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Research article

Retrospective analysis of Chlorophyll-a and its correlation with climate and hydrological variations in Mindu Dam, Morogoro, Tanzania

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ABSTRACT

The measurement of Chlorophyll-a in aquatic systems has usually correlated to harmful algae in water bodies. Harmful algal blooms (HABs) are as a result of massive proliferation of blue-green algae (Cyanobacteria). Harmful algal blooms (HABs) pose threats to both the environment as well as human health, and despite this well-known fact, their monitoring and management are still challenging. Climate change, extreme weather events, and hydrological changes are the main drivers and predicted to benefits HABs dynamics in most parts of the world. In Tanzania, studies of HABs proliferation and their possible correlation with variability in climate and hydrology still lag behind despite high demand for developing predicting tools and prevention of HABs proliferation. The present study reports on the retrospective analysis of HABs variation in Mindu Dam located in Morogoro, Tanzania using remote sensing techniques. In the present study comparison between in situ measurement and ocean color (OC2) Chlorophyll-a with the surface reflectance's (band and band combinations) of Landsat 7 and Landsat 8 Operational Land Imager (OLI), was performed. Another approach involved searching for patterns and trends, and teleconnection between Chlorophyll-a index (best band ration) and the climate and hydrological variations in the catchment. The findings demonstrated that minimum and maximum temperatures, solar radiation, Chlorophyll-a concentration registered significant increasing trends. Wind speed and directions, water levels for Mindu Dam showed a significant decreasing trend. On the other hand, rainfall showed no trend. The patterns suggest that there are link and causality between the HABs variations and meteorological parameters such as temperatures, solar radiations, and water levels. The study, therefore, contributes to the application of recent advances in remote sensing and retrospectively analysis of bloom dynamics and search for their link with climate and hydrological changes.

1. Introduction

Harmful algal blooms (HABs) are among the many environmental issues of concern in freshwater systems (Ho and Michalak, 2015). Climate and hydrological variations are associated with HABs proliferation (Paerl, 2014). However, program and schemes for monitoring HABs dynamics are not well developed and practiced, especially in developing countries (Ndlela et al., 2016). According to Kumar & Mutanga, (2018), the reasons for the lagging behind in the developing world include data accessibility, technological skills to process data, and opportunities for research.

Remote sensing has been widely used to measure water quality parameters including Chlorophyll-a measure which is related to HABs proliferation (Gholizadeh et al., 2016; Watanabe et al., 2015) and the data obtained using this approach has shown high reliability (Dörnhöfer and Oppelt, 2016). Chlorophyll-a is used as the proxy for quantification of total cyanobacteria (Pereira-Sandoval et al., 2019). Other metrics used for quantifying blooms are species-specific (morphological identification), toxic metrics, and remote sense-based metrics which can estimate chlorophyll-concentration data in areas where are out of reach (Ho and Michalak, 2015). Regarding remote sensing, several studies have developed different algorithms for Chlorophyll-a estimation for use as an indicator for HABs (Bohn et al., 2018; Chen et al., 2017; Ogashawara et al., 2017; Palmer et al., 2015; Shen et al., 2012; Wang et al., 2016; Yang and

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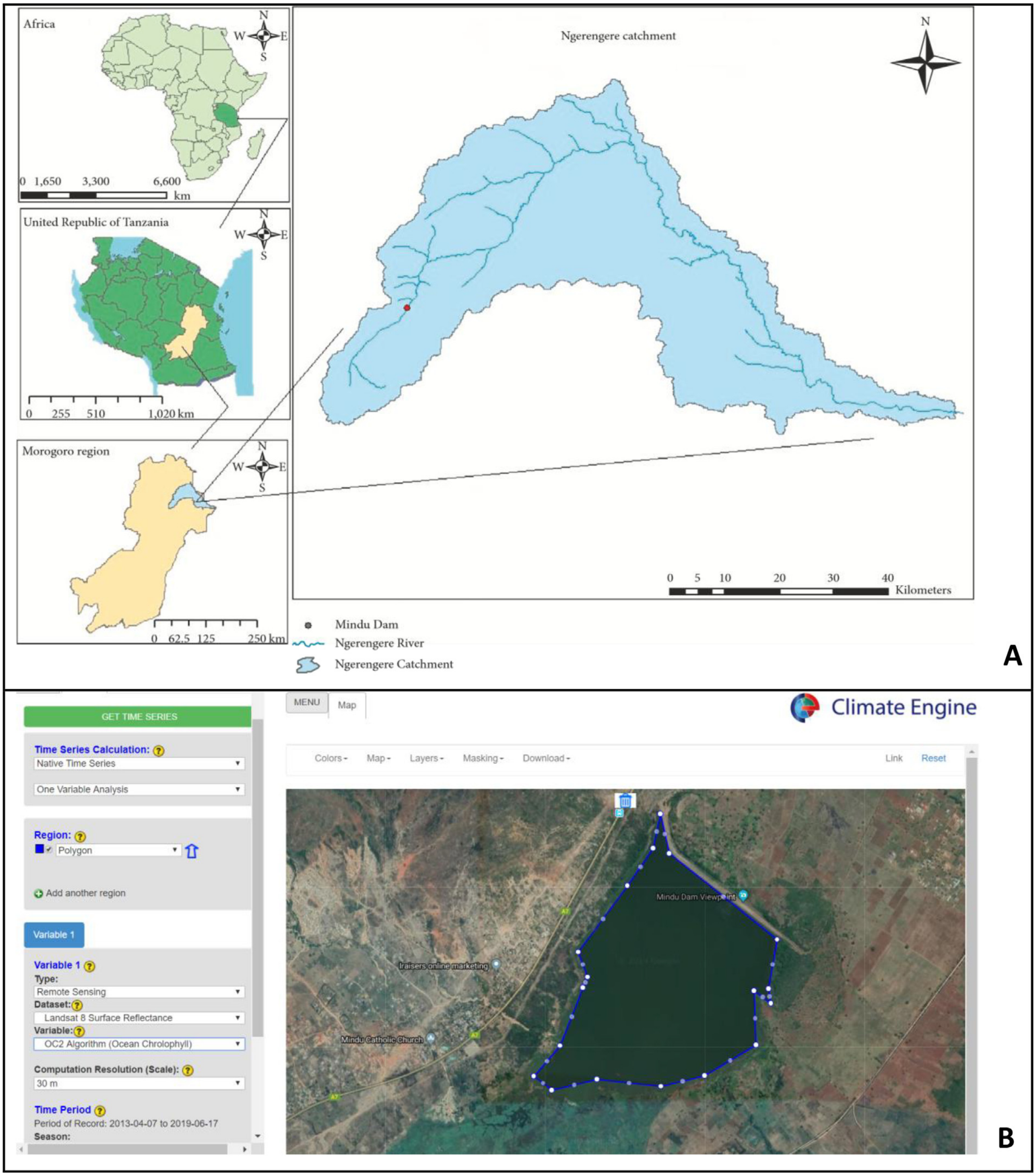

Fig. 1. Study area map depicting the location of Mindu Dam in the Ngerengere catchment (Kimambo et al., 2019) (A) and an interactive web-interface for the Climate Engine[2] (B) the region of interest (ROI).

Anderson, 2016; Yang et al., 2017).

Gholizadeh et al. (2016) narrated the significances of using remote sensing over other methods (Ho and Michalak, 2015), for example, traditional methods for the monitoring of water quality which are time-consuming, labor intensity and costly, unlike remote sensing methods. Other advantages of remote sensing methods include the coverage of the larger area and in some cases, high resolutions (Zamyadi et al., 2016). Moreover, the use of remote sensing techniques comprises factors such as spatial-temporal coverage, forecasting, the accuracy of

Table 1
Properties of Landsat 8 (Fu et al., 2018).

