Habitat Suitability Modeling For The Invasive *Opuntia Stricta* Using Remote Sensing And Maxent In Tsavo East National Park, Kenya

ABSTRACT

Biological invasions represent a major threat to ecosystem services and products, with the potential to disrupt ecosystems across a broad spectrum of bioclimatic regions. Consequently, it is essential to monitor the spread of invasive species systematically and over extensive areas. Remote sensing and geographic information systems have long been recognized as valuable tools for achieving this goal. This paper examines the efficacy of optical satellite data from different seasons in detecting the invasive species *Opuntia stricta* (Australian pest pear) within the southern portion of the Tsavo East National Park. Maximum Entropy (MaxEnt) modelling was employed to determine the most relevant environmental variables, with a total of ten predictors tested. The results demonstrated that ndvi2017dry, rvi2018wet, rvi2017wet, msavi2018dry and rvi2018dry were the most effective Vegetation Indices (Vis) for detection of *Opuntia stricta*. The study also found that seasonal variations played a significant role in enhancing detection accuracy. The fine-scale MaxEnt modelling predicted core areas of invasion, yielding a mean AUC of 0.718. Suitable habitat within the study area was classified into high, medium, low, and very low categories, with 51 km² identified as highly suitable for *Opuntia stricta* growth. Further classifications included 37 km², 83 km², and 3,589 km² for medium, low, and very low suitability, respectively. *Opuntia stricta* was detected in 4.15% of the study area. From this study we concluded that the invasive species remain a big risk to protected areas especially in the Tsavo East National Park. Continued monitoring is recommended especially in areas predicted to have high invasion in future. This study provides baseline data for prioritizing invasive species monitoring and management strategies.

Keywords: AUC, Biological invasion, MaxEnt, Opuntia stricta, Remote sensing, Sentinel-2, Vegetation indices (Vis)

1. INTRODUCTION

Global conservation strategies focus on protecting biodiversity, conserving representative ecosystems, and managing protected areas. The Convention on Biological Diversity (CBD) Strategic Plan for Biodiversity 2011–2020 has provided a crucial framework for international biodiversity conservation [1]. However, the creation of protected areas alone does not guarantee ecosystem integrity as they face various threats including the invasion of alien species [2]. Addressing these threats requires sustained active management. Invasive alien species, in particular, pose serious threats to protected area ecosystems worldwide [2]. The rise in the number and impact of invasive non-native species (hereafter referred to as "invasive species") is leading to biodiversity loss, ecosystem degradation, and the impairment of ecosystem services on a global scale [3,4,5,6,7,8]. Among these, "*Opuntia stricta* is listed in the 100 of the World's Worst Invasive Alien Species [9].

Relatively little has been done in terms of the study and management of *Opuntia* in Kenya in particular and East Africa in general". [10] "reviewed the existing literature on the invasion of *Opuntia* in Kenya. Her study involved a review of published information from a variety of sources, including online scientific publications, books, field guides and expert opinion on invasive alien species with a focus on *Opuntia stricta* species in Kenya.

Key priority pathways and impacts were categorized according to ecological and socio-economic impacts and also categorized based on the current framework of invasive species. Much review on the status and impacts of invasive alien species (IAS) in Kenya has been done to update knowledge on the occurrence and drivers of introduction. Such studies are crucial for developing protocols for prevention and management of *Opuntia stricta*. Nevertheless, further comparative studies on the target species, their pathways of introduction, and spatial distribution are essential to enhance understanding of the interacting factors driving their invasion" [10]

Impacts of invasive species have been examined from ecological and economic perspectives while studies based on social perspectives, though still limited, are gaining increased attention [11,12,13,14]. An understanding of the anthropogenic perspective is crucial, as human activities influence plant distribution and necessitate management of invasions to reduce negative impacts and maximize potential benefits. Local people's perception of the value, impact, and management of *Opuntia stricta* in the context of pastoralist in Kenya has been the area of focus of late with broad scale surveys being undertaken. Some progress has been made in integrating the management of invasive alien species with other management functions while emphasizing the human aspect [2]. According to [15], it is important to look at the underlying causes of alien plant invasions to avoid exacerbating their impact on rangelands.

"However, appropriate and effective measures for the monitoring, control, or elimination of these species are essential. Additionally, laws and regulations prohibiting the introduction and use of such species should be strictly enforced and consistently upheld. Effective policies are needed to prevent an increase in the significant negative impacts caused by IAS, including those that are not well established and with limited distribution" [10]. "Poor description of the species because of variation in growth form, lack of information on proper management, and poor monitoring and control measures contribute to the spread of the invasive species. Effective management of *Opuntia* in the country requires comprehensive mapping and inventory of the species across the affected counties. Additionally, creating awareness among the communities on the effects of invasions and possible solutions is vital" [10].

Studies done [16] support that high-resolution time-series images may result in new findings on the distribution of invasive species (*Opuntia stricta*) in Northern Kenya. [16] "predicted the potential distribution of *A*. *reficiens* and *Opuntia spp* under different climate change scenarios using bio-climatic variables. Furthermore, mapping on the distribution of *Acacia reficiens* and *Opuntia spp*. in the Samburu – Laikipia region using a time series of MODIS vegetation indices and topographic environmental variables was carried out. Similarly, a study on *Opuntia stricta* in Laikipia, Kenya was undertaken using ensemble machine learning classifiers" [17].

Recent advances in active and passive remote sensing technology have created new and cost-effective opportunities for the application of remote sensing to invasive species mapping. "Field observations are expensive and laborious, satellite imaging is likely the only cost-effective approach to map IAS across extensive areas" [18]. Studies by [19] using drones equipped with optical sensors could offer an effective and nearly real-time way to detect *A. altissima*. [20] "conducted long-term monitoring studies of the Amur honeysuckle (*Lonicera maackii*) using optical sensors like Landsat imagery. Specifically, remote sensing has emerged as a powerful tool for the detection and monitoring of invasive plant species" [21]. "MODIS was used in mapping presence and predicting phenological status of invasive buffelgrass in Southern Arizona where they accurately predicted buffelgrass patches in Saguaro National Park" [22].

[23] "took advantage of the amplified interannual response of invasive cheat grass (*Bromus tectorum*) to map infestations across the Great Basin watershed using Landsat and Advanced Very High-Resolution Radiometer (AVHRR) data. Cheat grass (*Bromus tectorum*), an invasive annual grass, has also been successfully detected because it germinates in winter months prior to most native grasses." [24] estimated and mapped percent cheat grass ground cover in Nevada on the basis of the invasive species' relatively early spring green-up and subsequent senescence, which were identifiable from two Landsat ETM+. Peterson was able to distinguish cheat grass from other vegetation by using scenes from Landsat 7 ETM+ on two different dates within a single year. In both cases, the researchers were able to exploit subtle phenological differences (i.e. extended growing season, rapid response) between the invaders and associated native flora within a growing season.

