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RESEARCH ARTICLE

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Mapping rangeland ecosystems vulnerability to *Lantana camara* invasion in semi-arid savannahs in South Africa

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Abstract

We mapped and modelled the potential areas vulnerable to *Lantana camara* (*L. camara*) invasion in semi-arid savannah ecosystems in the communal lands of Bushbuckridge and Kruger National Park, South Africa. Specifically, we modelled potentially vulnerable areas based on remotely sensed data and environmental variables. The Maximal Entropy (Maxent) algorithm was used to model the vulnerable area. The reliability of the modelled results was assessed using Skills Statistic (TSS), Area Under Curve (AUC) and Kappa statistics. According to the results, Bushbuckridge communal lands are more susceptible to *L. camara* invasions than Kruger National Park. The risk of *L. camara* invasion in the study site was modelled with high accuracy (AUC score of 0.95) using the best model (Model 7), which is a composite of all model variables (remote sensing and environmental variables). The spatial distribution maps derived from Maxent showed that *L. camara* was more likely to invade communal lands than protected areas. Using remotely sensed spectral indices as standalone model variables (Model 4) showed the lowest accuracy, with an AUC score of 0.85. Overall, model input variables such as elevation had a significant influence on the spatial distribution of *L. camara* in the study area.

KEYWORDS
environmental variables, invasive plants encroachment, *L. camara*, Maxent, rangeland ecosystems, semi-arid environments

Résumé

Nous avons cartographié et modélisé les zones potentielles vulnérables à l'invasion des écosystèmes de savane semi-arides situés dans les terres communales de Bushbuckridge et du parc national de Kruger, en Afrique du Sud, par l'espèce *Lantana camara* (*L. camara*). Plus précisément, nous avons modélisé des zones potentiellement vulnérables à partir de données de télédétection et de variables environnementales. L'algorithme Maximal Entropy (Maxent) a été utilisé pour modéliser la zone vulnérable. La fiabilité des résultats modélisés a été évaluée à l'aide des méthodes TSS, de l'aire sous une courbe (ASC) et du Kappa. Selon les résultats, les terres communales de Bushbuckridge sont plus vulnérables aux invasions par l'espèce *L. camara* que le parc national Kruger. Le risque d'invasion par l'espèce *L. camara* sur le site d'étude a été modélisé avec une grande précision (score ASC de 0,95) à l'aide du meilleur modèle (modèle 7), qui est un composite de toutes les variables du modèle (télédétection et variables environnementales). Les cartes de répartition spatiale dérivées de l'algorithme Maxent ont montré que l'espèce *L. camara* était plus susceptible d'envahir les terres communales que les aires protégées. L'utilisation d'indices spectraux de télédétection comme variables de modèle autonomes (modèle 4) a présenté le niveau de précision le plus faible, avec un score d'ASC de 0,85. Dans l'ensemble, les variables relatives aux entrées du modèle, comme l'altitude, ont eu une influence significative sur la répartition spatiale de l'espèce *L. camara* au sein de la zone d'étude.

1 | INTRODUCTION

Non-native species are important agents of global ecological change. After anthropogenic environmental damage and natural ecosystem destruction, these species are perceived as a threat to biodiversity (Gooden et al., 2009). Plant invaders, also known as environmental weeds, change ecosystem structure due to their impact on native vegetation density and distribution (Mack et al., 2000). Globally, *L. camara* is one of the most prevalent invasive alien plant (IAP) species and has become a major invader of agricultural areas and natural ecosystems (Dobhal et al., 2011). Once established, the species is extremely difficult to manage, contain and eradicate and poses a serious threat to savannah rangelands. Thus, preventing its introduction or rehabilitating the affected areas may be the most cost-effective management method (Gallien et al., 2012).

Lantana camara was introduced as an ornamental plant in various countries, globally. Since then, it has become invasive in most countries including South Africa; it has been ranked by the invasive species specialist group (IUCN 2001) one of the world's top invasive species (Sharma et al., 2005). The invasion by *L. camara* associated with the reduction in grazing pastures, invertebrate diversity (Vardien et al., 2012). In South Africa alone, *L. camara* had invaded about two million hectares in the year 2000. Its invasion has been associated with increasing thickets, which obstruct pathways to sources of water, and reducing the quality of water within various river catchments such as Hartenbos and Klein Brak (Taylor & Kumar, 2014). A good example is Bushbuckridge, which is an area located at the edge of the Kruger National Park in South Africa, where most of the land is reserved for wildlife and livestock grazing. The intrusion of *L. camara* in this area has resulted in increased replacement of natural ecosystems such as grasslands, which are vital for the provision of forage for livestock and wildlife (Masocha et al., 2017).