Channel Name	Spectral range (μm)	Central wavelength (μm)	Spatial resolution (m)
B1 Coastal	0.433–0.453	0.443	30
B2 Blue	0.450–0.515	0.4825	30
B3 Green	0.525–0.680	0.5625	30
B4 Red	0.630–0.680	0.655	30
B5 NIR	0.845–0.885	0.865	30
B6 SWIR 1	1.560–1.61	1.61	30
B7 SWIR 2	2.100–2.300	2.2	30
B8 Panchromatic	0.500–0.680	0.59	15
B9 Cirrus	1.360–1.390	1.375	30

[2] https://clim-engine.appspot.com/#

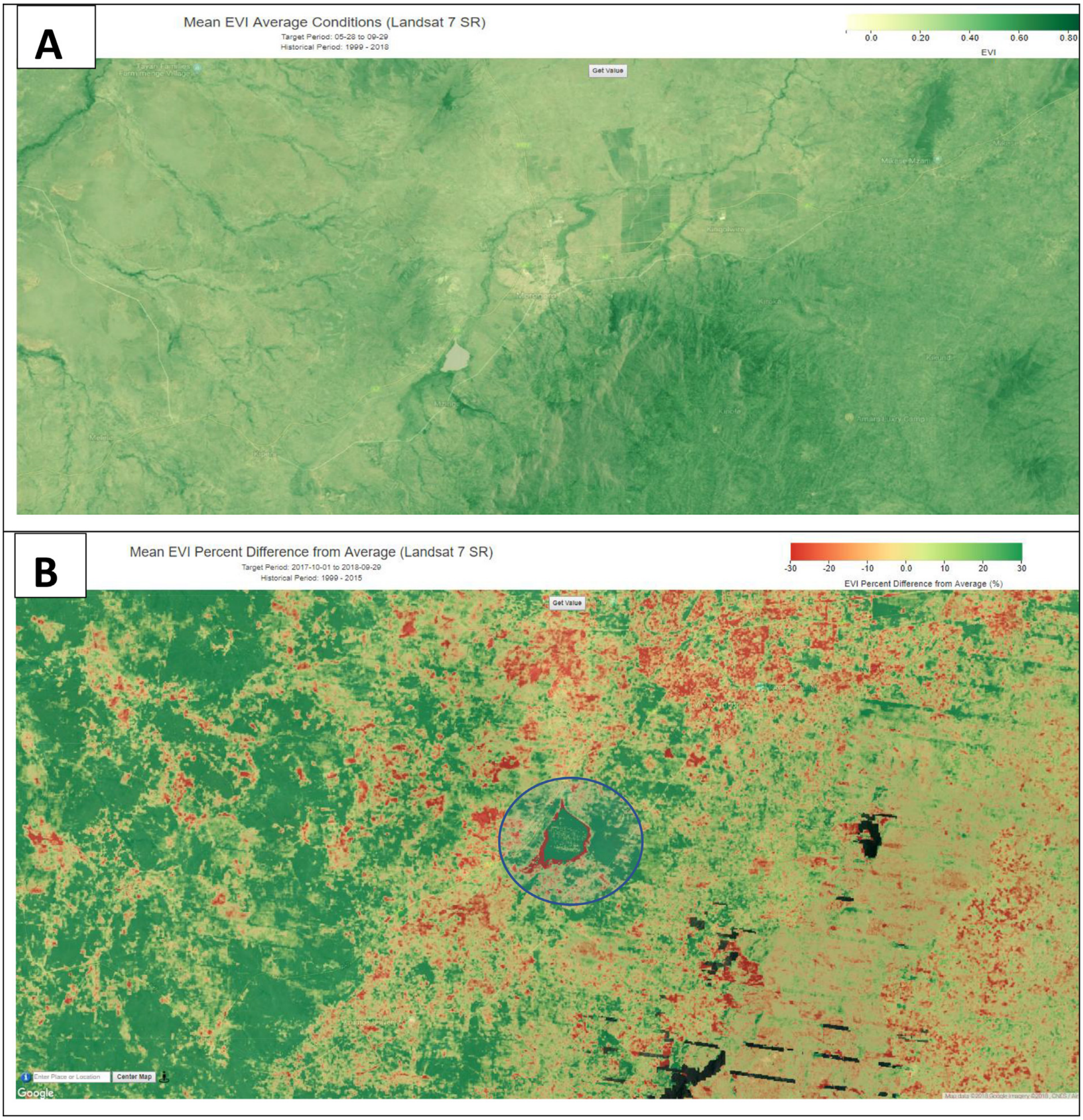

Fig. 2. Enhanced Vegetation Index (historical period 1999 to 2018) (A) and Enhanced Vegetation Index showing the percentage of change of vegetation (target period 2017–2018) (B) (images retrieved from climate engine web tool available on https://clim-engine.appspot.com/climateEngine#). The circled area on the map shows the location of Mindu Dam.

collected information although no single method can give an accurate understanding of HABs (Shen et al., 2012). Despite all the advantages, remote sensing suffers from limitations such as the need for atmospheric corrections if working with raw images, as well as requirements for calibrations and validation (Gholizadeh et al., 2016). Another disadvantage attributed to the use of remote sensing is that some analyses are limited to specific conditions not applicable to images taken under different conditions (Zamyadi et al., 2016).

The present study aimed to review and examine new algorithms for estimation of Chlorophyll-a in Mindu Dam using google engine (GE) and climate engine tools. It also seeks to investigate Chlorophyll-a variation (retrospectively) overtime in the catchment. Additionally, a comparison of Chlorophyll-a with climate and hydrological status in the catchment. Ideally, the hypothesis tested in the present study is that climate and hydrological dynamics have played a significant role in cyanobacteria bloom in the catchment. Herein, the assumption set forward is that the estimated values of Chlorophyll-a and or band ratios are a true representative of the time in which the capture occurred. The assumption is due to lack of monitoring data and the difference between Landsat 7 and 8 in capturing images (i.e., days that they revisit the same place).

2. Materials and methods

2.1. Study site description

Mindu Dam (Fig. 1A) is located in Wami Ruvu Basin, with an estimated area of 3.8 km^2 (Ngoye and Machiwa, 2004). Mindu Dam is the primary source of water and freshwater fishery supplies in urban and peri-urban communities of Morogoro (Mdegela et al., 2009). Land use characteristics, soil erosion, and sedimentation are more prominent challenges (Natkhin et al., 2015) that continuously reduce the depth of the Dam and Ngerengere River (Yanda and Munishi, 2007).

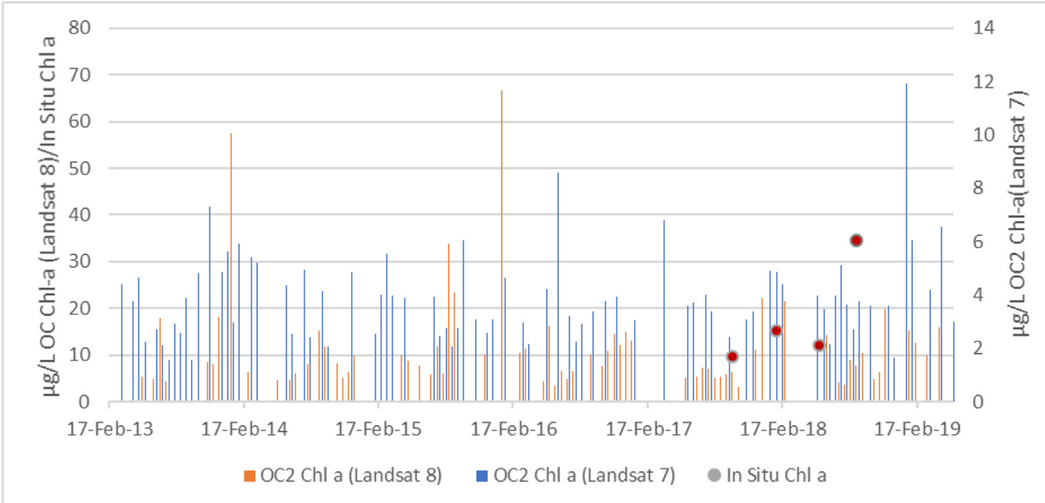

Fig. 3. Typical OC2 Chlorophyll-a for both Landsat 7 and Landsat 8 surface reflectance (from 2013 to 2019), and in situ (selected phases in the year 2017/2018) Chlorophyll-a variation.

2.2. *Climate and hydrological data*

Data used in the current study include meteorological parameters (i.e., monthly rainfall, monthly maximum and minimum temperatures, solar radiations, wind speed, and directions), collected in the span of 30 years (1988–2017) courtesy of the Tanzania Meteorological Agency. Hydrological data (Mindu Dam's water levels for a period of 1997–2017) in the catchment courtesy of Wami Ruvu basin office, and Nino-3.4 index (NCEP Reanalysis data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at https://www.esrl.noaa.gov/psd/0).

2.3. *Generation of remote sensing data*

Surface reflectance's for different bands for both Landsat 7 and Landsat 8/OLI from 1999 to 2017 and 2013 to 2017 respectively (depending on their launch date) for the estimation of Chlorophyll-a concentration for the Mindu Dam were obtained from the climate engine (https://clim-engine.appspot.com/#). The climate engine is powered by google earth engine, the University of Idaho and Desert Research Institute (http://climateengine.org/app). This facility has not been used effectively for studies in developing countries (Kumar and Mutanga, 2018). In remote sensing, most surface features are derived based on surface reflectance measurements (Vermote et al., 2016). In the present study climate engine web-interface (Fig. 1B) was used to extract Landsat 7 (LANDSAT/LE07/C01/T1_SR)[1] and Landsat 8/OLI surface reflectance. Data, according to the source, can be at a point or polygon (average). The location (region of interest) over Mindu Dam on the map was drawn in order of polygon vertices as illustrated in Fig. 1. The dataset, according to the source (https://explorer.earthengine.google.com/#detail/LANDSAT%2FLE07%2FC01%2FT1_SR) is atmospherically corrected (i.e., cloud, shadow, and water were filtered) as well as per-pixel saturation mask and that they are ready for use. Studies trials and system development are underway (Zlinszky et al., 2017).

