Detecting Agricultural and Meteorological Drought With Gross Primary Production Recovery Including Spatiotemporal Statistical Analysis in East Africa's Lake Victoria Basin

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Abstract

Drought imposes severe, long-term effects on global environments and ecosystems. A better understanding of how long it takes a region to recover to pre-drought conditions after drought is essential for addressing future ecology risks. In this study, drought-related variables were obtained using remote sensing and reanalysis products for 2003 to 2016. The meteorological drought index (standardized precipitation evapotranspiration index [SPEI]) and agricultural drought index (vegetation condition index [VCI]) were employed to estimate drought duration time (DDT) and drought recovery time (DRT). To the basin’s west, decreasing rainfall and increasing potential evapotranspiration led to decreasing SPEI. On the east side, decreasing soil moisture from each depth effects vegetation condition, which results in a decreasing gross primary productivity and VCI. Extreme meteorological drought events are likely to occur in the basin’s northeastern and middle western areas, while the southern basin is more likely to suffer from extreme agricultural drought events. The mean SPEI-based DDT (2.45 months) was smaller than the VCI-based DDT (2.97 months); the average SPEI-based DRT (2.02 months) was larger than the VCI-based DRT (1.63 months). Most of the area needs 1 or 2 months to recover from drought except for the basin’s northwestern area, where the DRT is more than 8 months. DDT is the most important parameter in determining DRT. These results provide useful information about regional drought recovery that will help local governments looking to mitigate potential environmental risks and formulate appropriate agricultural policies in Lake Victoria Basin.

1. Introduction

As a devastating hazard, drought not only imposes extensive and long-term effects on the global environmental system, it also causes significant losses to the economy and human life (Mishra and Singh, 2010; Sternberg, 2011; Van Dijk et al., 2013). To reduce drought risk and prevent drought under global climate change and global warming (Trenberth et al., 2014), several research contributions have been made in the fields of drought monitoring (Aadhar and Mishra, 2017; West et al., 2019) and prediction (AghaKouchak, 2015; Hao et al., 2018, 2014). Those studies considered hydrological and meteorological variables to better understand regional drought event causes and quantification.

Other studies use ecological variables to identify this natural hazard at the ecosystem level (Anderegg et al., 2018; Banerjee et al., 2013; Schwalm et al., 2017; Van der Molen et al., 2011). In particular, drought recovery time (DRT) has received growing research attention in recent years (Ahmadi et al., 2019; Ahmadi and Moradkhani, 2019; He et al., 2018; Huang et al., 2021; Liu et al., 2019; Schwalm et al., 2017; Seneviratne and Ciais, 2017; Zhang et al., 2019). DRT will likely become longer than the time between drought events (Schwalm et al., 2017). Regional drought effects are compounded if a new drought event occurs before recovery from a preceding drought event is complete (Seneviratne and Ciais, 2017). Therefore, accurate DRT assessments are essential for understanding possible ecological risks.

DRT is defined as the time required for a region to fully return to its pre-drought conditions (Schwalm et al., 2017). Drought identification and recovery parameter selection are the key steps in DRT calculations.
To identify a drought event, previous studies used the meteorological drought index (Standardized Precipitation Evapotranspiration Index, SPEI) and Drought Severity Index (DSI) (Liu et al., 2019; Schwalm et al., 2017; Yu et al., 2017). Climate data-based SPEI is easy to estimate for long-term analysis but it is not linked to plant condition (Vicente-Serrano et al., 2010). Satellite-based DSI includes greenness information with high spatial resolution. However, DSI data is only available from 2000 to 2011 with uncertainties from the satellite (cloud cover, atmospheric aerosols, and low solar illumination) and single input data (Mu et al., 2013).

Many factors such as water quantity (streamflow and total water storage), water quality (water temperature, turbidity, and dissolved oxygen), ecosystem fluxes (carbon and energy fluxes), and gross primary productivity (GPP) are used in drought recovery assessments (Ahmadi et al., 2019; He et al., 2018; Schwalm et al., 2017; Seneviratne and Ciais, 2017; Zhang et al., 2019). For example, the change in total water storage was used to identify hydrological DRT (between 3.6 and 5.7 months) for the Yangtze River in China (Zhang et al., 2019). Ahmadi et al. (2019) analyzed drought recovery by considering both streamflow and water quality parameter changes. They found that the average recovery time in the contiguous United States is around 1.2 months. The time required for carbon and energy fluxes to recover from the 2012 U.S. drought (0.5–2 months) and the 2003 European drought (1–2 months) were examined by He et al. (2018). Based on changes to GPP, global spatiotemporal DRT patterns were examined by Schwalm et al. (2017) and Yu et al. (2017). All of these studies focused on the DRT length and response functions. Among the factors, GPP is the most impactful due to its high drought sensitivity and spatiotemporal patterns. It can accommodate increasingly fine spatial resolution and frequent repeat measurements (Schwalm et al., 2017). Schwalm et al. (2017) estimated that DRT can be determined at 0.5° spatial resolution and 6 months of temporal resolution from 1901 to 2010 around the world. They found that most of the world can recover from a drought in less than six months. Unlike a conventional drought, a flash drought typically occurs during warm seasons and can occur more frequently - in one or two months (Ford and Labosier, 2017). Therefore, DRT should be examined in more detailed studies at a high spatiotemporal resolution. Yu et al. (2017) calculated global DRT from 2000 to 2011 at 0.5° spatial resolution and 1 month temporal resolution, but the results were different for Schwalm et al. (2017) in terms of spatial pattern and DRT length. As reported by Liu et al. (2019), using different methods to define drought events and recovery levels are the key factors contributing to the contradictory conclusions. Despite the large amount of research on meteorological and hydrological DRT, there has been very little work integrating long-term agricultural DRT at a high spatiotemporal resolution in dry regions such as East Africa, where people are largely dependent on rain-fed agriculture and livestock farming (Gebremeskel et al., 2019).

