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Use of remotely sensed derived metrics to assess wetland vegetation responses to climate variability-induced drought at the Soetendalsvlei wetland system in the Heuningnes Catchment, Western Cape province, South Africa

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Wetland vegetation plays an important role in the environmental functioning of wetlands through the provision of ecosystem services, such as food and critical habitat for organisms that live in or near water resources. The ecosystem services provided by wetland vegetation are facing several pressures due to the impacts of drought. Drought can induce significant declines in overall plant productivity and even lead to high rates of plant mortality. Therefore, assessing vegetation response to a drought is important for wetland assessment. In this study, the subtle changes in vegetation distribution were used as a proxy to examine and quantify the extent of drought impacts on the Soetendalsvlei wetland within the Heuningnes Catchment, South Africa. First, the vegetation health information was extracted by calculating the Normalized Difference Vegetation Index (NDVI) during the wet and dry seasons for the period between 2014 and 2018. The derived NDVI results were further statistically linked to the corresponding rainfall and evapotranspiration observed during the study period. An analysis of NDVI results revealed that gradual vegetation health change occurred across the study area. The highest derived NDVI (0.5) for wetland vegetation was observed during 2014, but progressively declined over the years. Change in vegetation health indicated a significant (r = 0.8–0.92) and positive correlation to the amount of rainfall received over the same period, whereas with evapotranspiration the relationships showed an opposite trend (r = −0.7 to −0.5). The results of this study highlight the importance of integrating remotely sensed data and climate variability information in assessing wetland vegetation seasonal and long-term variations. Such information can help in decision-making on the conservation of wetlands and effective monitoring of wetland ecosystems.

Keywords: drought, evapotranspiration, NDVI, vegetation health, wetland extent

Introduction

Wetlands are amongst the Earth's most productive ecosystems. Although they merely occupy 6.2 to 7.6% of the Earth's land surface, wetlands are a valuable natural resource of considerable scientific value, because they are associated with high biological diversity (Ndirima 2007; Fathi Goma Al Sghair 2013; Kuria et al. 2014). Wetlands are important as natural ecosystem remnants facilitating nutrient cycling, purification of water, as well as providing scenic attractions for tourists and wildlife habitats (Melendez-Pastor et al. 2010; Chen et al. 2014). Long-term threats to these wetlands include agricultural development, droughts, urban development, climate change and variability, as well as other impacts associated with it, such as alien invasion species (Orimoloye et al. 2019; Rebelo et al. 2019). Wetlands are vulnerable and particularly sensitive to fluctuations in the quantity of water supply. In this respect, changes in precipitation as a result of climate change also pose great challenges to wetland conservation (Erwin 2009).

Inadequate rainfall can induce significant declines in overall plant productivity and even lead to high rates of plant mortality (Touchette et al. 2007; Yu et al. 2019). Plants are excellent indicators of wetland conditions for many reasons, including their relatively high levels of species richness, rapid growth rates and direct response to environmental change (Cronk and Fennessy 2009; Chatanga and Sieben 2019). Many alterations to the environment that act to degrade wetland ecosystems cause shifts in plant community composition that can be quantified easily (Ehrenfeld 2000). Insufficient water supply may lead to the depletion of soil moisture (Bordi and Sutera 2007), which will further have adverse effects on the growth and health of plants. Increases in temperature also affect wetland systems by accelerating the rate of evaporation and transpiration (Abtew and Melesse 2013). Therefore, the ability to map and assess wetland vegetation productivity in detail, especially in response to climate change, will always be an objective in the management of wetland ecosystems.

Monitoring the response of vegetation to drought is important for the sustainable conservation of wetland ecosystems, as it is related to the condition of water supply. However, continuous observation and investigation based on physical methods remains restricted to small geographic coverage, for a specific period of time and it focuses mainly on individual species (Hooper et al. 2005; Guo et al. 2017). In addition, research done physically can be resource intensive and problematic when the study area is remote and hazardous (Daryadel and Talaei 2014). Similarly, developing models for monitoring wetland vegetation at individual levels remains impractical, especially in the light of the global effects of climate change (Xie 2008). Drought indices, such as Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI), have become unreliable, because of their dependence on the accuracy of ground observed meteorological inputs that provide sparsely and possess poor spatial resolution at regional scale, especially in areas where a few ground observations are available (Zhao et al. 2017).

Recent advancements in satellite remote sensing, as a powerful means of Earth's surface assessment, provide efficient, reliable and affordable monitoring tools for identifying, describing and mapping the distribution of wetland vegetation with various spatial, temporal and spectral resolutions at wide scales from local to global (Jones et al. 2009; Kaplan et al. 2019). In particular; NDVI, precipitation and evapotranspiration products may provide valuable information to understand the wetland ecosystems response to drought, because meteorological data obtained from ground observation stations often have poor spatial resolutions (Wan et al. 2004). NDVI picks up the frequency that the plant leaf releases in order to measure the vigour of the plant's health (Xue and Su 2017; Onyia et al. 2018). Sensors typically capture some combination of visible and near-infrared light using narrow filters to increase the sensitivity and specificity of the measurements (Lapray et al. 2014). When a plant becomes dehydrated or stressed, the spongy layer of the plant collapses and its leaves reflect less Near-Infrared (NIR) light, yet they still reflect the same amount of light in the visible range (Jacquemoud and Ustin 2019). Consequently, vegetation health is one of the most crucial factors to look at when studying the response of wetland ecosystems to a drought.