Other approaches employed in this study involved the use of OC2 Chlorophyll-a concentration as in Keith et al. (2016) in near-surface water. This work further followed time series analysis approach as in Malahlela et al. (2018), a study which was conducted in Vaal Dam in South Africa. Similar approach was also used in Lake Victoria by comparing OC2 Chlorophyll-a and climate parameters to asses teleconnection between climate phenomena and algal blooms proliferations (Cózar et al., 2012). The study used the OC2 Chlorophyll-a algorithm (retrieved from climate engine web tool) for both Landsat 7 and 8 surface reflectance for comparison. The time frame from their launch date (Landsat 7 will have a larger dataset than Landsat 8 for that purpose) was also considered to have a considerable number of observations. In the present study, we found four mostly studied bands (**Band 2**, **Band 3**, **Band 4**, and **Band 5**) and their combinations as suggested in the previous reports (Gholizadeh et al., 2016; Ho et al., 2017).

2.4. *Spectral characteristics and their justifications*

Previous assessments for spectral type and features were explicitly reviewed in terms of their advantages and disadvantages (Gholizadeh et al., 2016). These Authors indicated that **Band 2**, **Band 3**, **Band 4** and band ration (**Band 5/Band 3**) at a significant level $p < 0.01$ (the single and or combinations) showed good correlation with Chlorophyll-a concentration. Other researchers have reported **Band 2, Band 5,** and **Band 2/Band 4** as a useful measure for Chlorophyll-a (see Table 1).

2.5. *Field campaign and sample analysis*

Samples collected for *in situ* Chlorophyll-a data were in four (4) phases (5th October 2017, 2nd February 2018, 31st May 2018, and 9th September 2018) and as per the design of the parallel experiment.

2.6. *Data analysis and test statistics*

Individual patterns and Mann-Kendall trend tests for all the meteorological (rainfall, temperatures, solar radiations, and winds), hydrological (water levels), and blooms (OC2 Chlorophyll-a) were performed using XLSTAT (Addinsoft, 2019). We compared Nino-3.4 Index anomalies by tracking the negative anomalies with cases the high concentration of blooms (due to lack of monitoring data, OC2 Chlorophyll-a values meant as an indicative measure for the occurrences of Chlorophyll-a in the reservoir) as in Cózar et al. (2012).

3. Results and discussion

3.1. *Vegetation changes in the catchment*

The trend of vegetation in the catchment depicted in Figs. 2A and 2B. Fig. 2A shows the land presentation of an enhanced vegetation index

[1] Landsat 7 Collection 1 Tier 1 and Real-Time data Surface reflectance.

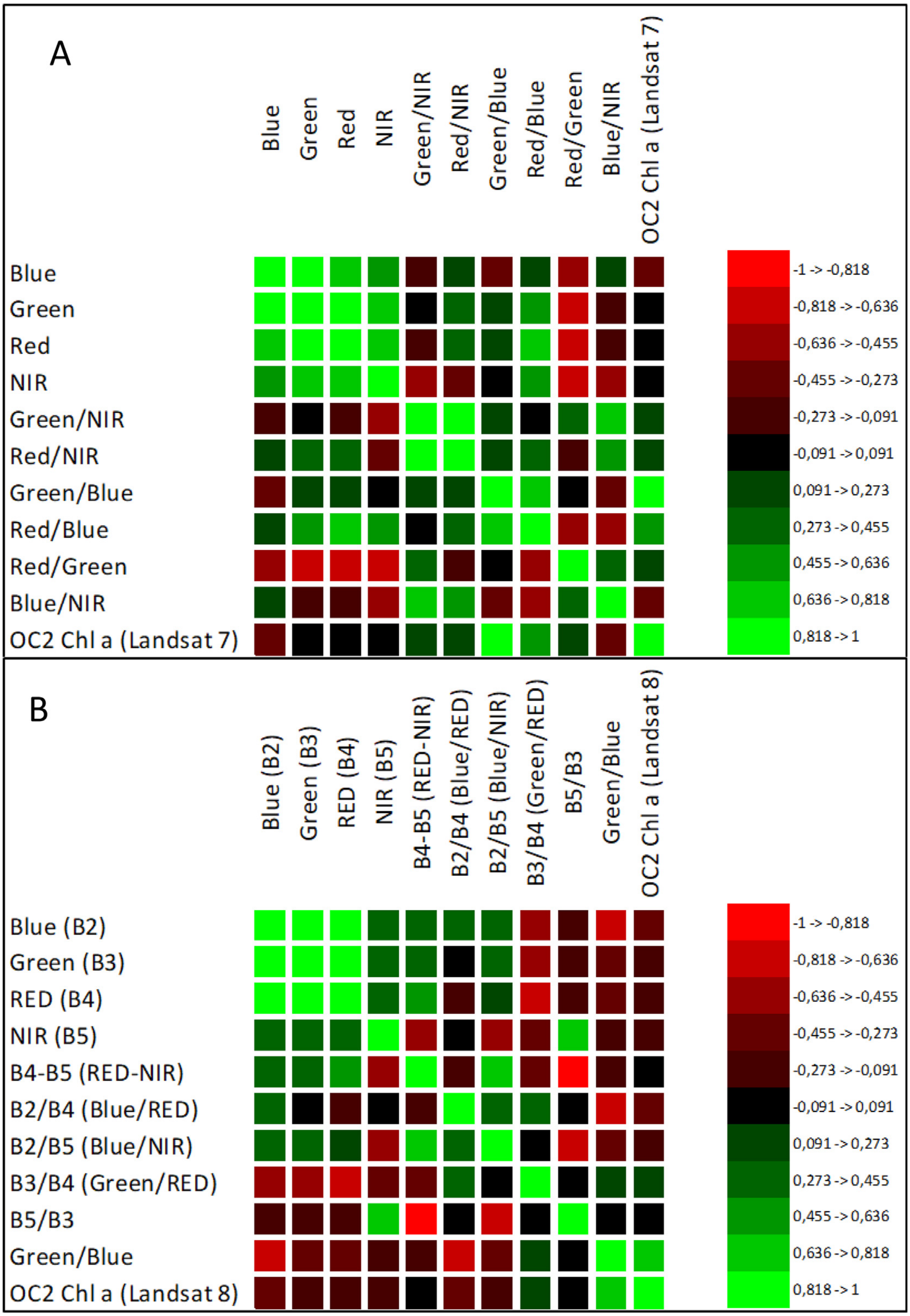

Fig. 4. Correlation coefficient for individual bands, bands-combination, and OC2 for both Landsat 7 surface reflectance (A) and Landsat 8 surface reflectance (B).

(EVI) (historical period 1999 to 2018) while Fig. 2B shows the percentage of change of vegetation (target period 2017 to 2018). The results show up to about 30% decrease in vegetation is registered when using Landsat 7 surface reflectance. The change in vegetation implies that anthropogenic activities coupled with climate and hydrological variations are the main factors that directly influence the proliferation of algae. Farming practices and deforestation are issues of concern and are believed to have contributed to the siltation of the Mindu Dam (Paavola, 2008).

Similar study conducted by Cózar et al. (2012) compared OC2 Chlorophyll-a with meteorological conditions (for example, ENSO) and found a teleconnection between the phenomenon's over Lake Victoria. In this study, the Authors highlighted the potential role of cultural-eutrophication (human-induced) in moderating the dynamics of phytoplankton in Lake Victoria. Changes in vegetation in the study area, also imply levels of human-induced activities. The vegetation changes

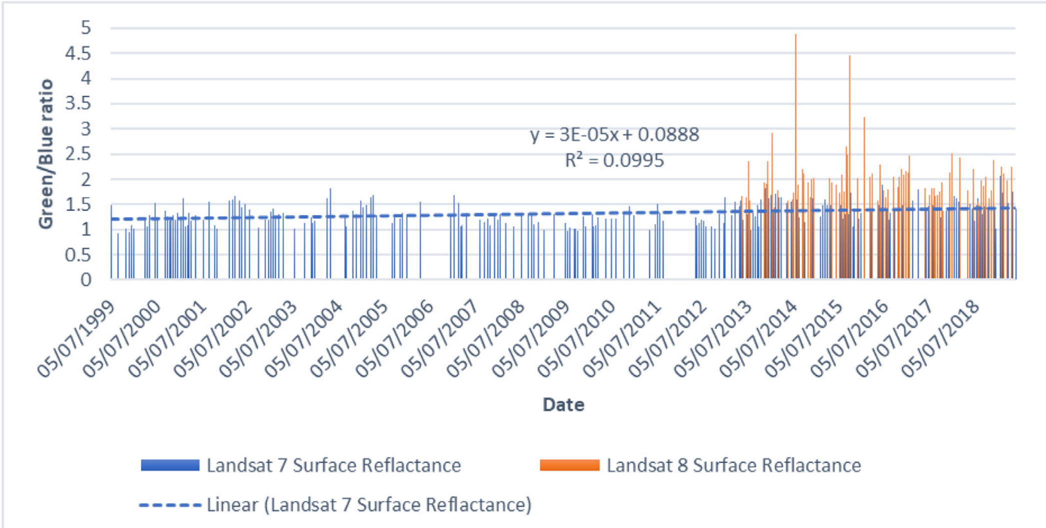

Fig. 5. Plot for the Band ratio (Green/Blue) for both Landsat 7 and Landsat 8/OLI surface reflectance. Landsat 8 registered a slight superior ration than that of Landsat 7.

corroborate with the observations in the previous reports (Yanda and Munishi, 2007). Intensive human activities directly affect or plays a role in water quality and hence, the proliferation of algal blooms. For example, a study by Michalak et al. (2013) noted a link between agricultural activities and an increasing phosphorus loading coupled meteorological conditions (not specific) in controlling HABs formation. Furthermore, Michalak et al. (2013) suggested that the factors are inconsistent with the predicted future conditions.