To better understand drought recovery in the Lake Victoria Basin, our objectives are 1) check the seasonal patterns and trends of drought-related variables; 2) capture drought events using meteorological (SPEI) and agricultural (vegetation condition index [VCI]) drought indices from 2003 to 2016; 3) investigate SPEI based- and VCI based-DRT for high spatiotemporal resolution; and 4) examine parameter importance for determining DRT across the Lake Victoria Basin. To the best of our knowledge, this is the first comprehensive study to quantify agricultural DRT at a high spatiotemporal resolution.
2. Study Area And Dataset

2.1 Study area

As the second largest freshwater lake in the world, Lake Victoria supports one of the world’s poorest and densest populations. Its catchment covers a 194,200 km$^2$ area and has a total population of 30 million people (Mailu, 2001). Basin agriculture supports more than 70% of the local population (Zhou et al., 2014). Figure 1 shows the land cover distribution in the Lake Victoria Basin. Grassland (16%) is predominantly in the west, open water (26%) in the middle, and cropland (36%) in the east. Maize is the main crop (Zhou et al., 2014).

The Victoria Basin is shared by 5 agricultural East African nations: Kenya, Uganda, Tanzania, Rwanda, and Burundi. Kenya is in the northeastern part of the basin, and contains three provinces: Nyanza, Western, and Rift Valley. They are predominantly cropland. The northwest comprises central Ugandan districts Masaka and Mpigi, which are characterized by large farming communities. Tanzania, located in the basin’s south, also has a large cropland area. Most of the farmland is located in the Mwanza and Mara provinces, though it also covers the Kagera region, a key region for food production and distribution whose landcover is a mixture of cropland and grassland. Rwanda is located in the western part of the study area and is mainly covered by cropland. Burundi is also in the western basin and is half cropland. According to the Köppen-Geiger climate classification (Peel et al., 2007), Lake Victoria Basin's climate zone is tropical with four distinct seasons: hot dry (Dec. to Feb., DJF), major rainy (Mar. to May, MMA), short dry (Jun. to Aug., JJA) and short rainy (Sept. to Nov., SON) (Awange JL, 2006). Annual precipitation ranges between 670 and 2,200 mm, with a mean value of 1,202 mm (Kizza et al., 2009). Several studies discuss droughts in the Lake Victoria Basin during the twentieth century’s last two decades (Funk et al., 2014; Gebremeskel et al., 2019; Lyon and Dewitt, 2012). Since 2003, drought has continued to occur every 3 years on average, with a significant increase in severity and frequency (Funk et al., 2014). Drought re-emergence has had devastating effects on local people, flora, and fauna.

2.2 Dataset

To estimate SPEI, we used global hydrological datasets (Global Land Data Assimilation System Noah Land Surface Model L4 monthly 0.25° × 0.25° Version 2.1 [GLDAS_NOAH025_M _V2.1] and Tropical Rainfall Measurement Mission Rainfall Estimate L3 1 month 0.25-degree x 0.25-degree V7 [TRMM-3B43]). First, we used the GLDAS-2.1 net radiation flux, ground heat flux, air temperature, and surface pressure to calculate potential evapotranspiration (PET) based on the Priestley and Taylor (PT) method. Next, we used the GLDAS-based PET and rainfall data from TRMM-3B43 to compute SPEI.

In this study, we used the GLDAS_NOAH025_M _V2.1 dataset (Beaudoing and Rodell, 2020) for soil moisture (0–10cm, 10–40cm, 40–100cm, and 100–200cm) data, net radiation flux, ground heat flux, air temperature, and surface pressure. GLDAS combines ground and satellite data via assimilation methods along with land surface models. The National Centers for Environmental Prediction (NCEP), National
Aeronautics and Space Administration (NASA), and National Oceanic and Atmospheric Administration (NOAA) created GLDAS (Rodell et al., 2004) (http://disc.sci.gsfc.nasa.gov/hydrology/data-holdings).