Similarly, studies [25] show that the detection rates for low cover plots were considerably higher for invasive herb (*Centaurea solstitialis*) than for invasive grass (*P. aquatica*) using airborne imaging spectroscopy. According to a study done classified IKONOS imagery may be useful for inferring landscape patterns that relate to the persistence and spread of Melaleuca and other invasive species [26]. In southern California [27] used discriminant analyses of presence/absence data and hierarchical clustering with hyperspectral imagery collected in October. Overall accuracy of their research varied by scene and minimum patch size, and results tended to over classify tamarisk distribution. These studies demonstrate an evolution of remote sensing and image processing for detecting tamarisk and other invasive species. "The development of new airborne and satellite sensors and platforms, coupled with advanced statistical software, geographic information systems (GIS), and predictive models, give researchers a variety of tools to detect and predict the distribution of invasive species. The insight applied in quantifying the suitability areas for the invasive species can be extrapolated to other protected areas with the same species."

Besides, most previous studies have used remote sensing to map invasive species *Opuntia stricta* [16], but seasonal composites have not been used. In this study, we used Sentinel-2 satellite images and the MaxEnt model to map *Opuntia stricta* in Tsavo East National Park. To examine the effect of seasonality on the mapping, we created seasonal composites for both the dry and wet seasons. From these composites, we calculated various vegetation indices to identify the optimal set of features for mapping *Opuntia stricta*

To the best of our knowledge, this is the first comprehensive study of that uses seasonal composites to model the *Opuntia stricta* in the Tsavo National Park. The research findings will assist policymakers and Park managers on prioritizing control efforts on areas vulnerable to species invasion. The results and the proposed control strategies, from this study, will enhance conservation efforts by providing insights in the management of the *Opuntia Stricta* species in the protected area.

2. MATERIAL AND METHODS

2.1 Site Description

The study was carried out in the southern part of Tsavo East National Park situated in Taita Taveta County in Kenya (Fig. 1). The park lies between latitude 2.659°S and longitude 38.973°E and the altitude ranges between 300 and 500 m above sea level (m.a.s.l.) and covers an area c. 4120 Km^2. The study area experiences a mean annual rainfall varies locally between 250 and 500 mm [28]. Most of the rain falls in two rainy seasons namely: March–May and November–December [29]. Meanwhile, June–October constitutes a long dry season [28,30,31]. The study area is dominated by *Acacia–Commiphora* bushlands and thickets [29]. The study area also supports a diversity of wildlife species and is an important tourist destination [32].

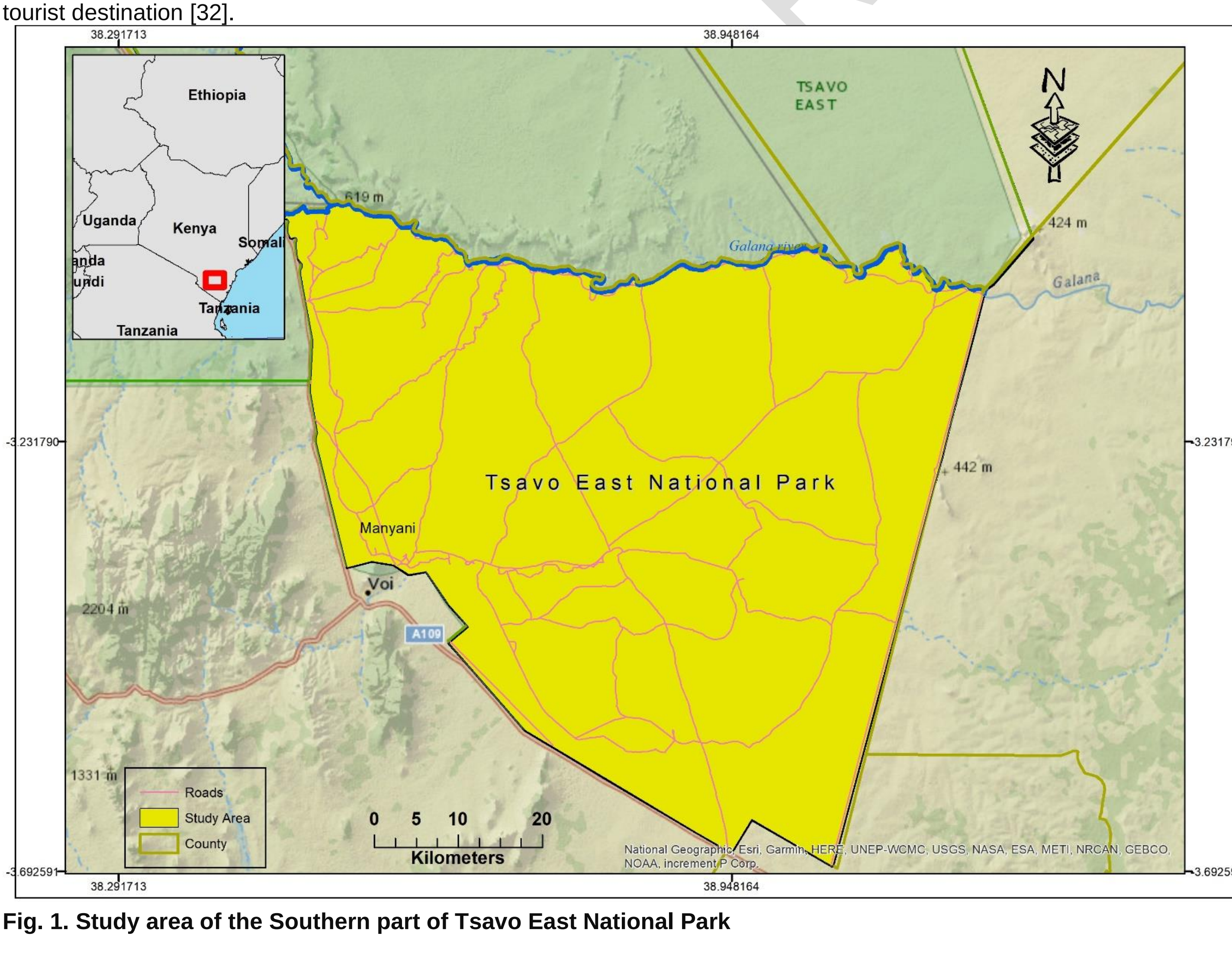


Fig. 1. Study area of the Southern part of Tsavo East National Park

2.2 Remote sensing data – Sentinel-2 imagery

European Space Agency (ESA) Sentinel-2 mission provides open access to earth observation data at a high spatial as well as temporal resolution [33]. Sentinel-2 constellation comprises two satellites Sentinel-2A and Sentinel-2B with approximately 5 days' revisit time. Each satellite has 13 bands (Table 1) ranging from visible to short wave infrared portion of the electromagnetic spectrum with a maximum spatial resolution of 10 m (https://eos.com/find-satellite/sentinel-2/). In this study data were acquired between January 2017 and 2018 December, which almost matched with field survey dates to ensure that any observed differences were due to the variables of interest rather than the timing discrepancies. Furthermore, we selected the images with cloud cover of less than 10%. In this study, Band 1 and Band 9 were excluded in the analysis resulting in only ten bands being utilised.