3.2. Comparison between in situ and ocean colour chlorophyll-a (Landsat 8 surface reflectance) concentrations

Fig. 3 indicate a graphical relationship for OC2 Chlorophyll-a for Landsat 7 and Landsat 8 for a period of 2013–2017 as well as the in situ observation (all field campaigns). In situ Chlorophyll-a concentration (doted) seems to be varying in the same way satellite retrieved Chlorophyll-a were varying. In situ Chlorophyll-a ranged from 9.43 to 34.52 μg/L which falls within the range of OC2 for Landsat 8. On the other hand, most of Landsat 7 OC2 values are <10 μg/L which were inferior to Landsat 8 OC2. The observed high pick for Landsat 8 OC2 Chlorophyll-a are 57.50 and 66.67 μg/L corresponding to January 11, 2014, and January 17, 2016, respectively. [Note: in the first place we omitted the two extreme values for OC2 Chlorophyll-a (Landsat 8) as they seemed to be an outlier, but for this study, they were extracted and then mapped for future discussions].

Previous studies, for example, Malahlela et al. (2018) used Landsat 8 Operational Land Imager (OLI) for estimating Chlorophyll-a concentrations. Contrary to the present study, these Authors developed an

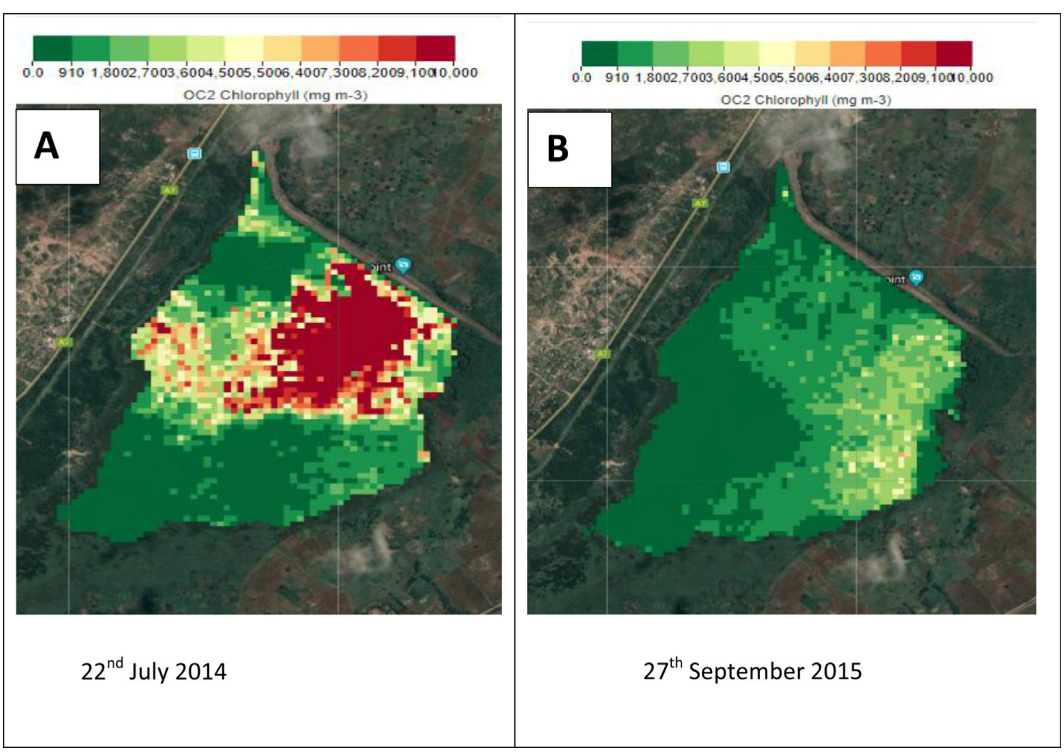

Fig. 6. Maximum values for OC2 Chlorophyll-a concentration as extracted from the two dates that registered or signalled high strength.

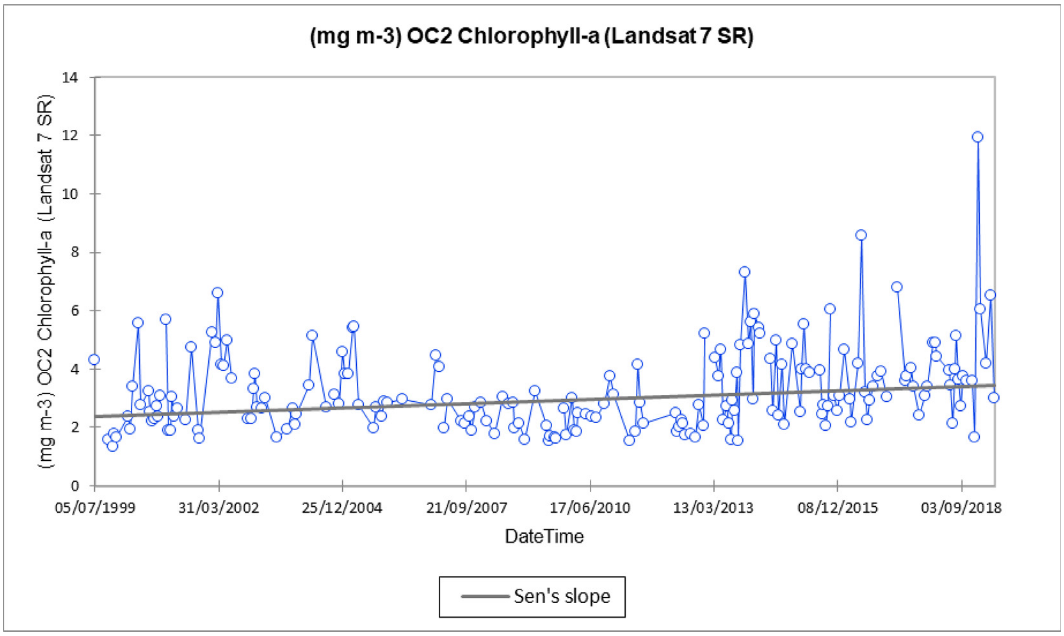

Fig. 7. Mann-Kendall trend series for the OC2 Chlorophyll-a concentration using Landsat 7 surface reflectance. The plot exhibits a significantly increasing trend with relatively more considerable variation starting from 2013.

algorithm which worked better with Red and NIR bands. As stated earlier our study used OC2 which is based on the Blue and Green bands (https://oceancolor.gsfc.nasa.gov/atbd/chlor_a/) algorithm. From Fig. 3, in situ values patterns (doted) are in accordance to both Landsat 7 and 8 OC2 Chlorophyll-a. The correlation between OC2 and individual band and bands combination are studied to assist selecting the best combination.

3.2.1. *Correlation tests*

Biplot correlational analysis for band and band combination for both Landsat 7, Landsat 8 surface reflectance, and OC2 are shown in Fig. 4 A and B, and these were used to provide the criterion to estimate Chlorophyll-a (i.e., considered as Chlorophyll-a index).

Over the tropics in situ monitoring data for cyanobacteria blooms are lacking, therefore developing a time series pattern for comparison with other environmental variables is challenging. A review of Mowe et al. (2015) for example, failed to do a detailed analysis on the light intensity, stratification of lakes, flushing of water bodies because of data scarcity. As discussed earlier, that band and bands combination has been previously used to estimate Chlorophyll-a concentration. In the current study, Green-Blue ratio showed a strong correlation with OC2 for both Landsat 7 and 8 (see Figure 4 A and B). Specifically, of all band ration tested the ration between green and blue (**Green/Blue)** for all the sensors registered a strong correlation of 0.942 and 0.729 for Landsat 7 and Landsat 8 respectively.

On the other hand, the coefficient of determination was 0.888 and 0.532 for Landsat 7 and Landsat 8, respectively. The results corroborate with a study of Ha et al. (2017) which used Landsat 8 OLI that obtained the best estimation by a ratio of two reflectances at 562 and 483 nm (corresponding to the OLI Band 3 and Band 2, respectively). The band ratio (as in Fig. 5) differ in terms of time scale since both Landsat 7 and Landsat 8 were launched in 1999 and 2013 respectively, and both satellites continue to acquire data.