TRMM is a two-country collaboration between NASA and Japan’s National Space Development Agency that gathers information related to tropical and subtropical precipitation (Tropical Rainfall Measuring Mission. 2011). The TRMM mission became defunct in 2015 and was succeeded by the Global Precipitation Mission (GPM), with some TRMM products continuing with GPM, such as TRMM-3B43 (Huffman et al., 2007). TRMM-3B43-Monthly gives the best latitudinal precipitation estimate and is available at 0.25° spatial resolution with a 1 month granule size. Data has been collected from 1998 to the present and covers 50° N to 50° S (https://disc.gsfc.nasa.gov/datasets/TRMM_3B43_7/summary).

Kogan (1990) proposed and modified NDVI to VCI to normalize NDVI values relative to their minimum and maximum. We estimated VCI from NDVI using one of Terra Moderate Resolution Imaging Spectroradiometer (MODIS)’s standard products, the MODIS Vegetation Indices (MOD13C2). It has a temporal and spatial resolution of 1 month and 500 m, respectively. TRMM data and MOD13C2 have the same temporal coverage. The MODIS NDVIs are processed from atmospherically rectified two-way surface reflectance values that have been suppressed for cloud shadows, heavy aerosols, clouds, and water (Didan, 2015). The MODIS NDVI product can be accessed from the Oak Ridge National Laboratory Distributed Active Center (http://daac.ornl.gov/MODIS/).

To estimate DRT, we used the Global Monthly GPP from an Improved Light Use Efficiency (LUE) Model (GMPILUEM) between 1982–2016 with an 8 km spatial resolution (Madani and Parazoo, 2020). This GPP product uses climate data from the Modern-Era Retrospective Analysis for Research and Applications Version 2, canopy and fraction of photosynthetically active radiation data from Global Inventory Modeling and Mapping Studies (GIMMS 3g), and improved LUE based on flux tower data. The dataset can be downloaded from https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1789. All dataset spatiotemporal resolution was converted to 0.05° x 0.05° (monthly). Detailed information about this study’s dataset is shown in Table 1.

3. Methods

3.1 Potential evapotranspiration

In this study, we calculated PET using the PT method (Eq. (1)) (Priestley and Taylor, 1972) because it only requires wind and relative humidity climate data. Additionally, PT model PET estimates in tropical areas were found to be acceptable in Gunston and Batchelor, (1983). The PET is estimated as shown below:

\[
\lambda \times PET = \alpha \times \frac{\Delta}{\Delta + \gamma} \times (R_n - G)
\]

where \(\Delta\) is the slope vapor pressure curve (kPa/°C); \(R_n\) is net radiation (MJ/m\textsuperscript{2}/day); \(\gamma\) is a psychrometric constant (kPa/°C); \(G\) is the soil heat flux (MJ/m\textsuperscript{2}/day); \(\lambda\) is the latent heat of vaporization (MJ/kg); and \(\alpha\)
is the PT coefficient, usually with a default value of 1.26 (Priestley and Taylor, 1972).

### 3.2 Drought indices

Kogan (1990) proposed the VCI equation using current, minimum, and maximum NDVI values for each pixel:

\[ VCI_{amy} = \frac{NDVI_{amy} - NDVI_{a, min}}{NDVI_{a, max} - NDVI_{a, min}} \times 1002 \]

where \( VCI_{amy} \) is the value of VCI assigned to pixel \( a \) for the duration of month \( m \) for year \( y \); \( NDVI_{amy} \) is a value of the monthly NDVI for pixel \( a \) for month \( m \) and year \( y \); and \( NDVI_{a, min} \) and \( NDVI_{a, max} \) are the multiyear minimum and maximum NDVI, respectively, corresponding to pixel \( a \). The observed values’ resulting percentage is positioned between the maximum and minimum values of prior years. Higher and lower values signify good and bad vegetation state conditions, respectively.

SPEI is a meteorological drought index based on the log-logistic distribution of the difference between precipitation and PET (Vicente-Serrano et al., 2010). To estimate SPEI, the monthly difference between precipitation and PET is calculated first:

\[ d_i = P_i - PET_i \]

where \( d_i \) is the difference between precipitation (\( P_i \)) and PET in month \( i \). Next, the probability density function of the log-logistic distributed variable \( f(x) \), which has three parameters (Singh et al., 1993), is shown as:

\[
 f(x) = \frac{\theta}{\omega} \left( \frac{x - \phi}{\omega} \right)^{\theta-1} \left[ \left( \frac{x - \phi}{\omega} + 1 \right)^{\theta} - 1 \right]^{-2} \]

\[
 \theta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2}
\]

\[
 \omega = \frac{(w_0 - 2w_1)\theta}{\Gamma(1 + \theta^{-1})\Gamma(1 - \theta^{-1})}
\]

\[
 \phi = w_0 - \omega \Gamma(1 + \theta^{-1})\Gamma(1 - \theta^{-1})
\]

\[
 w_i = \frac{\sum_{i=1}^{n} d_i (1 - \frac{i-0.35}{n})^i}{n}
\]