Table 1. Sentinel-2 spectral bands

Band	Spectral region	Central wavelength(um)	Resolution(m)
1	Coastal aerosol	0.443	60
2	Blue	0.490	10
3	Green	0.560	10
4	Red	0.665	10
5	Vegetation Red Edge	0.705	20
6	Vegetation Red Edge	0.740	20
7	Vegetation Red Edge	0.783	20
8	Near Infrared	0.842	10
8A	Vegetation Red Edge	0.865	20
9	Water vapor	0.945	60
10	Shortwave Infrared	1.375	60
11	Shortwave Infrared	1.610	20
12	Shortwave Infrared	2.190	20

2.3 Precipitation data

The conditions of vegetation cover largely depend on climatic parameters such as rainfall. We generated a composite image for the time of interest using Google Earth Engine (GEE), where vegetation indices served as predictors in our model. CHIRPS (Climate Hazards Group Infrared Precipitation) data aided in creating dry-season and wet-season composites, helping us to identify months with different rainfall amounts in the study area in the years 2017 and 2018 (Fig.2).

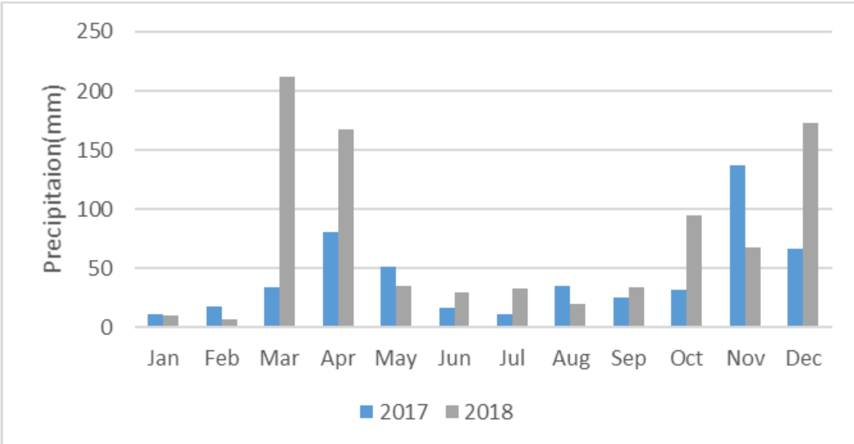


Fig. 2. Rainfall trends in 2017 and 2018

2.4 Target species and occurrence data

A total of 432 occurrence records were gathered between January 2017 and December 2018 within the designated study area. These records include the X and Y coordinates (referencing WGS 1984, UTM Zone 37M) indicating the precise locations where *Opuntia stricta* was directly observed. Species occurrence points were collected using a handheld GPSMAP 64s unit in areas close to road networks, owing to the challenging terrain within the study region. The records were subsequently compiled in an Excel spreadsheet and exported as a comma-separated values (CSV) file, formatted for use in MaxEnt modelling. Additionally, supplementary occurrence points of *Opuntia stricta* were digitised from high-resolution Google Earth (Digital Globe) imagery.

2.5 Calculation of Vegetation Indices (Vis)

The selection of vegetation indices (Table 2) aimed to enhance the model's predictive accuracy while accounting for the unique characteristics of dryland environments and mitigating atmospheric and soil effects. Specifically, we incorporated the following vegetation indices into our analysis: Ratio Vegetation Index (RVI): Calculated as the ratio between the red band and the near-infrared (NIR) band, RVI captures vegetation characteristics based on their spectral reflectance properties Normalized Difference Vegetation Index (NDVI): Computes the difference between NIR and red reflectance divided by their sum, highlighting vegetation presence. NDVI values range between −1 and 1. Modified Soil Adjusted Vegetation Index (MSAVI): A modified version of the Soil Adjusted Vegetation Index (SAVI), MSAVI minimizes soil background effects to improve vegetation detection in dryland environments. Red EVI (Red Edge Vegetation Index) focuses on the red-edge portion of the spectrum, which is sensitive to changes in chlorophyll content and leaf structure. *Opuntia stricta* may exhibit distinct spectral responses in the red-edge region, allowing Red EVI to capture subtle differences between *Opuntia stricta* and other vegetation types or background materials. These vegetation indices were chosen for their robustness in characterizing vegetation cover, particularly in arid areas like those where *Opuntia stricta* thrives. By leveraging these indices, we aimed to enhance the discriminatory power of our classification model, thereby improving its ability to accurately identify *Opuntia stricta* presence We integrated data across three distinct seasons—dry, wet, and short-dry—in 2017 and 2018 to enhance *Opuntia stricta* detection in our study area. The Google Earth Engine (GEE) platform [34] was employed to obtain, process, and compute textural metrics from Sentinel-2 metrics data (see Table 1) during these specific seasons. Ground truthing data for Opuntia were gathered using both our field knowledge and imagery from Google Earth (http://earthexplorer.usgs.gov/). An image composite from several different image dates was deployed to improve target detection. Next, we calculated median composites using the Google Earth Engine platform. The temporal windows were selected based on the general climatological patterns of the study area, as well as the specific rainfall dynamics observed during the years under investigation (i.e., 2017 and 2018). These windows account for the short wet and short dry seasons, as outlined in Table 3.

Table 2. Formulas of the existing Vegetation indices and references

Index	Description	Formula	Reference
NDVI	Normalized Difference Vegetation Index	(NIR-RED) / (NIR+RED)	Sun et al.,
RAVI	Ratio Vegetation Index	(R/NIR)	Sun et al.,
MSSAVI	Modified Secondary Soil Adjusted Vegetation Index	1/2 * ((2*(NIR+1)) - (((2*NIR)+1)2 - 8(NIR-red))1/2).	Sun et al.,
Red Edge NDVI	Red Edge Normalized Difference Vegetation Index	(NIR − RE) (NIR + RE)	Sun et al.,

Table 3. Sentinel-2 image dates and image composites used to classify *Opuntia stricta* within the southern part of Tsavo East National Park*.*