When the Mann-Kendall trend test for OC2 Chlorophyll-a using Landsat 7 surface reflectance, the results showed an increasing trend which is in line with the raw OC2 Chlorophyll-a (Fig. 7). Fig. 5 shows the graphical representation for band ratios (Chlorophyll-a index) for both Landsat 7 and 8.

From Fig. 5, the observed highest band ratio values (4.7 and 4.8) in Landsat 8 values correspond to the extreme values of OC2 Chlorophyll-a (Fig. 6) which occurred on July 22, 2014 (4913.51 mg/m^3 of Chlorophyll-a) and September 27, 2015 (1233.91 mg/m^3 of Chlorophyll-a). The two values were omitted in Fig. 3 because they were suppressing other values if presented as raw OC2. The band ratio (Green/Blue) depicted the magnitude of both the observations (Fig. 5) mentioned above. An interesting finding is that extreme values occurred during the dry months/seasons from June to September as well as January, which is also relatively dry. With regards to images extracted using the climate engine web interface (Figure 6 A and B), observed more concentration at the centre towards the north-eastern side of the Mindu Dam.

Threshold values of Chlorophyll-a in recreation and ponds for example, in New England Lakes, based on world health organization (WHO) are set to be low (Chlorophyll-a <10 μg/L), moderate (10–50 μg/L) and high (50–5000 μg/L) (Keith et al., 2012). According to the same Authors, health effects associated with contaminated water if consumed or exposed are in three categories.

i. Low: skin irritation and gastrointestinal illness
ii. Moderate: all the symptoms of the group (i) with long term illness
iii. High: all the signs of the group (ii) and potential for acute poisoning

The extreme values of OC2 Chlorophyll-a as well as in situ Chlorophyll-a in the current study fall under the moderate to high and low categories when using Landsat 8 Landsat 7 OC2 algorithm surface reflectance, respectively. The observation suggests further investigation on refining monitoring techniques for assessing possible health effects associated with algal blooms in the catchment.

3.3. *Trend for the ocean colour chlorophyll-a using Landsat 7 surface reflectance*

Fig. 7 shows OC2 Chlorophyll-a using Landsat 7 surface reflectance as obtained from the Climate Engine web interface and which has a duration

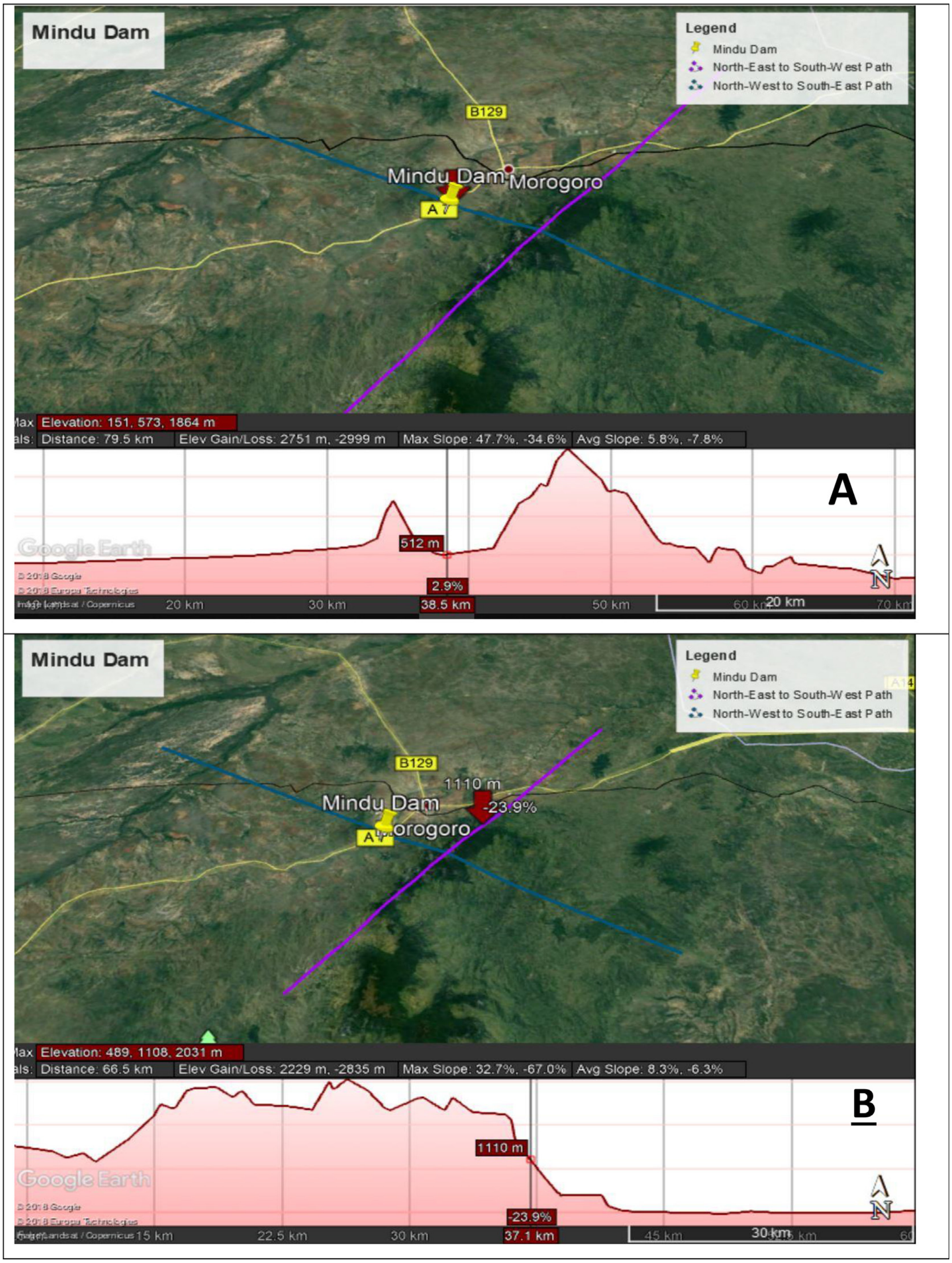

Fig. 8. A cross section of relief features near the study area. From North West (NW) to the South East (SE) path (A) and North East (NE) to the South West (SW) path (B) (courtesy of google earth). The relief demonstrates the escarpment of which is responsible for the local weather influences (orographic effect).

that is relatively close to the period of the climatological dataset. After performing a Man-Kendal trend test, the results indicated a significant ($p < 0.001$) increasing trend for the Chlorophyll-a in Mindu Dam.

3.4. Climate and relief features in the upper Ngerengere Catchment

Several studies have reported on the hydrological and climate variability in the Ngerengere catchment (Natkhin et al., 2015; Ernest et al., 2017; Kimambo et al., 2019). One factor that miss in the previous studies is the topographical influence. The present research articulates and deduces the implication of the studied variations and changes on HABs (forgotten factor). Fig. 8 illustrates the relief features that are responsible for local weather variations (for example, orographic effects). The reservoir (Mindu Dam) situated in a valley, surrounded by the Uluguru Mountains (as illustrated in Fig. 8) is surrounded by which part of eastern arch mountains (Uluguru Mountains) which are influencing the local weather in Morogoro Urban.

Regarding the importance of relief features on algal blooms dynamics, a widespread discussion is that topography (such as a mountain) control the temperature say for the leeward side of the hill (Birdwell, 2011). Wind speed and directions variability probe the chance for having higher temperatures in the leeward side of the

Table 2
Correlation matrix (Pearson).

Variables	Monthly Total Rainfall (mm)	TMX (°C)	TMN (°C)	SLR (MJ/M2)	WD0900Z (Degree)	WD1200Z (Degree)	Wind Speed (Knots)	Water Level (cm)	Nino-3.4
Monthly Total Rainfall (mm)	**1**	**0.153**	**0.583**	0.025	-0.021	-0.047	**-0.146**	0.018	**0.144**
TMX (°C)	**0.153**	**1**	**0.756**	**0.736**	0.060	**0.148**	**0.674**	**-0.551**	-0.043
TMN (°C)	**0.583**	**0.756**	**1**	**0.491**	0.060	0.064	**0.389**	**-0.396**	0.043
SLR (MJ/M2)	0.025	**0.736**	**0.491**	**1**	0.100	**0.130**	**0.554**	**-0.394**	0.031
WD0900Z (Degree)	-0.021	0.060	0.060	0.100	**1**	**0.825**	**0.534**	0.039	-0.045
WD1200Z (Degree)	-0.047	**0.148**	0.064	**0.130**	**0.825**	**1**	**0.587**	0.048	-0.063
Wind Speed (Knots)	**-0.146**	**0.674**	**0.389**	**0.554**	**0.534**	**0.587**	**1**	**-0.423**	-0.099
Water Level (cm)	0.018	**-0.551**	**-0.396**	**-0.394**	0.039	0.048	**-0.423**	**1**	**0.146**
Nino-3.4	**0.144**	-0.043	0.043	0.031	-0.045	-0.063	-0.099	**0.146**	**1**

Note: Bolded figures are significant at $\alpha = 0.05$.

mountain. The correlation test (Table 2) showed a significantly ($p < 0.05$) strong correlation between maximum temperature, solar radiation, and wind speed but a weak relationship with wind direction at 1200Z.