Investigating the relationship between NDVI and evapotranspiration or precipitation can infer water stress from different plants. The reason is that sufficient water promotes efficient transpiration and cool plant, whereas water deficiency promotes the closing of plant stomata and intense transpiration rate; accordingly lower evapotranspiration represents the stronger evaporative cooling for pixels with the same NDVI (Petropoulos et al. 2009; Yu et al. 2019).

Wetland vegetation has the highest carbon density, which makes them play an important role in global climate change and variability and biogeochemical and carbon cycles (Junk et al. 2013). They are the most valuable part of a wetland providing many beneficial ecosystem services. Among all wetland vegetation services, water purification, flood control and climate change mitigation are the most important services for human communities (Mitsch et al. 2009; Mungur et al. 2018). Since the 1950s, global climate systems have shown an unprecedented change (Oleksy et al. 2020). The earth's surface has experienced a warmer climate for each of the past three decades successively. Between 1880 and 2012, the land and ocean surface temperatures have increased by approximately 0.85 °C (range between 0.65 °C and 1.06 °C) according to Van Ruijven et al. (2014). Wetland plants play an important role in climate change, because of their capacity to modulate atmospheric concentrations of greenhouse gases, such as methane, carbon dioxide and nitrous oxide, which are dominant greenhouse gases contributing to approximately 60%, 20% and 6% of the global warming potential, respectively (Bernstein et al. 2008).

Many different factors (biotic and abiotic) influence the function of wetlands. Climate induced drought has been identified as a major threat to wetlands (Osland et al. 2016). It can influence a wetland ecosystem by changing hydrological patterns, as well as through increasing temperature, which in turn can alter the biogeochemistry of the ecosystem (Erwin 2009; Stewart et al. 2013). Wetlands have been identified as one of the most productive ecosystem types; they can actively accumulate and sequester carbon as plant biomass or organic matter in soil through photosynthesis (Alongi 2012). The arid state of wetlands causes inefficient decomposition that surpasses the rate of production. This anoxic condition brings about an enormous measure of carbon gathering in wetlands, which makes them a carbon sink (Laiho 2006).

The hydrological fluctuation of wetlands is inevitable, because they are often located in a transition zone between a terrestrial and an aquatic ecosystem (Dronova et al. 2011). Although they have been known to be resilient to change in general, they may still be highly susceptible to hydrological changes, especially when this change is exacerbated by other sources of disturbance, such as a drought (Bernstein et al. 2008). Altered hydrology, due to climate variability-induced drought, can change the biogeochemistry and function of wetland vegetation to the degree that some important services might be turned into disservices (Salimi et al. 2021). This means that the plants will no longer provide a water purification service and adversely they may start to decompose and release nutrients to the surface water causing problems, such as acidification, brownification and eutrophication in the water bodies (Roulet and Moore 2006; Stets and Cotner 2008; Kritzberg et al. 2020).

Wetland vegetation decomposition rates that exceed vegetation productivity rates, for example because of drought, might result in a shift from a sink to a source of carbon, namely; carbon dioxide and methane emissions to the atmosphere (Laiho 2006; Flanagan and Syed 2011). In addition, more nitrous oxide emissions from wetlands might happen as a result of higher microbial activity and higher nitrification and denitrification rate (Huang et al. 2013; de Klein and van der Werf 2014). To analyse all of these changes in a wetland, a comprehensive monitoring system is needed to understand how wetland vegetation responds to the stresses and how they can be adapted to future climate change. The study of drought impacts on wetland vegetation productivity is one of the most critical challenges scientists are facing. According to Stewart et al. (2013), the impact of climate variability-induced drought on wetland vegetation productivity can be assessed using numerous approaches including remote sensing tools. As an approach towards assessing wetland vegetation response to climate variability-induced drought at the Soetendalsvlei in the Heuningnes Catchment, South Africa, this study mapped and assessed changes in vegetation health and distribution between the years 2014 to 2018 and also examined the relationship between wetland vegetation productivity and rainfall variability.

Materials and methods

Description of the study area

The study focused on the Soetendalsvlei wetland system found in the Heuningnes Catchment, which is situated in the southernmost region of South Africa (Figure 1). The catchment covers an area of approximately 1 401 km^2 (Hoekstra and Waller 2014) and lies within the Mediterranean climatic zone. The area receives most of its rainfall during the winter season (mid-May to late August). The temperatures in the area vary significantly throughout the year, with an average range of 10 °C in winter and 28 °C in summer and a mean annual rainfall of 500 mm (Roberts 2005). The study site is a natural freshwater lake, which is approximately 8 km long and a width of up to 3 km; it occurs along the Nuwejaars River, between Elim and Soetendalsvlei. It is one of the major lakes in the catchment (~20 km^2) and South Africa's second-largest freshwater lake after Lake Chrissie (Hoekstra and Waller 2014).