where \( \omega, \theta, \) and \( \phi \) are scale, shape, and origin parameters, respectively, for \( d \) values in the range \( \theta > d < \infty \); \( \Gamma \) is the gamma function; \( w_i (i = 0, 1, 2 \ldots) \) are probability-weighted moments for order \( i \); and \( n \) is sample size. Following this, we can estimate the probability distribution function of \( d \) as:
Finally, SPEI can be estimated by converting $F(x)$ into corresponding SPEI 1-month Z-standardized normal values (Abramowitz and Stegun, 1965):

$$F(x) = \left( \frac{\omega}{x - \phi} \right)^{\theta} + 1$$

According to SPEI classification (McKee et al., 1993), the drought severity scale from −2 to 2 is divided into 7 levels, with less than −2 indicating extreme drought and larger than 2 indicating extreme wet conditions. With the same drought severity scale as SPEI, VCI has only 5 levels (Kogan, 1995). Detailed information about their classifications can be found in Table 2.

### 3.3 Drought Recovery Time (DRT)

We determined DRT using a combination of monthly drought index (SPEI or VCI) and GPP values for each pixel in the 14-year period from 2003 to 2016. A drought starts when $\text{SPEI} \leq -1$ ($\text{VCI} \leq 30$), and ends when $\text{SPEI} \geq -1$ ($\text{VCI} > 30$). These conditions have to persist for at least 3 months for it to be considered a drought event. After defining a drought event using SPEI or VCI, DRT can be estimated based on pre-drought and post-drought GPP values. The pre-drought GPP is described as the 14-year GPP average for a particular month without considering drought events (Liu et al., 2019). It shows the basic metabolism conditions of an ecosystem without drought events. To determine pre-drought GPP, we removed all values in tandem with an $\text{SPEI} \leq -1$ ($\text{VCI} \leq 30$), and only used the mean of the remaining monthly values. For example, the January pre-drought GPP is represented by a single mean value for every January without a drought over the 14-year period. That pattern is repeated for all 12 months across the same time frame. Post-drought GPP refers to real GPP values including all drought events. In contrast with the pre-drought GPP, in which the mean monthly value is the same for each year, post-drought GPP indicates actual values (Liu et al., 2019; Schwalm et al., 2017). DRT is the time taken after a drought event has concluded in tandem with the time taken for the post-drought GPP to exceed the pre-drought GPP. It is the difference between the drought recovery ending time (post-drought GPP returning to pre-drought GPP) and the drought ending time (Liu et al., 2019; Schwalm et al., 2017).

### 3.4 Boruta algorithm

We used the Boruta algorithm to examine which parameters are most important when determining DRT. The Boruta method selects variables and ranks them in order of importance while rejecting parameters that do not improve - or adversely affect - the model’s accuracy. Boruta operates by initially adding randomness to a dataset by creating shuffled duplicates of all parameters. These are termed ‘shadow parameters’ (Kursa and Rudnicki, 2010). The extended dataset is then trained with a random forest classifier using decision trees to select appropriate class. The appropriate class is reached by applying a
measure that determines each parameter's importance. A higher result translates to more important class. The algorithm performs iterations where it checks whether the real parameter has a higher importance than the best shadow feature at every stage. This is done by comparing “z scores”; the real parameter must have a higher z score than the maximum shadow parameter z score. In this process, parameters considered unimportant are eliminated. The algorithm terminates when all parameters are confirmed or rejected or when random forest runs are exhausted. The equation and further technical breakdown can be found in Prasad et al. (2019).

4. Results And Discussion

4.1 Seasonal patterns and trends for drought-related variables

To elucidate seasonal drought variation in Lake Victoria basin, we used six variables: rainfall (mm/month); PET (mm/month); GPP (g/m²/d); SM (m³/m³) for depths of 0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm; VCI; and SPEI (Fig. 2). We studied four seasons, DJF, MMA, JJA, and SON, and used seasonal mean values from 2003 to 2016 (Table 3).

As shown in Fig. 2, we found a clear seasonal rainfall pattern, with large amounts of rainfall (151.79 mm/month) in MAM and the least (53.67 mm/month) in JJA. Although the different season PET did not vary greatly (175.00 to 180.11 mm/month), it increased significantly in the northeastern part of the basin during DJF. GPP was the same for DJF (6.69 g/m²/d) and MMA (6.79 g/m²/d) though it dropped significantly in JJA (5.46 g/m²/d) and SON (5.38 g/m²/d), particularly in the basin's southern and eastern areas. 0 to 100 cm SM did not change significantly except for JJA, when the entire basin experienced very low SM levels (0.20 m³/m³) and MMA, when the soil moisture was quite high (0.27 m³/m³). From 100 to 200 cm, SM was high for all seasons (0.27 m³/m³) compared to the average SM across seasons from 0–100 cm (0.23 m³/m³). SM from 100 to 200 cm remained similar for all seasons, including JJA, even though that season had the lowest soil moisture from 0–100 cm. VCI was significantly high and did not vary greatly between DJF (63%) and MMA (69%). JJA and SON had very low VCI, with SON (44%) having a much lower VCI than JJA (46%). VCI was generally low in the southern and eastern parts of the basin during JJA and SON. SPEI was high during MMA (0.47) and SON (0.23). A significant SPEI drop was observed for DJF (-0.11), and it was low throughout the entire basin in JJA (-0.90).