3.5. Rainfall, temperature and solar radiations for the Morogoro synoptic station

Fig. 9 depicts the trends for monthly precipitation, maximum and minimum temperatures as well as solar radiation for Morogoro synoptic weather station. In the study area, Mann-Kendall trend analysis (1988–2017) demonstrated a significant increasing trend for both maximum and minimum temperatures, solar radiations, while rainfall showed no significant trend (see Fig. 9). Observed temperatures have been considered as the central organizing factor in determining the potential for HABs to occur (Gobler et al., 2017) although synergistic functions with other parameters such as phosphorus. Several studies have indicated a link between climate variability and bloom changes in different geographical regions, for example, Zhang et al. (2012) investigated a link between climate variables and bloom phenology using multiple regression models. Zhang et al. (2012) found that the phenological changes for Lake Taihu, China are strongly linked to climate. The study further demonstrated that blooms occur earlier and last longer with the increase in temperature, sunshine hours, and global radiations and decrease of wind speed.

A recent study which was conducted in Morogoro region (Ernest et al., 2017) performed a Mann-Kendal trend test to assess the influence of urbanization on an urban heat island (UHI) using normalized difference vegetation index (NDVI) and climate data. The study found a significant increase in the impervious surface of 9, 48, and 82 km^2 in 1999, 2000, and 2015 respectively. The same Authors further noted that UHI was not apparent in 1999 but 2000 and 2015 with a temperature increase of 1.8 and 1.22 °C, respectively. Another phenomenon that Ernest et al. (2017) could have investigated is the contribution of relief features (as in

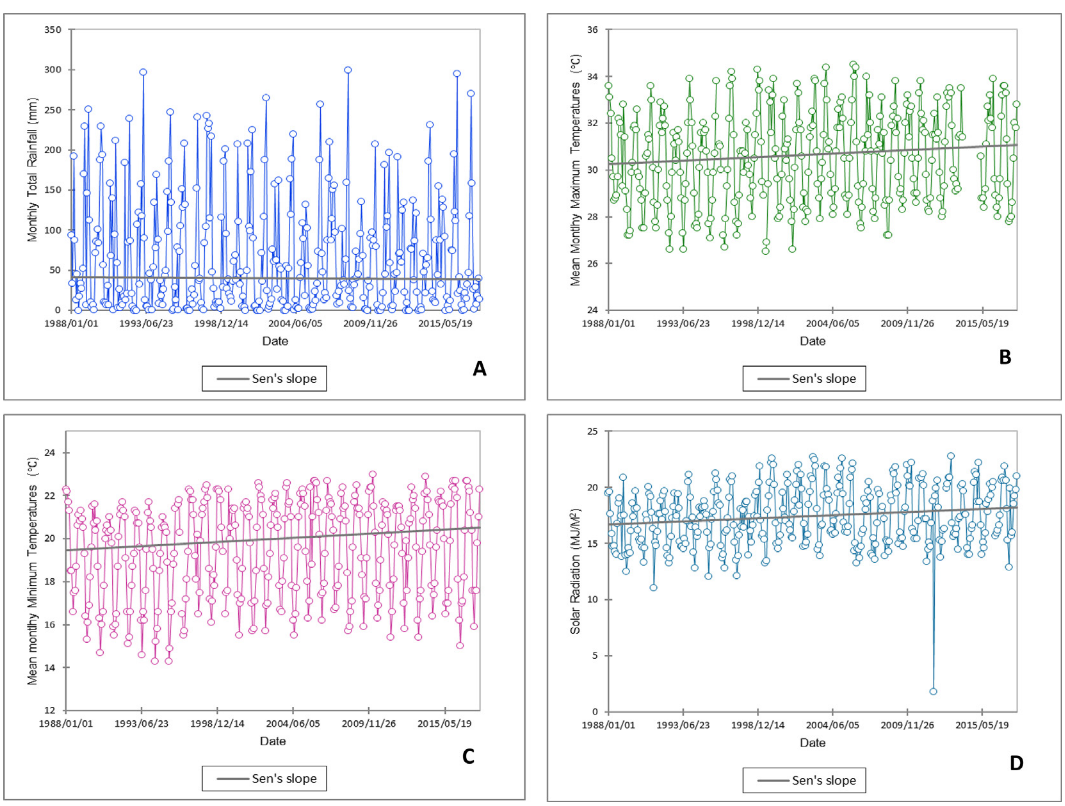

Fig. 9. Monthly total rainfall (mm) (A), monthly maximum (B) and minimum temperatures (°C) (C) and Solar radiation (MJ/M^2) (D) for a period of 1988–2017 for Morogoro Synoptic Weather stations. Mann-Kendall trend test indicated that with exception total monthly rainfall Mean maximum and minimum monthly temperatures and solar radiations registered a significant increasing trend ($p < 0.05$).

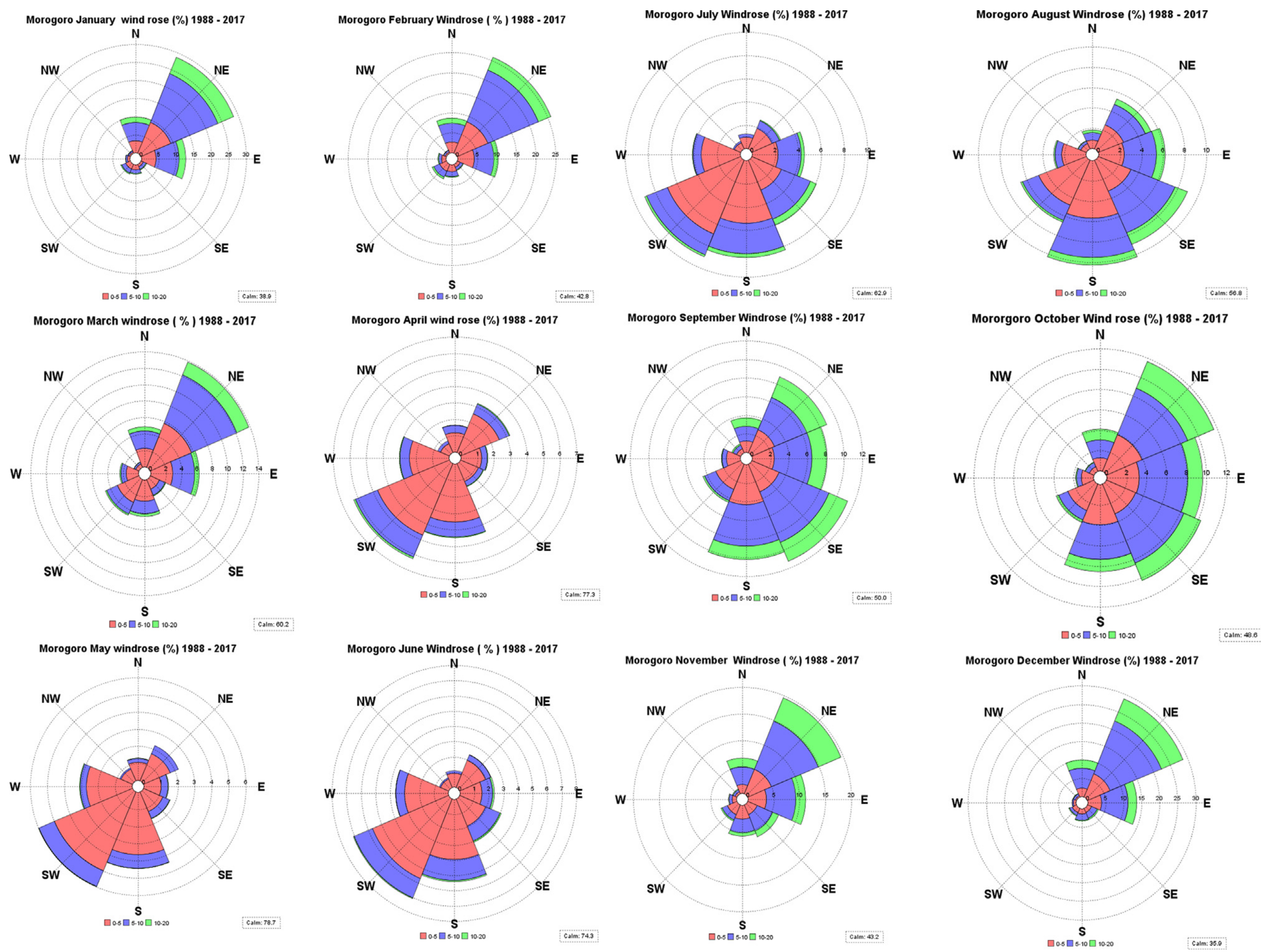

Fig. 10. Mean monthly winds roses charts with wind speed (km/hr) at Morogoro synoptic weather stations from 1988-2017.