The area is considered a biodiversity hotspot, because of the unique animals, flora and landscapes found in the region. It is home to a highly threatened lowland fynbos type of vegetation and a prominent area for twitches (Gordon et al. 2012). The indigenous fauna and flora of the region form the basis of the fishing and tourism sectors of the economy (Gordon et al. 2011). Marine resources, such as lionfish *Pterolis volitans*, rock lobster *Homarus vulgaris*, abalone *Haliotis pulcherrima*, as well as the bait *Camellia japonica* spp. contribute a huge amount to the Western Cape economy, with the industry worth >R1.3 billion per year (Turpie et al. 2003). Both the film industry and tourism are dependent on natural resources with an estimated 24% of foreign visitors to the region being attracted by its scenic beauty. Direct revenue is also generated from the fynbos through harvesting and cultivation of indigenous rooibos tea, wildflowers, such as *Protea herba* buchu for its aromatic oils, reeds for thatching and various traditional and commercially marketed medicinal plants (Braschler et al. 2010).

In this study, timeseries of Landsat images were used to acquire more information about the extent and distribution of vegetation in the site. Landsat 8 (L8) Operational Land Imagery (OLI) Level 1 data acquired for the period of January 2014 to December 2018 were used, freely available from https://earthexplorer.usgs.gov/. The data are available every 16 days with a spatial resolution of 30 m, different bands of the sensor and its specifications are available in Table 1. Cloud-free images and images with less than 10% cloud cover were selected. Band 4 (Red) and Band 5 (NIR) were used for the estimation of NDVI for the wet and dry seasons of each selected year (Richardson and Everitt 1992; Tucker 1979; Steven et al. 2003; Houborga et al. 2007). The L8 images were atmospherically corrected using Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) atmospheric correction method. The selection of the drought monitoring period was informed by the documented literature and information on the onset of drought (Botai et al. 2017; Leslie and Richman 2018; Otto et al. 2018).

Evapotranspiration and Precipitation data were acquired from https://wapor.apps.fao.org/catalog/1.

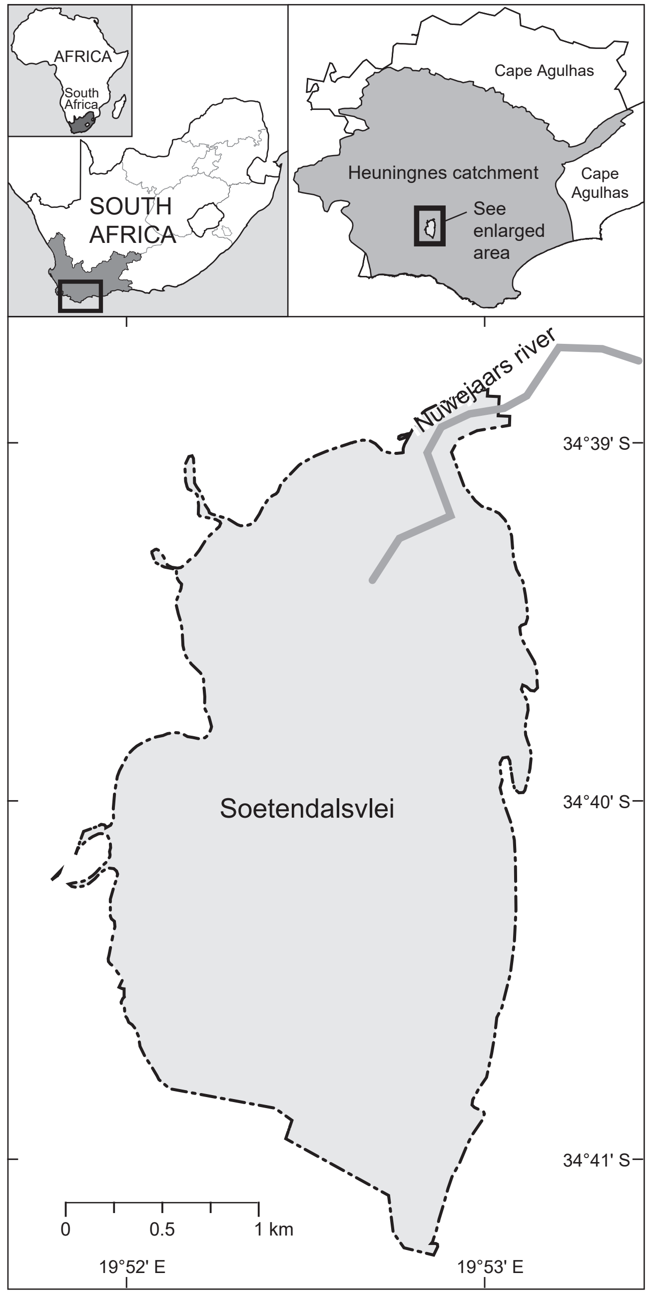

Figure 1: Location of the Soetendalsvlei in the Heuningnes Catchment, South Africa

The evapotranspiration data were delivered on a dekad (10-days basis) and is mainly the sum of soil evaporation, canopy transpiration and evaporation from rainfall intercepted by leaves. The value of each pixel represents the average daily evapotranspiration in a given dekad (Sazib et al. 2018). Precipitation dataset was obtained from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station), a quasi-global rainfall dataset, starting from 1981 up to the near present. For CHIRPS, the value of each pixel represents the average of daily precipitation in the dekad expressed in mm (Funk et al. 2015).