Generally, JJA showed low rainfall, GPP, SM, VCI, and SPEI, the driest season. SM from 0 to 100 cm increased when rainfall increased and decreased when there was less rainfall. In contrast, SM from 100 cm to 200 cm was significantly high for each season. This difference could be attributed to maize's root depth. Its fibrous roots reach a depth of up to 100 cm and draws most of its soil moisture from that depth (Leenaars et al., 2018). VCI and SPEI showed similar results, with very low values in JJA. SPEI was quite high in SON, however, whereas VCI was quite low. This can be explained by VCI only considering a greenness index, whereas SPEI also accounts for climate factors (rainfall and PET). While precipitation
and PET have cumulative effects on vegetation conditions, these is a time lag (Gebrehiwot et al., 2011; ZHANG et al., 2013).

Figure 3 shows Lake Victoria Basin climate variable trends from 2003 to 2016. The blue and red colors represent decreasing and increasing trends, respectively. The dark points mark significant (p < 0.1) decreased or increased areas. Rainfall decreased from 2003 to 2006 in the west basin along with a significant (p < 0.1) decrease trend in the mid-west area. A rainfall increase was found in the east with additional pockets showing significant increases in the east and southeast. PET increased significantly in the eastern part of the basin while the far west and southwestern basin area have pockets indicating decreasing PET. GPP in the northern portions of the basin increased while it decreased in the southern area. Soil moisture from 0–10 cm, 10–40 cm and 40–100 cm decreased, with a significant incremental decrease in the east. There is an overall significant (p < 0.1) soil moisture increase, however, from 100–200 cm throughout the basin. Similar to GPP, VCI’s trends are evenly distributed throughout the basin with scattered significant (p < 0.1) increases in the western and northeastern areas. SPEI decreases over almost the basin’s entirety with a significant trend decrease (p < 0.1) in the northwest and western portions. Overall, decreasing rainfall and increasing PET in the western basin led to decreasing SPEI. Although rainfall in the eastern basin increased from 2003 to 2006, the increasing PET and decreasing SM from each depth effects vegetation condition and results in a decreasing GPP and VCI. This is especially true in the basin’s southeast area.

4.2 Drought characterization

4.2.1 Annual drought conditions

To assess drought conditions in the study area, we estimated SPEI and VCI annual spatial distribution (Fig. 4). Generally, mean SPEI and VCI values indicate that near-normal conditions imply a potentially stable canopy cover and greenness. As shown in Fig. 4a, SPEI mean annual spatial distribution showed near-normal conditions with very moderate drought tendencies. For example, in 2007, the entire basin was almost normal. But drought prevalence has progressed since then, with conditions peaking in 2016 when the majority of the basin experienced moderate to severe drought conditions.

VCI mean annual spatial distribution shows almost no drought, with light to moderate drought occurring in the southeastern part of the basin (Fig. 4b). 2004, 2005, 2006, and 2016 had the largest spatial coverage (almost the entirety of the basin) for drought. In other years, however, the western side was not affected. 2005, 2009, 2011, and 2016 have the lowest VCI values, indicating moderate to severe drought conditions on the eastern outskirts of the study area. 2016 was the driest year, with both the lowest VCI value and largest drought spatial coverage. The highest VCI value and largest non-drought spatial coverage was in 2007. This is consistent with the observed SPEI drought conditions, which indicates that the driest and wettest years were 2016 and 2007, respectively.

SPEI and VCI differed spatially in 2006 and 2015, presumably because of a potential temporal lag between VCI and SPEI. For example, 2006 SPEI has high values even though VCI in the same year is low.
This is because VCI is an indicator of greenness, whereas SPEI considers PET and rainfall climate factors. That fundamental difference in approach implies a time lag in the results (Fig. 4); the low 2005 SPEI value led to the low 2006 VCI value. The same phenomenon can be found in 2015, when the high VCI value can be explained by the high SPEI value in 2014, not the SPEI value in 2015.

4.2.2 Monthly drought conditions

We calculated monthly SPEI and VCI spatial distributions to assess detailed monthly drought variation with a scale denoting drought severity from “extreme wet” to “extreme drought” (Fig. 5). The results shown in Fig. 2, Fig. 4, and Fig. 5 are consistent with the evidence from several reports referenced in Table 4. From 2003 to 2016, July has consistently experienced the most severe to extreme drought conditions. Generally, JJA has the most significant drought conditions, which are consistent with the results shown in Fig. 2, showing the most drought severity occurring in JJA. DJF also show significant drought conditions, especially in the northern parts of the basin. MAM and SON show near normal conditions with occasional oddly scattered spatial instances of drought. 2016 and 2009 had the highest drought severity conditions, which is consistent with average SPEI 2016 values and average 2009 VCI values, respectively. This result could be due to the different times in which the basin receives rainfall, as a rainfall deficit tends to correlate with drought conditions and vice versa.