Fig. 8) because the windward side of the mountain is usually cold and moist while the leeward side of the hills is warmer and drier (orographic effect- Birdwell, 2011). This information could have assisted in quantifying the contribution from natural climate variations and impervious surfaces, as claimed by the Authors. However, an observation made by Ernest et al. (2017) is enough to hypothesize that temperature increase might have influenced the proliferation of algal blooms in the Catchment. The popular concept mentioned above regarding the variation of temperature both in windward and leeward side of the mountains is also associated with seasonal wind shifts and the relief features that support the argument.

3.6. Wind patterns in the catchment

Fig. 10 narrates the results from mean monthly wind roses charts with wind speed (km/hr) for the Morogoro synoptic weather station, Morogoro, The United Republic of Tanzania. The sketch demonstrates that for November to February the winds have north-easterly dominance while backing to South Westerly to Southerly towards August (unlike other months which usually are 5–10 km/h and sometimes 20 km/h, wind speed for these months are ranging from 0-5 km/h). The considerable variation observed for September and October ranging from southerly to north-easterly but with a dominance of easterly component (Note: wind speed is in km/hr).

Apart from mean wind analysis for different months in the study area, Mann-Kendall trend analysis for both wind direction at 0900Z and 1200Z (degrees) and wind speed (knots) still indicates that there is a shift in both parameters and that wind direction are becoming more north-easterly component while speeds are tending to calm conditions. The Mann-Kendall trend test was significant ($p < 0.05$) for both wind speed and directions (Fig. 11 A, B and C, respectively). The decreasing trend in wind speed was not surprising because it was also reported in other reports (Cózar et al., 2012) over the East Africa Region as well as for the global scale (Karnauskas et al., 2017). The implication for the decreasing trend in both wind speed and directions directly imply a reduced vertical mixing of water. In combination with increasing temperature, it might escalate or intensify proliferation of harmful algal blooms.

3.7. Water level for Mindu Dam

Mindu waters levels (Fig. 12) depicted a significant variation in the catchment from 1997-2017. The significant decreasing trend (Kendal tau = -0.163, p = 0.05) in water levels observed at Mindu Dam insinuates to two factors, one is either increase in domestic water demand hence water abstraction or the increased evapotranspiration due to warming and or both. Previous studies have reported a decreased inflow in the catchment that is linked to both natural and human factors such as water abstraction cum demand and climate changes (Natkhin et al., 2015).

3.8. Nino-3.4 index

The variation of monthly rainfall and Nino-3.4 Index indicates a significant variability of both dry and wet fluctuations, i.e., positive anomalies for a high amount of monthly total precipitation and negative anomalies for a lower amount of monthly total rainfall (see Fig. 13). The Nino-3.4 index is used for monitoring and ranking the relative strength of

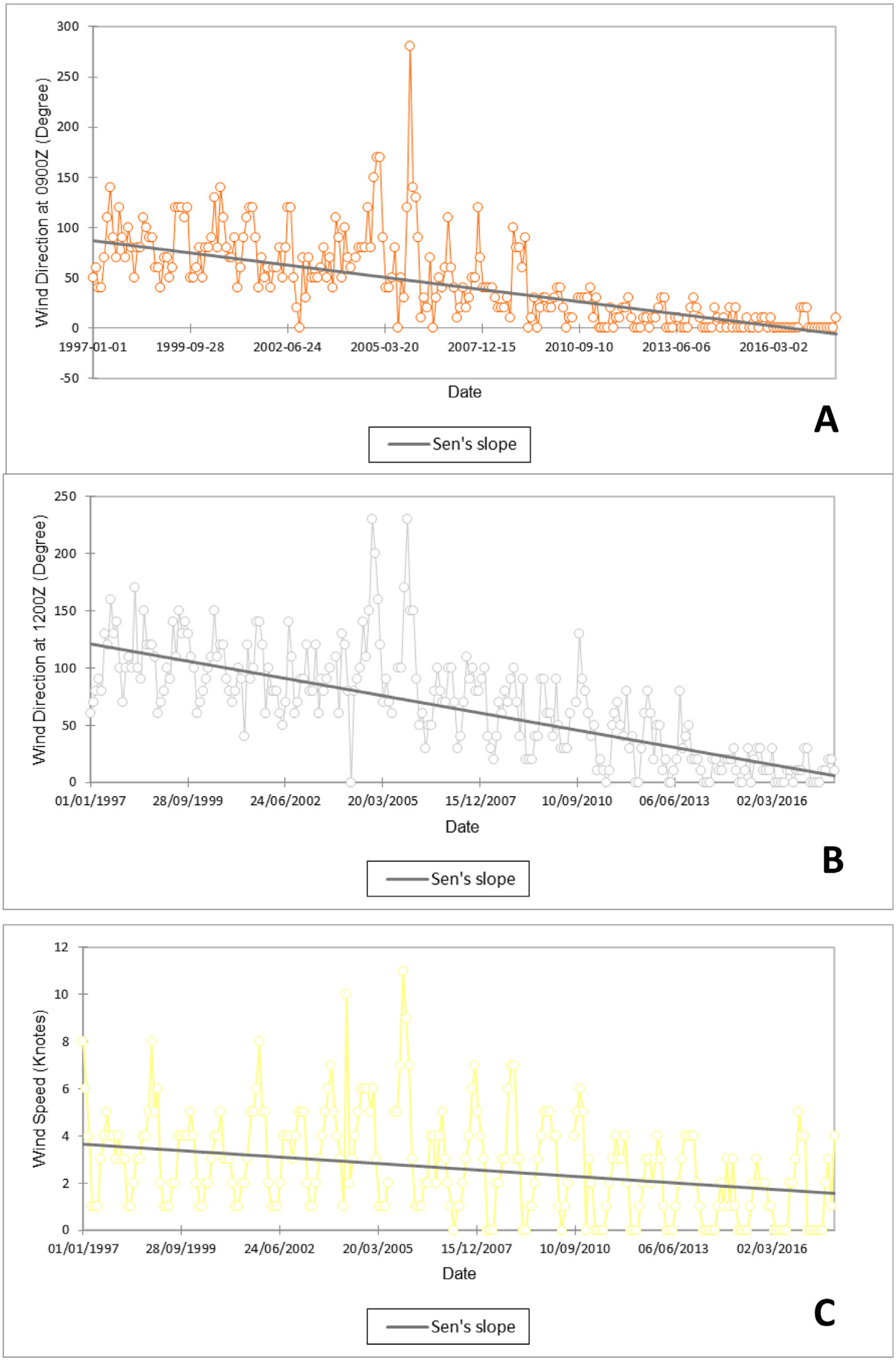

Fig. 11. Mann-Kendall trend test for mean monthly wind direction (1997–2017) at both 0900 and 1200Z and Wind speed (knots) at Morogoro synoptic weather station.

the El Nino-Southern Oscillation (ENSO), i.e., the rolling 3-month average sea surface temperature in the east-central tropical Pacific (Dahlman, 2009). When an index is 0.5 °C or higher, El Nino condition exists and when the index is -0.5 °C or lower La Nina conditions exist (Dahlman, 2009). Eastern Africa is usually associated with wet weather condition during El Nino and dry condition during La Nina (Anyamba and Glennie, 2018). ENSO, on the other hand, provides insight on drought in the East Africa region, which links to HABs proliferation.

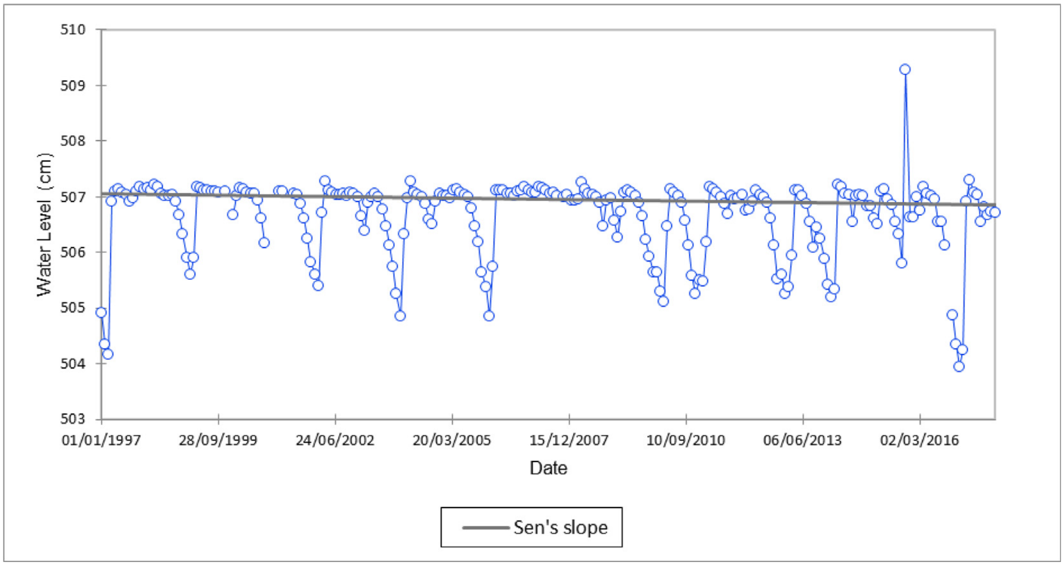

Fig. 12. Trend of monthly water variation for Mindu Dam. The Mann-Kendall trend test indicates a decreasing trend (Kendal tau = -0.163, $p < 0.05$).