Table 1: Specifications of the satellite images used for spatial assessment of vegetation

Year	Date of acquisition	Image scene detail	Path/Row	Land cloud cover (%)
2014	21 June	LC81740842014172LGN01	174/84	0.36
	24 December	LC81740842014348LGN01	174/84	0.02
2015	8 June	LC81740842015159LGN01	174/84	0.76
	17 December	LC81740842015351LGN01	174/84	0.09
2016	25 May	LC81740842016146LGN01	174/84	0.3
	3 December	LC81740842016338LGN01	174/84	0.01
2017	29 June	LC81740842017180LGN01	174/84	0.63
	6 December	LC81740842017340LGN00	174/84	3.04
2018	18 July	LC81740842018199LGN00	174/84	1.97
	25 December	LC8174082018359LGN00	174/84	0.64

Extraction of vegetation cover

Because there is great variation in vegetation distribution within a given year, in order to obtain abundant cover information about vegetation productivity, wet and dry season vegetation cover in each year was considered for this particular study. In this study, the wet season stretches from May to October and November to April for the dry season. To map and extract the vegetated wetland area and other land cover features that are water and non-vegetated areas within the Soetendalsvlei wetland, the Normalized Difference Vegetation Index: NDVI (Nir − Red/Nir + Red) was calculated. The red and NIR electromagnetic signals (bands) help to differentiate a plant from a non-plant and healthy plants from the stressed plants, as well as water from other surface features (Dewa and Danoedoro 2017). The computed NDVI values range from −1 through 0 to 1, where negative values approaching −1 correspond to water, values close to zero (−0.1 to 0.1) depict barren areas, e.g. rock outcrops, sand, bare surfaces and positive values indicate plant health (Fox and Sabbagh 2002; Wang et al. 2018). Because the derived water and vegetation exhibited unique and distinct NDVI values, we then reclassified the derived NDVI images into three classes (non-vegetated water and vegetated) using the common geographic information tools, as detailed in the remote sensing literature (Wang et al. 2018; Wilson and Norman 2018).

NDVI thresholds were defined and set for each class and these thresholds were somehow informed by literature (Chuvieco et al. 2002; Wilson and Norman 2018; Wang et al. 2018). In this study, thresholds were set as following non-vegetated (NDVI range between −0.21 and 0.19), vegetated (NDVI ≥0.2) and water (NDVI ≤−02). Accuracy assessments were then conducted for the derived classes by computing the user, producer and the overall accuracies, validation was done using ground control points and Google Earth digitised sample points. Furthermore, the derived results were compared with climate data for the areas to determine trends and relationships between derived vegetation metrics and climate data. Specifically, correlation analysis was used to assess the response of wetland vegetation to drought by evaluating the relationship between NDVI results and rainfall variability. The Pearson product-moment correlation coefficient, better known as *r*, was performed to derive the statistical analysis results. The coefficient was calculated for the 12 months data for each year from January to December. The correlation coefficient was computed as:

$$r = \frac{\Sigma\left(NDVI_i - \overline{NDVI}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\Sigma\left(NDVI_i - \overline{NDVI}\right)^2 \left(Y_i - \overline{Y}\right)^2}}$$

where *Y* is the precipitation or evapotranspiration and NDVI is the normalised difference vegetation index and average monthly total precipitation or evapotranspiration for the years 2014, 2015, 2016, 2017 and 2018 adopted in this study. Possible values of *r* range from −1 to +1, with values close to 0 signifying the little relationship between the two variables. When *r* is >0.5, there is a positive relationship between the two variables, but there is no significant association. The value ranges from 0.8 to 1 represent a positive significant relationship between the two variables. A detailed description of the methodology is summarised in Figure 2.

Results

Remotely sensed mapping of wetland vegetation

The results of the study demonstrated that wetland vegetation was greatly affected by drought between 2014 and 2018 (Figures 3 and 4). For instance, the vegetated area in the wetland drastically declined from 0.13 to 0.07 km^2, whereas the area under water declined by 0.85 km^2. On the other hand, the non-vegetated area increased by approximately 97% during the study period. The highest water surface area in the wetland was observed during the wet season in 2014. However, from 2014 to 2018, the water surface area shrank from 1.34 to 0.49 km^2 (63%). Comparatively, from 2014 to 2018, the minimum water surface area in the wetland was observed during the 2014 dry season period, which coincided with the onset of drought that took place during the same year.

Derived classification results showed that wetland vegetation can be mapped with very high accuracies. High classification accuracies in terms of producer, user and overall accuracies were observed (Table 2). For all the