To evaluate drought condition results, we analyzed recorded drought years for different countries in the study area, as shown in Table 4. Burundi, located in the southwestern part of the area, has almost 4 million people in the basin, and 95% of the country’s population is rural. Thus, drought impacts are quite severe (Gebremeskel et al., 2019; Yao et al., 2014). According to drought event records (Table 4), the drought progressed from 2003 to 2005 and again from 2008 to 2010, mostly affecting the northeastern parts of Burundi (East African Community (EAC), 2010). This finding matches the data shown in both Fig. 4 and Fig. 5, demonstrating moderate to extreme drought conditions in the southwestern part of the study area. For Western Kenya, located in the eastern and northeastern parts of the study area, drought events occurred in 2004 and affected 3.3 million Kenyans. Furthermore, as shown in both Fig. 4 and Fig. 5, Western Kenya suffered repeated drought events in 2005, 2008, 2010, 2012, 2014, and 2016 (Agutu et al., 2017; Ayugi et al., 2020; East African Community (EAC), 2010; Gebremeskel et al., 2019; Nyaoro et al., 2016; Opiyo et al., 2015; Schmidt et al., 2017). As a result, three major provinces, Nyanza, Western, and Rift Valley, bore the brunt of the drought impact (Awange et al., 2013). The 2003 drought event in Rwanda in the western basin was characterized by below-average rainfall. It disproportionately affected rural areas in Rwanda’s semi-arid east, where people are much more dependent on rainfall for both crops and animal husbandry (East African Community (EAC), 2010). This is consistent with the data in Fig. 4 and Fig. 5, which show moderate to extreme drought events in the western basin. The drought record in Tanzania, the southern part of the basin, shows drought first occurred in 2003, affecting the regions of Kagera, Mwanza, and Mara. In addition, as shown in Fig. 4 and Fig. 5, drought conditions in this region recurred in 2004, 2006, and 2011 but not in 2007. The failure of short-season rains caused severe drought in late 2005 and early 2006 (Bhaga et al., 2020). In early 2007, this region experienced heavy rains, (Fig. 5), with moderate wet conditions in January (Bhaga et al., 2020). Uganda lies in the northern portion
of the study area, with some parts in the western, central, and eastern areas. More than 600,000 people were affected by drought as of 2005 in the Masaka and Mpigi districts (Hakuza and Waita, 2008). Droughts recurred in 2008 and 2010 and affected similar areas. For this reason, farming communities in central, eastern and southwestern Uganda suffered economic and financial damage (Hakuza and Waita, 2008). The drought variation's spatial extent is shown in Fig. 5. It is notable that Fig. 5 shows a one-month delay in 'dry' conditions predominant from June to August using the SPEI index and from July to September, even extending into October, with the VCI index. This is because SPEI relies on meteorological data whereas VCI relies on vegetation conditions, implying drought is first observed meteorologically before it's observed in vegetation.

4.3 Drought duration time (DDT) and drought recovery time

4.3.1 Drought event identification based on drought severity

To understand drought event history based on SPEI and VCI results, we calculated the percentage of different drought events based on severity (Table 3). Spatial distribution is shown in Fig. 6. The most moderate SPEI drought events ($-1.5c_{ript} >$) were in the southern part of the study area (Fig. 6). Most of the study area has up to 70% possibility of experiencing moderate drought and a 10 to 20% possibility of experiencing a severe drought ($-2c_{ript} >$). Extreme drought events ($SPEI \leq -2$) mostly occurred in the eastern and northeastern tip of the study area (Fig. 6). Overall trends indicate that the basin has a higher spatial area percentage prone to moderate drought. Using VCI data, 50 to 80% of the study area may experience a moderate drought ($20c_{ript} >$) except for regions in the southeast and southern tip, where the percentage is only 10 to 30%. VCI-predicted severe drought ($10c_{ript} >$) is similar to SPEI. The majority of the study area has a 10 to 20% chance of experiencing extreme drought ($0c_{ript} >$) except for the southeast region, which shows a 40 to 70% likelihood (Fig. 6). Both VCI- and SPEI-based percentage coverage trends for moderate (M), severe (S), and extreme (E) drought are similar where the spatial drought coverage percentage decreases from moderate to severe. There are some differences, however, in the southeast region for SPEI_M, VCI_M, and SPEI_E, VCI_E which show an inverse trend. This is because VCI indicates drought based on actual vegetation conditions whereas SPEI indicates drought based on meteorological conditions.

Overall, more moderate and severe drought events occurred in the southern part of the study area; the eastern and western parts of the basin experienced extreme drought events. As previously discussed, the western area is mostly farming communities in Uganda, Tanzania, Rwanda, and Burundi, including large food crop (maize) belts in central and eastern Uganda. The areas prone to moderate, severe and extreme drought events (Fig. 6) should be considered high-risk drought areas and likely future bottlenecks for water balance. Drought mitigation strategies are imperative in these areas.