Index /Year	Start dates	End dates	Season
NDVI 2017	June 01, 2017	Oct 31,2017	Short Dry
	Nov 01,2017	Dec 31 2017	Short Wet
	Jan 01 2017	Dec 31 2017	Short Dry +Short Wet
NDVI 2018	Jan 01 2017	Feb 28 2018	Short Dry
	Mar 01 2018	May 31 2018	Short Wet
	Jan 01 2017	Dec 31 2018	Short Dry +Short Wet
RVI 2017	June 01, 2017	Oct 31,2017	Short dry
	Nov 01,2017	Dec 31 2017	Short wet
	Jan 01 2017	Dec 31 2017	Short Dry +Short Wet
RVI 2018	Jan 01 2018	Feb 28 2018	Short Dry
	Mar 01 2018	May 31 2018	Short Wet
	Jan 01 2017	Dec 31 2017	Short Dry +Short Wet
MSAVI 2017	June 01, 2017	Oct 31,2017	Short Dry
	Nov 01,2017 to	Dec 31 2017	Short Wet
	Jan 01 2017 to	Dec 31 2017	Short Dry +Short Wet

MSAVI 2018	Jan 01 2018 to	Feb 28 2018	Short Dry
	Mar 01 2018 to	May 31 2018	Short Wet
	Jan 01 2017 to	Dec 31 2018	Short Dry +Short Wet
DVI 2017	June 01, 2017 to	Oct 31,2017	Short Dry +Short Wet
	Nov 01,2017 to	Dec 31 2017	Short Dry
	Jan 01 2017 to	Dec 31 2017	Short Wet
DVI2018	Jan 01 2018 to	Feb 28 2018	Short Dry +Short Wet
	Mar 01 2018 to	May 31 2018	Short Dry
	Jan 01 2017 to	Dec 31 2018	Short Dry

2.6 MaxEnt Species Distribution Modelling

This study used MaxEnt (Maximum Entropy) version 3.3.3 e machine-learning algorithm to model the distribution of *Opuntia Stricta* in the southern Part of Tsavo East National Park, Kenya. MaxEnt uses presence-only data to define known conditions within the parameters of the independent variables to predict a species' distribution and excludes all conditions that are unfounded or undefined. The model is nonlinear, nonparametric, and not sensitive to multicollinearity. Besides having several evaluation features built into the program, MaxEnt also provides the percent contribution of each predictive variable. [35,36,37]

2.6.1 Model calibration

"For improving the model performance, a convergence threshold of 10^{-5} was calibrated with a maximum number of iterations at 5000. These settings provide the models adequate time for convergence of input information to build-up the models. It should be noted that a high number of iterations gives the models sufficient time to process the data, thus avoiding over- or under-prediction of the species distribution. Other calibrations for improving the models included setting the maximum number of background points at 10 000, with a regularization multiplier value of 1. The run type was a cross-validation method that divides the original samples into a set of training and testing of the models. The MaxEnt output was formatted to logistics with 75% of the occurrence records were used for training and 25% for random testing of the model. This means that 75% of the data inputs were used for suitability mapping of the invasive species in modelling and 25% of the data for random testing of the model generated by MaxEnt. Furthermore, an auto feature option was selected with 15 replications, and the rest were kept as default. By these, the occurrence data are randomly split into a number of equal-sized groups called 'folds', and models are created leaving out each fold in turn. These settings have been undertaken to give a broader and less discriminating prediction" [37]

2.6.2 Model evaluation

The accuracy of the model was calculated using the receiver operating characteristics curve (ROC) and the Area Under the Curve (AUC) [36,37,38]. An AUC value of 0.5 shows that model predictions are not better than random; < 0.5 are worse than random; 0.5–0.7 indicates poor performance; 0.7–0.9 reasonable/moderate performance; and > 0.9, high performance [39]. In evaluating the most important predictors influencing Invasive species occurrence, the percentage contribution column was used to select the most important predictors (Table 4, Percentage contribution >0).

2.6.3 Model Output

MaxEnt outputs included weighted environmental predictors ranked, showing each predictor's percentage contribution to the model's overall performance (Table 4) With the jackknife setting activated, MaxEnt weighed each variable contribution to the model's gain. The other outputs included response plots [Fig. 6] which were used to describe the tolerance limits of *O.stricta* to each variable. The plots showed each variable effect on the species being plotted and a final potential distribution model

2.6.4 Predictive occurrence and habitat suitability for the *Opuntia stricta*

Based on prediction models, probability of the *Opuntia stricta* and habitat suitability maps were created and probability values were categorized into four suitability levels: 'very low' (0–0.2), 'low' (0.2–0.4), 'medium' (0.4–0.6), and 'high suitability' (0.6–1) (Figs. 6 and 7). This classification scheme has been extensively applied in past studies [40,41,42]

3. RESULTS

3.1 Model performance

The MaxEnt models, run with 15 replications, provided reliable estimates for the distribution of *Opuntia stricta*, achieving a mean AUC of 0.718 (Fig. 3)