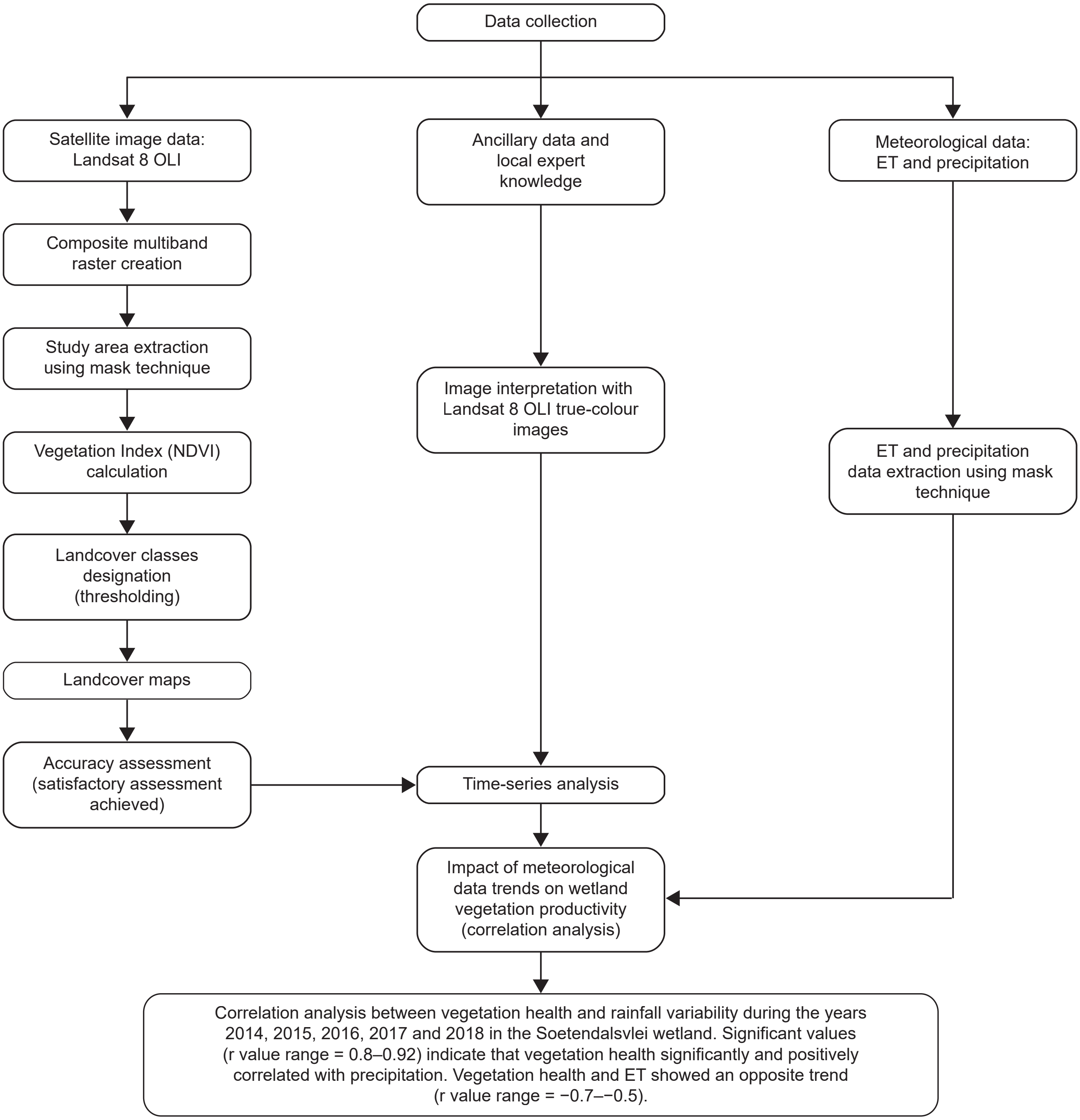

Figure 2: Methodological workflow used for wetland vegetation mapping and assessment of the 2014–2018 drought impact

remotely sensed derived wetland mapping results, all the accuracy assessment methods were ±80%, demonstrating a commendable classification model performance.

NDVI seasonal and interannual variations of wetland vegetation

Seasonal and inter-annual comparisons of wetland vegetation productivity were assessed, using the NDVI to determine the impact of drought on wetland vegetation conditions (Figure 5). The results showed that NDVI varied significantly between seasons and between years. Overall, the highest NDVI value (0.5) was observed in 2014. It is, however, important to note that during the same years NDVI from wetland vegetation was very low, approximately 0.20 in the wet season. Only the 2017 dry season exhibited a slight recovery, with NDVI increasing to approximately 0.25. However, between 2014 and 2018, the impact was largely observed during the 2018 dry season period where