It is the expectation that El Nino and La Nina alteration directly or indirectly influences blooms dynamics in the catchment through droughts/dry and wet/heavy rainfall conditions. In the search (visually) for the patterns, for example, cases for an extremely high concentration of blooms were noted corresponding to the highest peaks of green/blue ratio. Extracting the documented ENSO events and tracing their link with algal blooms events in the study area is the best approach for the understanding of HABs dynamics in the catchment.

By visual inspection, El Nino/La Nina phases seem to agree or match with total monthly rainfall variations in the catchment (Fig. 13). The underlying assumption is that during the drought/dry condition, there are chances for the proliferation of blooms and that Chlorophyll-a values are high. Cases of extreme values (i.e. OC2 Chlorophyll-a for 4913.5184 and 1233.9116 mg/m^3) of Chlorophyll-a concentration (Landsat 8 surface reflectance) for Mindu Dam at that time Nino-3.4 (monthly) corresponded to a negative value which indicated dry conditions and positive value which meant a wet status (-0.3 and 2.12 Nino-3.4 indices respectively). Other cases (when the first two cases omitted) observed high pick for Landsat 8 OC2 Chlorophyll-a of 57 and 66.7 μg/L corresponding to January 11, 2014, and January 17, 2016, respectively. The corresponding Nino-3.4 index for the same period were -0.34 and 2.66, respectively. The expectation was that all the high values of OC2 Chlorophyll-a goes hand in hand with negative values (La Nina phase), but that was always.

As part of health risk assessment, associated impacts such as cholera symptoms can also be issues to consider. Similar scenario features in the previous studies on El Nino and cholera (though it is not an intention for the present study) where cholera cases were found in El Nino years (Moore et al., 2017). However, the findings of the present study corroborate with the research of de Souza et al. (2018) which investigated signs of climate change effects on cyanobacterial bloom in a subtropical coastal lagoon. The same Authors found an association of blooming with negative anomalies in precipitation that occurs during La Nina periods. A similar approach which assessed the influence of El Nino-induced drought on cyanobacteria community of Koka Reservoir in Ethiopia noted a shift in the cyanobacterial community (Tilahun and Kifle, 2019). According to these Authors the drought condition caused nitrogen limitation which might have triggered unusual dominance of cyanobacteria genus *Cylindrospermopsis* over the persistent dominant genus *Microcystis* in the reservoir. There is a need for monitoring of the dynamics of the algal bloom in the catchment. The study approach has demonstrated the complexities in the dynamics of cyanobacteria in Mindu Dam in Ngerengere Catchment.

Climate change has been noted to be influencing phytoplankton dynamics in many water bodies in East Africa. A study by Barker et al. (2000) for example, conducted in the south-eastern highlands (Lake Masoko, Songwe region) in Tanzania in one of the Crater Lakes claimed that many Lakes in East Africa have shown to be relatively stable (during the Holocene period) and some resilient to environmental changes except

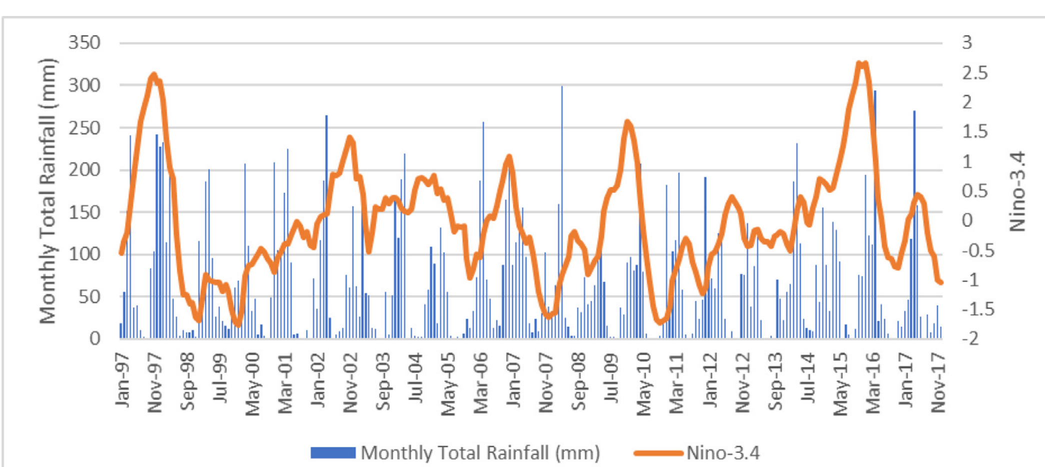

Fig. 13. Nino-3.4 Index for the period of January 1997 to May 2017 overlaid with total monthly rainfall (mm).

Crater Lakes. The study further noted that the Lake ecosystem was highly sensitive to both climate change and tephra (clastic volcanic materials) deposition. The significant findings, according to Barker et al. (2000), was the reductions in diatoms, increase in conductivity, and expansion of cyanobacteria. This evidence justifies the extrapolation of the hypothesis to other areas due to the experiences and predicted changes and or variations in the climate and hydrology in East Africa (World Wide Fund For Nature, 2006).

Generally, there is a consistent pattern for all the variables which agrees with the popular understanding of the mechanism for algal blooms proliferations. The influencing factors for the proliferation of harmful algal blooms include decreased trends in wind speed and shift in wind directions, the decline in the Dam's water levels as well as increased trends in temperatures and solar radiation in the catchment. There are also pieces of evidence of anthropogenic activities reported in the previous studies and watershed destruction leading to water shortage for domestic use and environmental flow in the basin in recent decades (Yanda and Munishi, 2007). On the other hand, tropical disturbances (episodic climate and hydrological events) such as heavy rains (Kimambo et al., 2019) and the variation in the intertropical convergence zone (ITCZ) may also play a key role on blooms dynamics in the study area (Cózar et al., 2012).

4. Conclusion

The results presented here suggest a teleconnection between meteorological and hydrological parameters and the Chlorophyll-a in the catchment. In summary, the Mindu Dam water levels registered a significant decreasing trend in recent decades. A substantial shift in both wind speed and directions, i.e., wind direction is becoming more north-easterly component while speeds are tending to calm conditions. Minimum and maximum temperatures, solar radiations had rising trends, while rainfall was found to be neutral (based on 1988 to 2017 data). The implication is that the factors and their patterns are in line with the widespread discussion on HABs development. It is exhibited in the increasing trend of OC2 Chlorophyll-a in recent decades when using Landsat 7 surface reflectance, which significantly showed a rising trend ($p < 0.05$). Moreover, there was a link between the Nino-3.4 SST index and extreme cases of blooms when using Landsat 8 surface reflectance, although other cases were against the Nino-3.4 index. Generally, the results suggest that the approach (retrospective analysis of algae and its comparison with the climate and hydrological changes) used in the present study is more informative. It can be utilized to inform policy and practices (e.g. education, planning, and monitoring) to all the responsible stakeholders. The study contributes to the application of recent advances in remote sensing and retrospectively analysis of bloom dynamics and search for their link with climate and hydrological changes. Since water levels registered a decreasing trend while rainfall was neutral future works can be to accurately assess the contribution of evapotranspiration as well as water abstraction for domestic uses. Furthermore, concentration on accurate monitoring of HABs (temporal and spatially) for developing an algorithm and or model for predicting the future proliferation of HABs is inevitable.

The study suffers several limitations. Lack of monitoring data (both *in situ* and remote sensing) for the dam was the main limitation. The study area lies in the deep tropics, characterized by frequent cloudiness, particularly during the rainy, i.e., March April May (MAM) season which might have affected data capture and coverage. The challenges forced the use of OC2 Chlorophyll-a algorithm for Landsat 7 surface reflectance to obtain a trend for blooms (band ratio) for comparison and search for a link with meteorological and hydrological patterns in the reservoir. Landsat 7 showed a few inferior values than that of Landsat 8 and *in situ* Chlorophyll-a. However, their long-term datasets could establish a significant trend. Another limitation which might have contributed to our conclusion is the approach of analyzing the trends individually and manual search for the link and or associations.

Declarations

Author contribution statement

Offoro Kimambo: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Hector Chikoore, Jabulani R. Gumbo, Titus A.M Msagati: Contributed reagents, materials, analysis tools or data.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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