4.3.2 Drought duration and recovery time based on SPEI and VCI
Using SPEI and VCI drought indices, we calculated and compared mean DDT and DRT spatial distributions in the Lake Victoria Basin from 2003 to 2016 (Fig. 7). The mean SPEI-DDT ranges from 2 to 4 months with a 2.45-day average value. The northeastern and southwestern study area were most likely to suffer from meteorological drought (i.e., SPEI) for at least 3 months, compared to 2 months in other areas. The VCI-DDT spatial distribution (2.97 months) was similar to SPEI-DDT (2.45 months) except for the southeast study area, where VCI-DDT is 2 months longer than SPEI-DDT. This means the southeastern part of the basin is more likely to suffer a long agricultural drought. The SPEI-DRT mean value is 2.02 months, though there are a few instances in the northwest basin area where SPEI-DRT took more than 8 months (black). The VCI-DRT mean value is 1.63 months, which is 0.39 months shorter than the SPEI-DRT mean value.

The study area's mean DDT is higher than the mean DRT, though the mean DDT and mean DRT are almost the same in the southern area, particularly in the southwest. The mean DRT significantly exceeded the mean DDT in the western and northwestern parts of the basin (in black), which show a mean DRT of 8 months compared to three months for DDT. Our results are consistent with Schwalm et al. (2017), who showed that most drought events in the study area required less than 6 months to recover, though parts of the western basin needed 7–12 months. This long mean DRT puts the western and northwestern basin regions at risk of excessively long drought periods. These include the semi-arid eastern parts of Rwanda, northeastern regions of Burundi, communities in the Kagera region of Tanzania, and central, and southwestern parts of Uganda. It is imperative to pay attention to areas with long DRTs because the northeastern (i.e., Nyanza, Western, and Rift Valley provinces) and southwestern (i.e., Uganda, Tanzania, Rwanda, and Burundi) study areas are mostly cropland (Fig. 1). These regions take 4 to 5 months to recover from drought events. Several sub-basins in the western and northern study area create microclimates that potentially affect land–atmosphere interactions. For example, the catchment's western portion is in the purview of the Kagera sub-basin, which encompasses Uganda, Tanzania, Kenya, Rwanda, and Burundi. Countries such as Uganda, Rwanda, and Burundi lie entirely in the Nile basin, which includes the Victoria basin. The various microclimates created by the sub-basins influence drought characteristics. The Great Rift Valley in the western part of the basin has several lakes and rivers, such as Lake Albert, Lake Edward, and Lake Kivu. These are connected by river systems west of the Victoria basin and affect the climate. The Great Rift Valley also passes close to the eastern side of the basin, but has no significant water bodies.

**4.4 Factors affecting DRT**

We ranked the importance of DDT, SM depths, PET, GPP, rainfall, and drought indices on DRT (Fig. 8). We selected and ranked these factors using a “z score” for SPEI-DRT and VCI-DRT, where a higher value means the factor is more important. The shadow Min, shadow Mean and shadow Max (blue box plots) add randomness to the data to allow for more precise parameter ranking. The green box plots show that each features’ z score is higher than the shadow value, which means they are all significantly important in determining SPEI-DRT and VCI-DRT.
DDT is the most important parameter for determining DRT for SPEI-DRT followed by GPP, PET, SPEI, and rainfall. Soil moisture, though still relevant, is the least important parameter for DRT determination. DDT is also the most crucial parameter for determining DRT for VCI-DRT followed by VCI and rainfall. Soil moisture is again classified as the least important parameter, though still important. Based on these results, DDT is the most important factor for determining DRT, regardless of drought indices. We examined DRT spatial distribution after 1, 2-, 3-, 4-, and 5-month drought events to understand the DDT and DRT relationship (Fig. 9). After a one-month drought, SPEI-DRT (SPEI_DRT_1) shows that the entire basin needs to recover from the drought event, with DRTs ranging from 1 to 4 months with some scattered pockets requiring up to 6 months. For a 2-month drought, SPEI_DRT_2, less areas need to recover from drought than for the SPEI_DRT_1 scenario, though there are some isolated pockets in the far east study area that require more than 8 months. SPEI_DRT_3 indicates similar DRTs to SPEI_DRT_2, but the area requiring longer time was larger than for SPEI_DRT_1 or SPEI_DRT_2. As larger basin percentages do not experience 4- or 5-month drought events, SPEI_DRT_4 shows only the southwest and northeast portions of the study area requiring drought recovery, and SPEI_DRT_5 indicates that almost all of the study area does not require any DRT other than sparse pockets in the south. VCI-DRT results are similar to SPEI-DRT except for the DRTs after 4- and 5-month droughts. Results show a significant number of pockets in the northwest part of the basin that need to recover from drought. These were not present in SPEI_DRT_4. VCI_DRT_5 shows the southeastern parts of the study area require time to recover from drought whereas none is needed for SPEI_DRT_5.