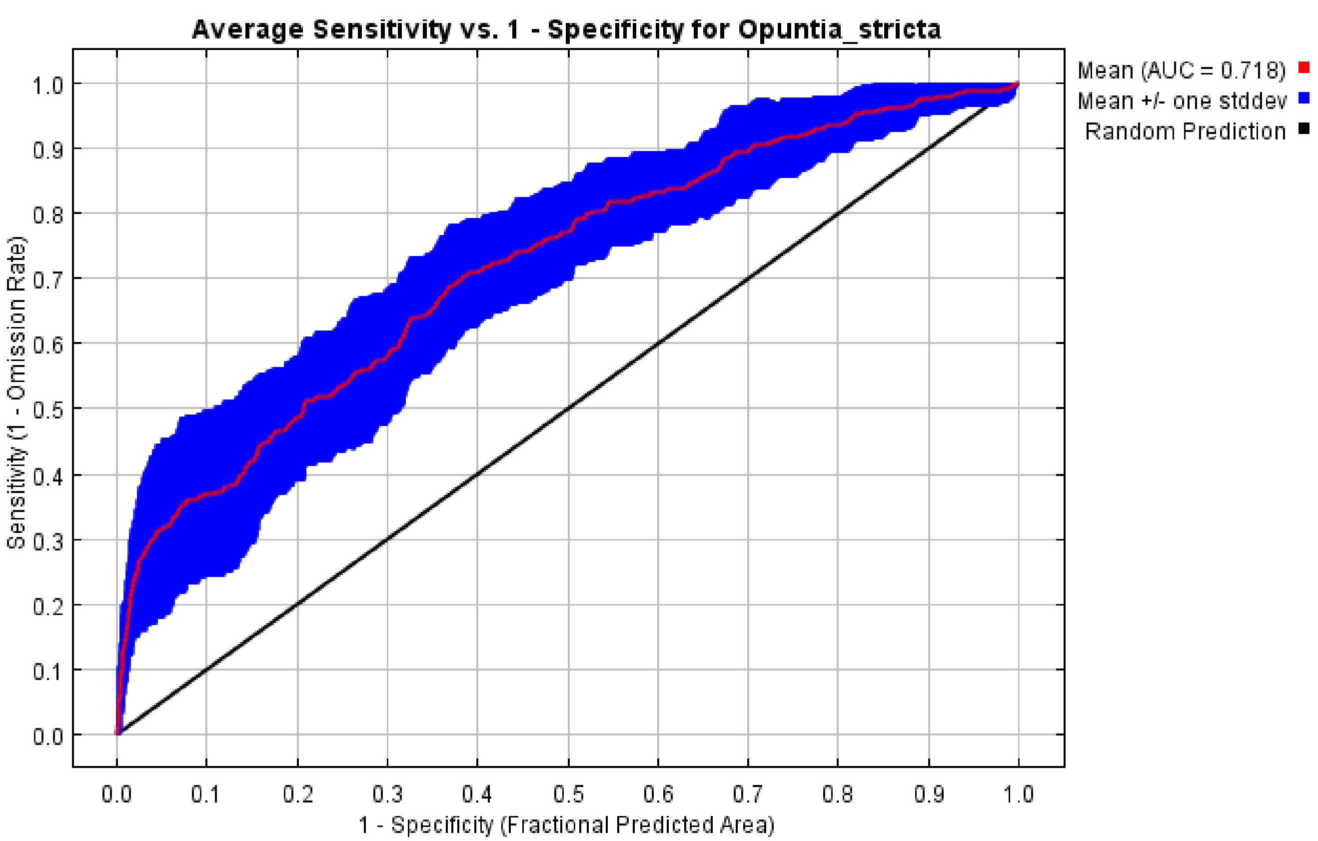


Fig. 3. Receiver operating characteristic (ROC) curve for the *Opuntia stricta* species

Fig. 4 depicts the jackknife measure of variable importance. The environmental variable with the highest training gain was used in isolation (blue bars) is NDVI 2017 short dry season which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain most (light green bar) when omitted is NDVI 2017 short dry season for both scenario, which therefore appears to have the most information that isn't present in other variables. This is followed by NDVI 2017jd (short dry and wet season), Ratio vegetation index 2017jd (short dry and wet season) and red edge NDVI 2017 short dry season. If MaxEnt uses only modified soil adjusted vegetation index (MSAVI short dry season) it achieves almost no gain, so that variable is not (by itself) useful for estimating the distribution of *Opuntia stricta* (Fig. 4).

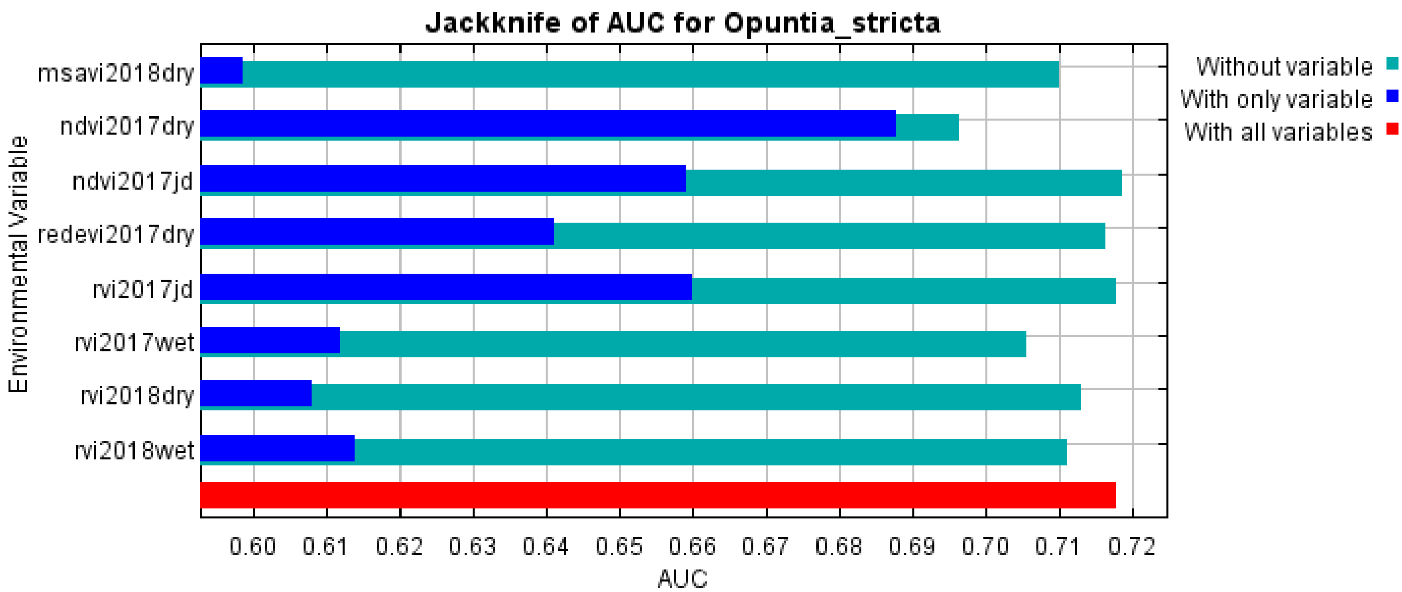


Fig. 4. The graph provided is a "Jackknife of AUC" (Area Under the Curve) analysis for the species *Opuntia stricta*. This graph shows the importance of different environmental variables in predicting the presence or suitability of habitat for the species

3.2 Analysis of variable contributions

Table 4 shows the contribution of each explanatory variable within the MaxEnt model. The percentage contribution column shows how each variable is important to the model's predictions. For example, "ndvi2017dry" contributes 50.2% to the model's predictions. This indicates the relative importance of each variable in influencing the model's output. Higher percentages suggest greater importance while Lower percentage shows least importance. A large decrease indicates that the model depends heavily on that variable