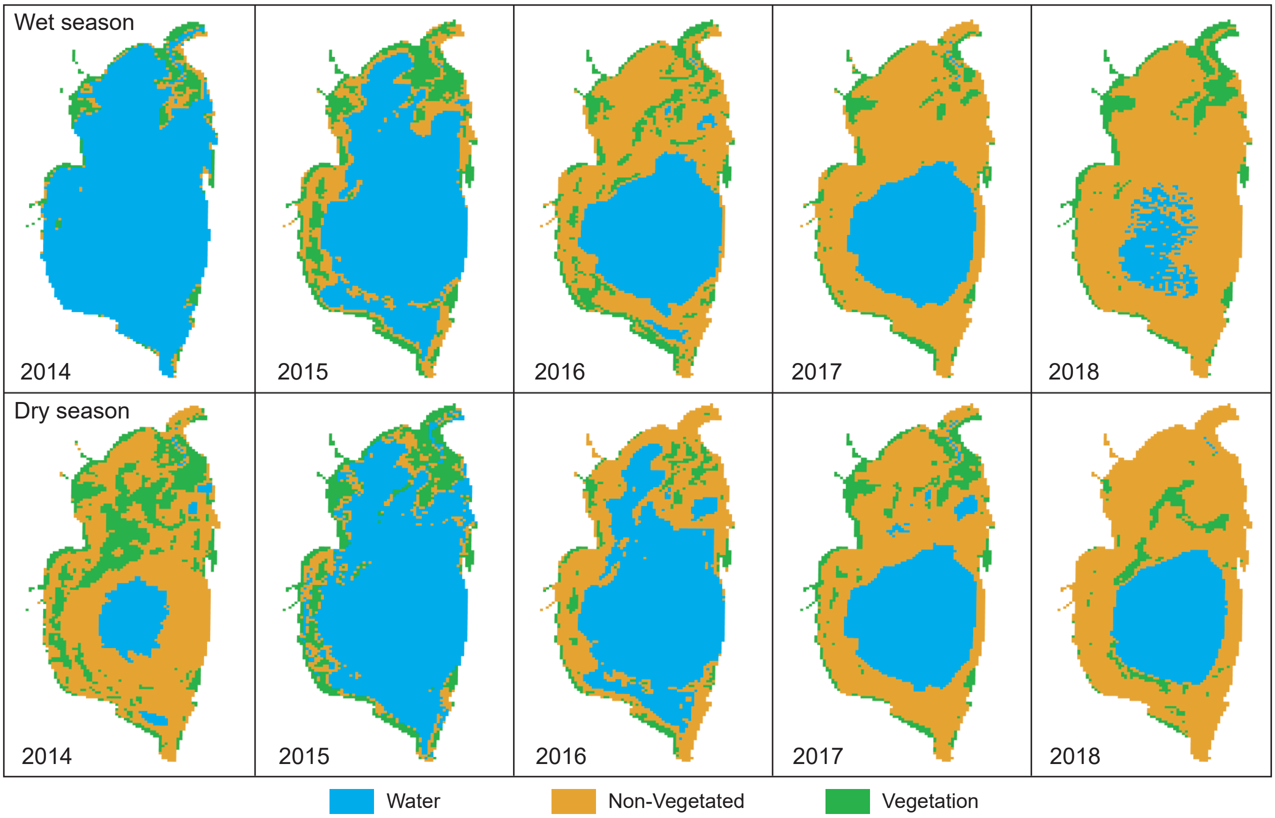

Figure 3: Remotely sensed derived wetland vegetation for the Soetendalsvlei in the Heuningnes Catchment, South Africa

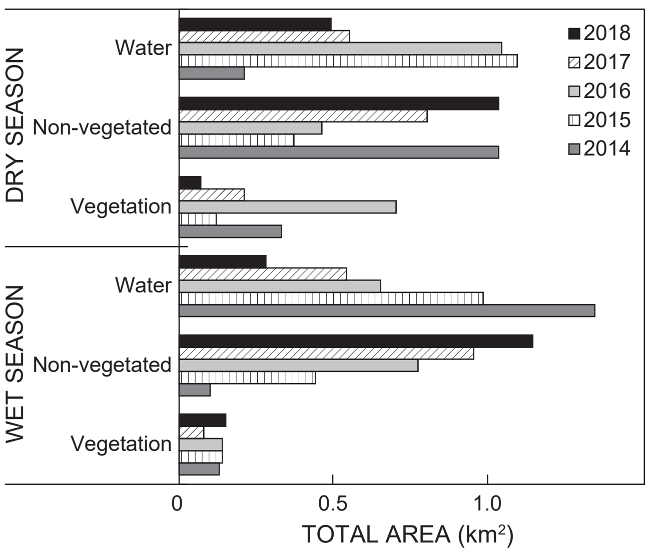

Figure 4: Detailed statistics on the areal extents and observed changes in wetland vegetation between the wet and dry season for the entire monitoring period

Table 2: Accuracy assessment of Landsat 8 images captured during the years 2014 to 2018 for Soetendalsvlei

	Class	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)
2014	Water	92.4	90.7	90.5
	Vegetation	79.3	88.5	
	Non-vegetated	100	100	
2015	Water	97	94.1	91.0
	Vegetation	95.9	85.5	
	Non-vegetated	93.5	95.6	
2016	Water	93.8	93.8	88.4
	Vegetation	89.8	90.1	
	Non-vegetated	81.3	100	
2017	Water	79.5	90.6	87.5
	Vegetation	99.2	77.7	
	Non-vegetated	83.6	98.3	
2018	Water	68.7	100	89.5
	Vegetation	77.1	100	
	Non-vegetated	95.8	86.5	

NDVI values were below 0.05. Inter-annual comparisons demonstrated a sharp decline in wetland vegetation productivity since the onset of drought in 2014 to 2018, with slight recoveries in between the years and seasons.

Relationships between derived NDVI and climate data

The results indicated that wetland vegetation productivity was largely controlled by rainfall availability and evapotranspiration rates. The results from Table 3 showed high correlations between wetland vegetation derived

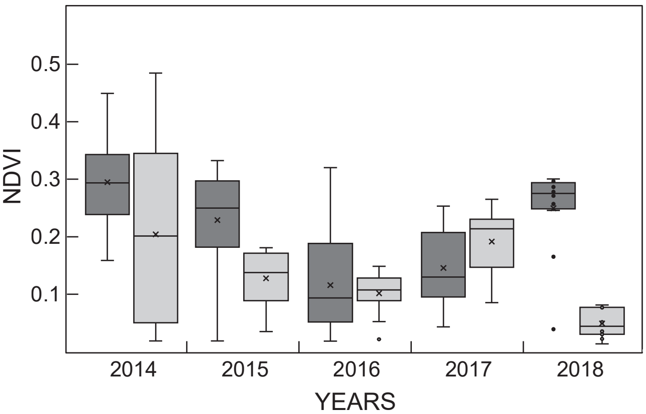

Figure 5: Seasonal and interannual variations and trends in wetland vegetation productivity

