Change and Extreme Weather Events-Implications for Food Production, Plant Diseases, and Pests.” https://digitalcommons.unl.edu/nasapub/24/ .

Roy, D. P., J. Li, H. K. Zhang, L. Yan, H. Huang, and Z. Li. 2017. “Examination of Sentinel-2A Multi-Spectral Instrument (MSI) Reflectance Anisotropy and the Suitability of a General Method to Normalize MSI Reflectance to Nadir BRDF Adjusted Reflectance.” *Remote Sensing of Environment* 199:25–38. https://doi.org/10.1016/j.rse.2017.06.019.

Roy, D. P., H. K. Zhang, J. Ju, J. L. Gomez-Dans, P. E. Lewis, C. B. Schaaf, Q. Sun, J. Li, H. Huang, and V. Kovalskyy. 2016. “A General Method to Normalize Landsat Reflectance Data to Nadir BRDF Adjusted Reflectance.” *Remote Sensing of Environment* 176:255–271. https://doi.org/10.1016/j.rse.2016.01.023.

Salvo, M. D., D. Begalli, and G. Signorello. 2013. “Measuring the Effect of Climate Change on Agriculture: A Literature Review of Analytical Models.” *Journal of Development and Agricultural Economics* 5 (12): 499–509. https://www.researchgate.net/profile/diego-begalli/publication/258437340_measuring_the_effect_of_climate_change_on_agriculture_a_literature_review_of_analytical_models/links/00b7d52838e06a79b7000000/measuring-the-effect-of-climate-change-on-agriculture-a-literature-review-of-analytical-models.pdf.

Sánchez-Bermúdez, M., D. Pozo, C. Juan, and M. Pernas. 2022. “Effects of Combined Abiotic Stresses Related to Climate Change on Root Growth in Crops.” *Frontiers in Plant Science* 13:918537. https://doi.org/10.3389/fpls.2022.918537.

Schlenker, W., and D. B. Lobell. 2010. “Robust Negative Impacts of Climate Change on African Agriculture.” *Environmental Research Letters* 5 (1): 14010. https://doi.org/10.1088/1748-9326/5/1/014010.

Shahzad, A., S. Ullah, A. A. Dar, M. F. Sardar, T. Mehmood, M. A. Tufail, A. Shakoor, and M. Haris. 2021. "Nexus on Climate Change: Agriculture and Possible Solution to Cope Future Climate Change Stresses." *Environmental Science and Pollution Research International* 28 (12): 14211–14232. https://doi.org/10.1007/s11356-021-12649-8.

Sharma, R. K., S. Kumar, K. Vatta, R. Bheemanahalli, J. Dhillon, and K. N. Reddy. 2022. "Impact of Recent Climate Change on Corn, Rice, and Wheat in Southeastern USA." *Scientific Reports* 12 (1): 16928. https://doi.org/10.1038/s41598-022-21454-3.

Sisay, B., J. Simiyu, E. Mendesil, P. Likhayo, G. Ayalew, S. Mohamed, S. Subramanian, and T. Tefera. 2019. "Fall Armyworm, Spodoptera Frugiperda Infestations in East Africa: Assessment of Damage and Parasitism." *Insects* 10 (7): 195. https://doi.org/10.3390/insects10070195.

Standfuß, I., C. Geiß, R. Nathan, S. Rotics, M. Scacco, G. Kerr, H. Taubenböck, N. Pettorelli, and G. Buchanan. 2022. "Time Series Enable the Characterization of Small-Scale Vegetation Dynamics That Influence Fine-Scale Animal Behavior – An Example from White Storks' Foraging Behavior." *Remote Sensing in Ecology and Conservation* 8 (3): 391–408. https://doi.org/10.1002/rse2.251.

Steffan-Dewenter, I., B. Kerr, and P. Rachel. 2024. "Insect Diversity for Agroecosystem Resilience in a Changing Climate." *One Earth* 7 (4): 541–544. https://doi.org/10.1016/j.oneear.2024.03.003.

Tambo, J. A., R. K. Day, J. Lamontagne-Godwin, S. Silvestri, P. K. Beseh, B. Oppong-Mensah, N. A. Phiri, and M. Matimelo. 2020. "Tackling Fall Armyworm (Spodoptera Frugiperda) Outbreak in Africa: An Analysis of farmers' Control Actions." *International Journal of Pest Management* 66 (4): 298–310. https://doi.org/10.1080/09670874.2019.1646942.