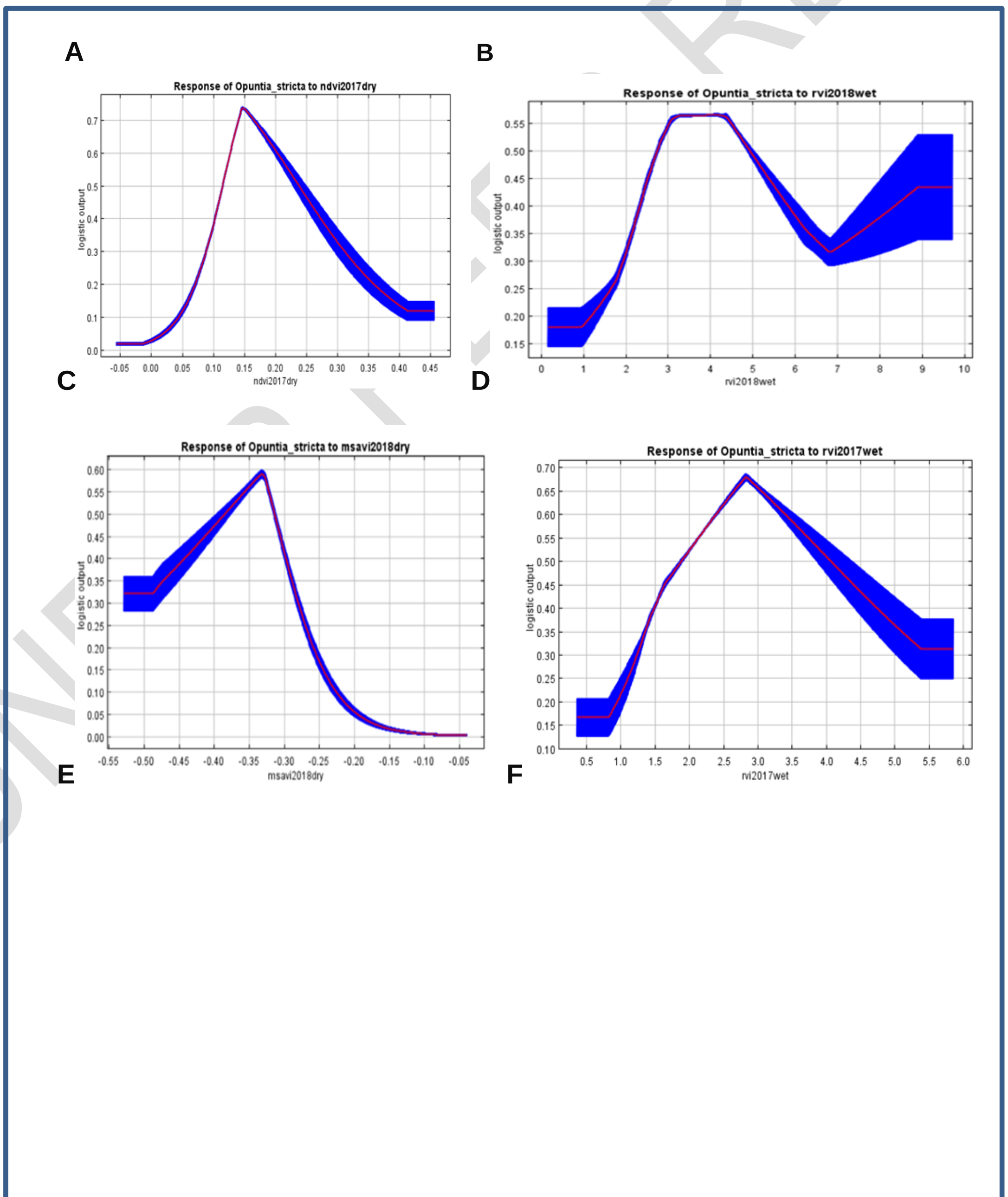
Table 4. Percentage contribution and permutation importance of predictor variables in MaxEnt models

Variable	Percentage contribution	Permutation importance
ndvi2017dry	55.5	50.1
rvi2018wet	15.4	7.6

rvi2017wet	9.9	7.7
msavi2018dry	7	17.8
rvi2018dry	6	10.7
redevi2017dry	5.4	1.9
rvi2017jd	0.5	0.9
ndvi2017jd	0.3	3.3

3.3 Response curves

The response curves shown in Fig. 5 depicts how each environmental variable affects the Maxent prediction. The curves illustrate how the predicted probability of presence changes as each environmental variable is varied, keeping all other environmental variables at their average sample value.



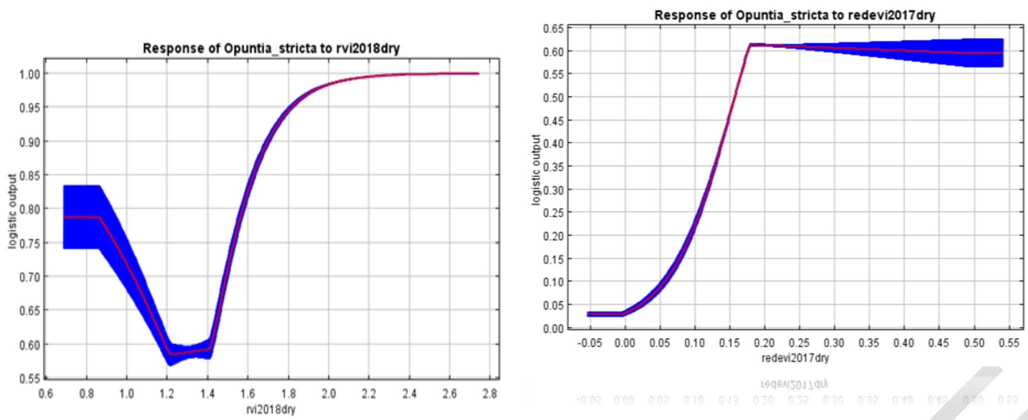


Fig. 5. The *Opuntia stricta* response curves for the environmental predictors, where: Normalized Difference Vegetation Index 2017 dry season (A), Ratio Vegetation Index 2018 wet season (B), Modified Secondary Soil Adjusted Vegetation Index 2018 dry season (C), Ratio Vegetation Index 2017 wet season (D), Ratio Vegetation Index 2018 dry season (E) and Red Edge Normalized Difference Vegetation 2017 dry season (F)

3.4 Predictive occurrence map for the *Opuntia stricta*

Predicted probability of the *Opuntia stricta* is displayed in Fig.6. Probability of *Opuntia stricta* presence was found to be high on the southern, eastern parts of the Tsavo East National Park.