NDVI and rainfall, as well as evapotranspiration. For example, for all the years NDVI and rainfall correlations coefficients were high and positive, on average above 0.80, whereas for NDVI and evapotranspiration the relationships were significantly, but above −0.50. Figure 6 presents further details of observed monthly NDVI, precipitation and evapotranspiration trends for the entire study period. It can be observed that evapotranspiration and precipitation controlled or had a bearing on NDVI or wetland vegetation productivity.

Discussion

Wetlands comprise notable attributes of species diversity, richness, abundance and succession and they are therefore considered to be the most dominant and important ecosystems, globally (Mitsch et al. 2015). This study examined changes in wetland cover to determine the ecosystem's response to drought by using remote sensing techniques. Work done in this study has relevance to the maintenance of ecological processes and quantification of natural disasters impacts, because it explores: 1) spatial, temporal and seasonal variations of wetland cover; 2) seasonal variability of wetland vegetation health; 3) the link between wetland vegetation growth dynamics and rainfall variability to assess the response of wetland ecosystems to drought.

The results of classified maps revealed that an abrupt ecosystem change occurred across the study area. The observed results showing the long-term effect of rainfall variability-induced drought on wetland ecosystems, in this study are confirmed by other recent studies, which have assessed the effects of drought on wetlands. Studies, such as that by Middleton and Kleinebecker (2012), done to assess the effects of drought on freshwater wetlands and that of Belle et al. (2018) in the eastern Free State, South Africa, confirms that vital wetland productivity processes that sustain biodiversity in the ecosystem may be critically affected by the occurrence of drought. Climate change-induced drought, especially in arid regions, drives change in hydrology and vegetation health, consequently affecting ecological processes within the wetland ecosystem.

Table 3: NDVI vs climate data statistical relationships

Year	NDVI vs precipitation	NDVI vs evapotranspiration
2014	0.8*	−0.70
2015	0.9*	−0.50
2016	0.92*	−0.70
2017	0.8*	−0.60
2018	0.8*	Insignificant association at $r = 0.06$

*represents significant positive relationships

This study also found that water deficiency caused a decline in vegetation extent, water, and increase non-vegetated area in the study area. Results for wetland transition shown in this study are comparable to Mitraki et al. (2004) who investigated reduction in water level and associated volume of Lake Koronia in Greece and found that the lake depth has declined progressively from 3.8 m in 1980 to <1 in 1997 with a reducing surface area and water volume by 50% and 80%, respectively. A study delineating wetland extent and assessing seasonal variations in South Africa from 2000 to 2015 by Nhamo et al. (2017) found a continuous decline in wetland area and the minimum value was observed in 2015, which coincided with an *El Niño* associated drought in the study area (Rembold et al. 2016; FAO 2016). Ridolfi et al. (2006), also observed that wetland ecosystems are vulnerable to disturbances, such as a severe drought, and may respond to biomass losses with irreversible catastrophic shifts to non-vegetated conditions. Furthermore, climate change is predicted to increase drought, the number of high heat days and the frequency of severe storms, all of which affect wetland ecosystems (Leblanc et al. 2012).

In addition, drought can have major impact on wetlands. With less precipitation there will be less interception, water tables will fall, evaporation will also increase (Bond et al. 2008; Euliss et al. 2014; McCauley et al. 2015). This together will reduce the valuable functions performed by wetlands. Impacts of drought pose a negative impact to the environmental functioning of a wetland ecosystem. The observed results of this study are further supported by the study done on Lake Chad. Lake Chad was once one of Africa's largest lakes, the lake's size has decreased by 90%, as a result of overuse of water, extended drought and the impacts of climate change (Musa et al. 2008; Ngamdu 2015). The reduction of a wetland ecosystem, caused by drought, results in a loss of invaluable biodiversity.

Based on long-term (five years) data, this study examined the influence of rainfall variability on the productivity of wetland vegetation in the Soetendalsvlei wetland system. The relationship between wetland vegetation health and quantity, as well as the temporal patterns of rainfall variability were assessed and yielded two key results. Firstly, over the past 5 years, NDVI (Vegetation health) significantly and positively correlated with precipitation; and secondly, the NDVI and evapotranspiration showed an opposite trend, evapotranspiration exceeds the amount of precipitation during the period of this study.