Taubenböck, H., J. Mast, C. Geiß, M. Wurm, T. Esch, and K. C. Seto. 2024. "Global Differences in Urbanization Dynamics from 1985 to 2015 and Outlook Considering IPCC Climate Scenarios." *Cities* 151:105117. https://doi.org/10.1016/j.cities.2024.105117.

Torres, M., R. Howitt, and L. Rodrigues. 2019. "Analyzing Rainfall Effects on Agricultural Income: Why Timing Matters." *EconomiA* 20 (1): 1–14. https://doi.org/10.1016/j.econ.2019.03.006.

Uhe, P., S. Philip, S. Kew, K. Shah, J. Kimutai, E. Mwangi, G. J. van Oldenborgh, et al. 2018. "Attributing Drivers of the 2016 Kenyan Drought." *International Journal of Climatology* 38 (S1). https://doi.org/10.1002/joc.5389.

UN. 2018. "World Urbanization Prospects: The 2018 Revision, Online Edition." *United Nations Department of Economic and Social Affairs, Population Division*. Accessed June, 2024. https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf.

Vrieling, A., J. D. Leeuw, and M. Said. 2013. "Length of Growing Period Over Africa: Variability and Trends from 30 Years of NDVI Time Series." *Remote Sensing* 5 (2): 982–1000. https://doi.org/10.3390/rs5020982.

Wainwright, C. M., D. L. Finney, M. Kilavi, E. Black, and J. H. Marsham. 2021. "Extreme Rainfall in East Africa, October 2019–January 2020 and Context Under Future Climate Change." *Weather* 76 (1): 26–31. https://doi.org/10.1002/wea.3824.

Wang, L., W. Zhuo, Z. Pei, X. Tong, W. Han, and S. Fang. 2021. "Using Long-Term Earth Observation Data to Reveal the Factors Contributing to the Early 2020 Desert Locust Upsurge and the Resulting Vegetation Loss." *Remote Sensing* 13 (4): 680. https://doi.org/10.3390/rs13040680.

Welch, B. L. 1947. "The Generalization of `student's' Problem When Several Different Population Variances are Involved." *Biometrika* 34 (1/2): 28. https://doi.org/10.2307/2332510.

White, M. A., K. M. de Beurs, K. A. M. E. L. Didan, D. W. Inouye, A. D. Richardson, O. P. Jensen, J. O'KEEFE, et al. 2009. "Intercomparison, Interpretation, and Assessment of Spring Phenology in North America Estimated from Remote Sensing for 1982–2006." *Global Change Biology* 15 (10): 2335–2359. https://doi.org/10.1111/j.1365-2486.2009.01910.x.

White, M. A., P. E. Thornton, and S. W. Running. 1997. "A Continental Phenology Model for Monitoring Vegetation Responses to Interannual Climatic Variability." *Global Biogeochemical Cycles* 11 (2): 217–234. https://doi.org/10.1029/97GB00330.

The World Bank. 2020. "Climate Risk Profile: Kenya. The World Bank." Accessed October 30, 2023. https://climateknowledgeportal.worldbank.org/sites/default/files/2021-05/15724-WB_Kenya%20Country%20Profile-WEB.pdf.

The World Bank. 2022. "Agriculture, Forestry, and Fishing, Value Added (% of GDP) - Kenya." Accessed October 27, 2023. https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=KE.

World Meteorological Organization. 1992. *International Meteorological Vocabulary. Vocabulaire météorologique International*. 2. ed. Genève: WMO.

Worrall, G., J. Judge, K. Boote, and A. Rangarajan. 2023. "In-Season Crop Phenology Using Remote Sensing and Model-Guided Machine Learning." *Agronomy Journal* 115 (3): 1214–1236. https://doi.org/10.1002/agj2.21230.

Yin, F., P. E. Lewis, and J. L. Gómez-Dans. 2022. "Bayesian Atmospheric Correction Over Land: Sentinel-2/MSI and Landsat 8/OLI." *Geoscientific Model Development* 15 (21): 7933–7976. https://doi.org/10.5194/gmd-15-7933-2022.

Zhu, Z., S. Wang, and C. E. Woodcock. 2015. "Improvement and Expansion of the Fmask Algorithm: Cloud, Cloud Shadow, and Snow Detection for Landsats 4–7, 8, and Sentinel 2 Images." *Remote Sensing of Environment* 159:269–277. https://doi.org/10.1016/j.rse.2014.12.014.

Ziska, L. H., and L. L. McConnell. 2016. "Climate Change, Carbon Dioxide, and Pest Biology: Monitor, Mitigate, Manage." *Journal of Agricultural and Food Chemistry* 64 (1): 6–12. https://doi.org/10.1021/jf506101h.