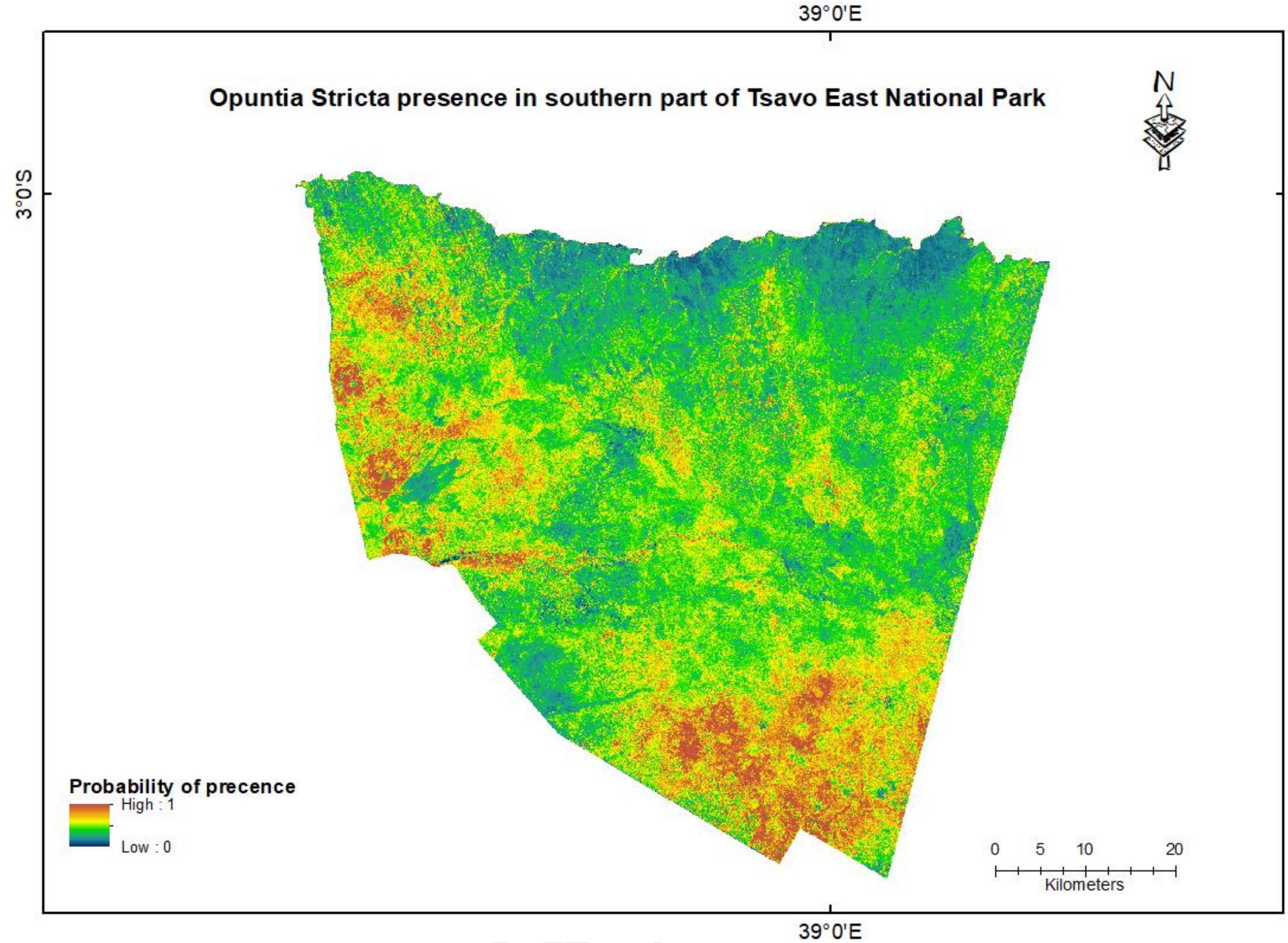


Fig. 6. Predictive occurrence map of *Opuntia stricta* in Southern part of Tsavo East National Park. Probability of one indicates a high likelihood of finding the species within the raster square, and zero indicates that it is unlikely that the species will be found there

3.5 Habitat suitability map for *Opuntia Stricta* species

The MaxEnt software was used to model suitable sites within the study area against selected environmental variables, which included the vegetation indices. This analysis generated distinct classifications, classifying *Opuntia* stricta suitable habitats into high, medium, low, and very low-preference areas within the study area (Fig 7). An area of 51km^2 was identified as highly preferred habitat for *Opuntia stricta* growth. Further, an area measuring 37 km^2 ,83 km^2 and 3589.36km^2 were classified as medium, and very low habitat suitability areas for *Opuntia stricta* occurrence respectively, within the southern part of the Tsavo East National Park ecosystem.

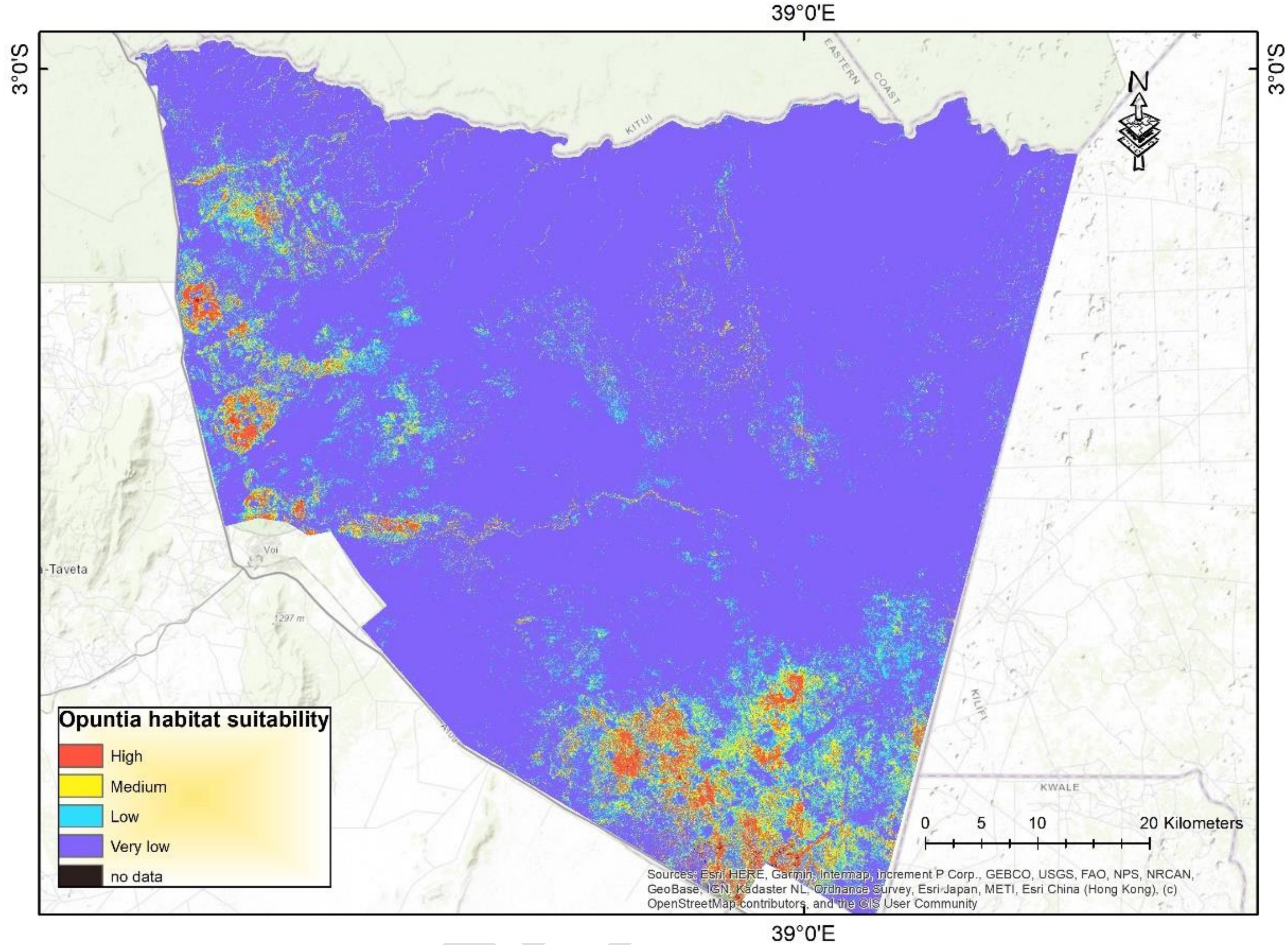


Fig. 7. The habitat suitability for *Opuntia stricta* in the Southern part of Tsavo East National Park