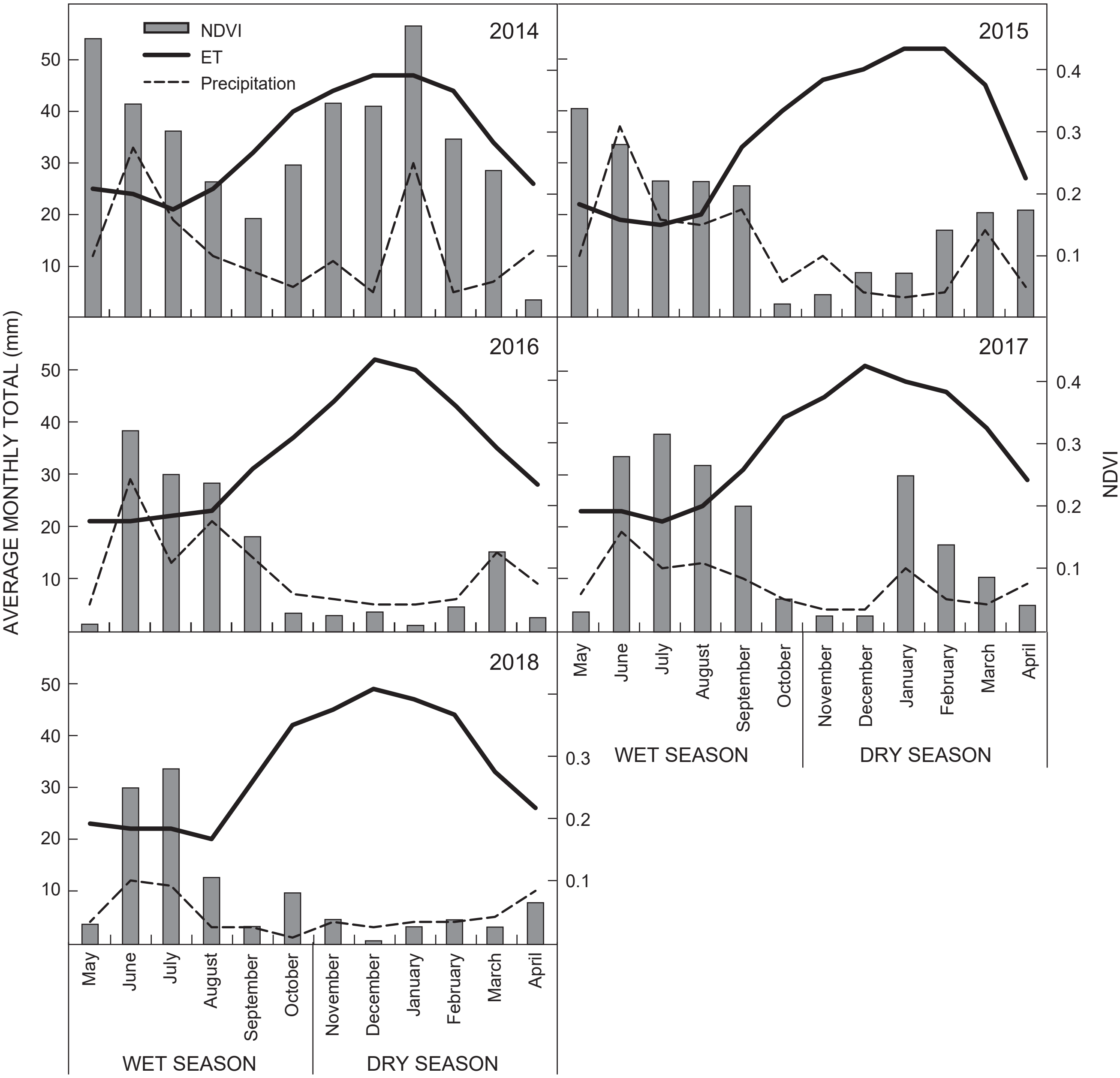

Figure 6: Monthly NDVI, precipitation and evapotranspiration relationships for the entire period under study during 2014–2018

The results of this study highlight the importance of rainfall variability on wetland vegetation productivity. One explanation is that rain events provide sufficient soil moisture and maintain high water availability (Merolla 2012). In arid and semiarid ecosystems, water is typically a limiting factor for plant health and available moisture generally increases plant biomass (Twisa and Buchroithner 2019). The photosynthesis of plants depends on water availability, therefore, insufficient water availability can minimise the assimilation of carbon, thereby decreasing wetland vegetation productivity (Pinheiro and Chaves 2011).

The results of the study by Barros and Albernaza (2014) found that an elevation in water availability leads to a reduction in wetland vegetation growth rates or the reproductive success of many species. Wetland vegetation has highly developed root systems that hold the soil in place and filter pollutants, naturally improving water quality (Finlayson et al. 2015). Therefore, a drought will likely cause the loss of, or reduction in wetlands and will challenge the adaptability, composition and distribution of wetland plants. Moreover, if wetland vegetation productivity is challenged, pollutants could become more concentrated in wetlands and this will affect water quality.

Conclusions

Temporal and spatial distribution of wetland cover classes and vegetation cover was assessed using NDVI to examine the impact of rainfall variability (drought) on wetland vegetation. Results showed a significant variation in the wetland surface area from 2014 to 2018. Specifically, vegetation and water decreased significantly over the monitoring period, whereas the extent of bare surface increased rapidly. Wetland extent mapping was achieved with average overall accuracies (85–90%) in this study. Furthermore, vegetation productivity significantly and positively correlated with precipitation over the past five years, whereas evapotranspiration showed a negative significant relationship, evapotranspiration exceeds the amount of precipitation during the period of this study. From the observation of the whole study period, healthy vegetation has deteriorated, as a result of a drought that occurred in the study area between the monitoring periods. The amount of rainfall entering into an ecosystem is typically a limiting factor for plant health, the results of this study highlight the importance of rainfall variability on wetland vegetation productivity.

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