In the western portion of the study area, SPEI_DRT_1 to SPEI_DRT_4 trends indicate that as the number of drought months increase, drought recovery time also increases. Schwalm et al. (2017) found similar results. Long droughts affect the water balance, hydrometeorological cycles, and natural land–atmosphere relationships. Thus, it makes sense that long droughts have long recovery times. High PET correlates with a low DRT. This can be attributed to Lake Victoria's natural hydrological cycle, where a high PET yields high precipitation levels and wards off drought; low PET will allow little to no precipitation to reach the basin (Avanzi et al., 2019). As noted in Schwalm et al. (2017), low SPEI values correlate with a high DRT. Low SPEI values indicate severe drought conditions from which it often takes a long time to recover. Low GPP implies long DRTs because it indicates an unhealthy plant eco-system requiring a long recovery time. Rainfall has a negative relationship with DRT because rainfall encourages plant growth; thus, more rainfall results in a shorter DRT. He et al. (2018) also found that more rainfall shortened the ecosystem’s DRT. Overall, increasing DDT is the most important factor influencing DRT. Tropical environments take a long time to recover after droughts in dry conditions. Our results are consistent with Wright et al. (2002), who found that drought recovery is more likely to occur in wet conditions. Furthermore, wet conditions with high PET and high levels of rainfall shortened DRT, whereas dry conditions, with a large SPEI values and long DDTs, led to low GPP and lengthened DRT. This also agrees with Schwalm et al. (2017).

5. Conclusions
Access to accurate drought duration and recovery time information is vitally important in drought-prone areas used for agricultural purposes. Using grid-based data with high resolution, we investigated seasonal patterns in drought-related variables, identified drought events, and examined both SPEI- and VCI-based DRTs in the Lake Victoria Basin from 2003 to 2016. This study is the first to determine meteorological and agricultural DRTs for the Lake Victoria Basin on a 0.05° monthly scale. Of the four seasons, JJA was the driest, with lower values of rainfall, GPP, SM, VCI, and SPEI. Decreasing GPP and VCI is caused by increasing PET and decreasing SM from each depth in the basin's eastern area. Decreasing SPEI is due to decreasing rainfall and increasing PET in the basin's western area. Drought indices SPEI and VCI showed that 2016 and 2007 were Lake Victoria Basin's driest and wettest years in the study range. Meteorological drought calculations showed that moderate droughts occurred at higher frequency in the southeastern part of the basin, whereas the northeastern and mid-western areas were more likely to suffer from extreme drought events. Agricultural drought measurements showed that extreme drought events occurred at higher frequency in the basin's southern areas. On average, SPEI-based DRT (2.02 months) was longer than VCI-based DRT (1.63 months). SPEI-DRT and VCI-DRT showed similar spatial distribution though SPEI-based DRT (2.02 months) was longer than VCI-based DRT (1.63 months) on average. DDT is the most important parameter for determining DRT, though regions with higher PET, SPEI, GPP, and precipitation values are also associated with shorter recovery times. These results improve understanding of drought on an ecosystem level. Nevertheless, a global DRT product with high accuracy and good spatial and temporal resolution remains challenging, and requires additional investigation.

**Declarations**

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Tables

Due to technical limitations, table 1 to 4 is only available as a download in the Supplemental Files section.

Figures

Figure 1

Land cover map for the Lake Victoria Basin. Bold lines represent country boundaries and dotted lines represent key districts for countries in the basin. Land cover data is from the ‘S2 prototype LC map at 20m of Africa 2016’ (CCI Land Cover. 2017). The map can be downloaded from http://2016africalandcover20m.esrin.esa.int/.
Figure 2

Seasonal spatial patterns of rainfall (mm/month); PET (mm/month); GPP (g/m²/d); SM (m³/m³) for depths of 0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm; VCI; and SPEI in the Lake Victoria Basin based on seasonal mean data from 2003 to 2016.

::: marks the statistically significant (p<0.1) increased or decreased areas.
Figure 3

Spatial trends of climate variables including rainfall, PET, GPP, SM for depths [0-10 cm, 10-40 cm, 40-100 cm, 100-200 cm], VCI, and SPEI) in the Lake Victoria Basin from 2003 to 2016.

Figure 4

Annual spatial distribution and drought characterization using SPEI (a) and VCI (b) indices in the Lake Victoria Basin from 2003 to 2016. Calculations include the mean for all years.
### Figure 5

Spatial extent and drought characterization using the SPEI and VCI indices for the Lake Victoria Basin from 2003 to 2016 for each month in each year.

#### Figure 6
SPEI- and VCI-based drought calculations. Percentage of the spatial extent indicates moderate (M), severe (S) and extreme (E) drought.

Figure 7

Spatial coverage of SPEI- and VCI-based mean drought duration and recovery times from 2003 to 2016 in the Lake Victoria Basin.
Figure 8

Parameter ranking for SPEI_DRT and VCI_DRT determination using the Boruta Random Forest Parameter Selection Algorithm

Supplementary Files

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- Table.pdf