Table 5. Habitat suitability area for *Opuntia Stricta* in the Southern part of Tsavo East National Park

Suitability areas	**Very Low (km^2)**	**Low (km^2)**	**Medium (km^2)**	**High (km^2)**
South of TENP	3589.36	83.25	37.85	51.34

Predicted Potential distribution of the invasive cactus *Opuntia stricta* on the maximum entropy model in the southern part of Tsavo East National Park. Cooler areas indicate low habitat suitability while warmer areas correspond with high habitat suitability. According to [43] study on land cover mapping in savannah using combination of seasons and sensors found out that short-dry season outperform the dry and wet season models, as the effect of season is able to provide cloud free data and is wet enough to allow for the distinction between woody and herbaceous vegetation.

4. DISCUSSION

Our findings suggest that a MaxEnt model using limited presence-only data can effectively estimate habitat suitability for invasive species across the Tsavo landscape. Most suitable habitat for *Opuntia stricta* was predicted in the southern tip of the Tsavo East National Park (TENP) parts that include the Bachuma areas, Ndara plains and Mukwaju areas (Fig. 6), and its distribution was quite fragmented. The MaxEnt model's internal jack knife test of variable importance showed that 'ndvi 2017 dry)', and 'rvi2018wet)' were the two most important predictors of *Opuntia stricta* habitat distribution (Fig. 5 and Table 4). These variables presented the higher gain (that is, contained most information) compared to other variables (Fig. 2 and Table 1). Using four arbitrarily defined probability classes, the high suitability class had an area of 51 km^2; medium-37 km^2;

low- 83 km^2; and very low-3589 km^2 (Fig. 5 and Table 5). This study provides the first predicted potential habitat suitability map for invasive species (*Opuntia stricta*) in the TENP. Our findings are in agreement that vegetation indices such as NDVI can be used to detect the occurrence of *Opuntia stricta* in the park.

"From this view our study agrees with findings of other researchers like" [23,24,44,45,46]. "TVI and DVI indices were used for mapping the invasive species Tamarisk in the lower Arkansas River in Southwestern Colorado" [45]. Studies by [46] on Identification of invasive species using remote sensing and vegetation indices showed that NDVI, RVI, TVI and NRVI were the most suitable indices for the discrimination of *Cirsium arvense* species. These studies are consistent with our findings.

"The applications of medium spatial resolution (20m) satellite imagery in the rangeland for vegetation condition assessment and monitoring has proven successful in yielding acceptable results. For instance, the study by" [47] on MODIS NDVI index at different landscapes indicates that this index has high potential in detecting vegetation cover and discriminating different condition classes. The NDVI index was able to discriminate rangeland condition classes, especially extreme classes, across and within the vegetation types. Similarly, potential of Sentinel-2, was used in the detection of *Opuntia stricta* abundance based on only the spectral bands as well as in combination with different season [17]. Our study confirms that vegetation indices such as NDVI can be used to detect the occurrence of *Opuntia stricta* in the park

This is the first comprehensive study that employs optical satellite images data for both wet and dry seasons in identifying invasive species *Opuntia stricta* in the Tsavo East National Park. Furthermore, no study has explored on how vegetation indices can be used in detecting the invasive species. Medium resolution (30m) Sentinel-2 multi-time imagery from the Google Earth Engine was used to create composite images of interest. This study incorporated both wet season, dry season and all-season indicators to effectively capture the complexities of the change, and sought to develop a comprehensive model for spatial-distribution of the impact of *Opuntia stricta* in the study area.

4.1 Role of Season Indices

Both dry and wet season Sentinel-2 composites were used for classification. The integration of data from several seasons and sensors provided a more accurate classification. The target vegetation types were taken into consideration while analysing the data [48]. A study done by [48] on Sentinel-1 and Sentinel-2 data for Savannah Land Cover Mapping: Optimizing the Combination of Sensors and Seasons proved that the short-dry season should be preferred over the wet and dry seasons for both multisensor combinations and optical data. Similarly, our study analysis found out that short dry season composites performed best in detecting the *Opuntia stricta* plant. The grasses, woody cover and other herbaceous vegetation turn brown in dry seasons (January to March, July to September 2017 and 2018 respectively), while the *Opuntia stricta* vegetation would appear green throughout both seasons and thus making it possible to differentiate positively.

The difference between the dry and the combination of wet and dry is minimal. We therefore considered the dry season, characterised by no rains, to be equally suitable for *Opuntia stricta* detection. Field observations during the dry period indicated that *Opuntia stricta* remained relatively green throughout the year due to retention moisture in their succulent stems. These *Opuntia stricta* stands are easily identifiable during this extreme dry seasons of the year. The invasive species survive during dry periods by retaining their moisture in their succulent stems. *Opuntia* species normally thrives in arid and semi-arid areas, and has adaptations to water scarcity and high temperatures. The semi-arid environments are the habitats of plants which have adapted in severe hot and dry regions [47]. Vegetation indices improved the detection accuracies, signalling better habitat suitability areas where *Opuntia* are likely to occur. Similarly, studies by [46] support our findings that combined remotely-sensed data (vegetation indices) with the invasive species occurrence data can be used in a predictive model to identify sites vulnerable to species invasion. Since MaxEnt is an important tool for mapping the plant invasions, the results can help scientists and Park Managers to decide when and where to prioritize monitoring efforts for the likely invasion of habitat in future [47].

5. Conclusion and future recommendation

Our study sought to examine how the vegetation indices can detect the Invasive *Opuntia stricta* using Remote Sensing and MaxEnt in Tsavo East National Park, Kenya. This was the first time that *Opuntia stricta* suitability mapping has been conducted based on satellite seasonal composites hence providing novel insights into its suitability especially in the protected areas. The results demonstrated that ndvi2017dry, rvi2018wet, rvi2017wet, msavi2018dry and rvi2018dry were the most effective Vegetation Indices (Vis) for detection of *Opuntia stricta*. Finally, the potential habitat distribution map developed in this research could inform the management where to prioritize restoration efforts and guide-evidence based conservation strategies. In the future, we intend to improve on this work by calculating composites from all the bands individually to improve on the accuracy of *Opuntia stricta* detection in remote sensing imagery for generating subsequent species distribution maps

DISCLAIMER (ARTIFICIAL INTELLIGENCE

Authors hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

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