Interestingly, the distribution of the *L. camara* species differs, depending on the biotic and abiotic conditions (West et al., 2016). These variations affect the plant species in various ways as they limit, disturb or provide conducive conditions for these plant species (Guisan & Thuiller, 2005). Environmental variables such as topography and climate affect the spatial distribution of invasive alien plants (Guisan & Thuiller, 2005). For example, topographic variables such as slope, elevation and aspect influence microclimatic conditions, which later regulate the amount and quality of soil nutrients and light availability (Wang et al., 2017). In addition, rainfall and temperature have a significant effect on the establishment and dispersal of the IAP's species (Zhu et al., 2007). The relationship between the species and their overall environment can result in variations in their distribution, a common characteristic across various landscape scales (Pearson et al., 2004). Thus, for the estimation of the potential niche of the IAP's species and their spatial distribution, it is important to establish precise environmental factors limiting its distribution as well as those that favour its growth. However, such detailed information is lacking for most species (Priyanka & Joshi, 2013a,b). As such, the inclusion of environmental factors in understanding the occurrence and the spatial distribution of *L. camara* can enhance management of these species, particularly in semi-arid savannah ecosystems.

To date, two broad approaches, namely field traditional-based methods and remote sensing (RS) techniques, are used to quantify alien invasive species. Although traditional methods based on visual interpretations and field surveys are highly accurate, they are often difficult to conduct across large regions, besides time-consuming, expensive and labour-intensive (Odindi et al., 2014; Taylor et al., 2011; Thamaga & Dube, 2018a,b). In contrast, the RS technique offers the ability to acquire valuable and relatively cheap primary data that are necessary for timely and accurate quantification of different species (Thamaga & Dube, 2018a,b). Additionally, RS has successfully overcome the challenges associated with conventional approaches, such as time, cost and the accessibility of large geographic unit (Dube et al., 2018). The increasing number of sensors has provided scientific researchers with spatial data, creating opportunities to map and model the distribution of these invasive species.

The utility of RS technologies in mapping invasive species has gained increasing attention globally (Dube et al., 2016; Dube & Mutanga, 2015). Over the years, numerous satellite datasets have been successfully used in mapping and modelling *L. camara*, with different degrees of accuracy. For instance, Dhau (2008) utilized Landsat TM and Aster datasets in mapping and monitoring the invasion of *L. camara* across three different land tenure systems in Zimbabwe. Kimothi and Dasari (2010) also explored the Indian satellite data in mapping the spatial distribution of the intrusive *L. camara* in forest landscapes. The study demonstrated the ability of Linear Imaging Self-Scanning Sensor (LISS) IV and Cartosat-1 data for the detection and mapping of *L. camara*. However, there has been a paradigm shift in satellite remote sensing because of their limitations and the need for continuous improvement in mapping (DeFries et al., 2004). The application of medium spatial resolution in *L. camara* modelling has been limited by the insufficient spatial and spectral capabilities (Xie et al., 2008). The application of moderate spatial resolution sensors such as the Landsat 8 OLI, Landsat 7 ETM+ and SPOT-5 has been restricted when dealing with the world's worst understory plant species such as *L. camara*, mainly because they are unable to detect species occurrence in small and isolated patches (Zhang & Foody, 1998). For example, Mullerova et al. (2013) tested the effects of image classification with different spatial resolutions in the detection of invasive *Heracleum mantegazzianum* (Giant hogweed). Between the two tested satellite datasets, the results revealed that the high spatial resolution VHR performed better than the Rapid Eye.

According to Huang and Gregory, (2009), the use of moderate spatial resolution images in mapping and monitoring of IAPs is not yet fully understood in a background of native vegetation and it is therefore challenging, in terms of detection and mapping. Huang and Gregory (2009) further noted that these data could only be used to detect large patches of weeds that rely more on the phonological time. For instance, a study done by Fernando et al. (2016) produced low accuracies in mapping *L. camara* at species level, using the 30 m Landsat TM and SPOT data with moderate spatial resolutions. Nonetheless, the spatial, spectral and temporal characteristics of Sentinel-2 provide unique opportunities (Addabbo et al., 2016). Sentinel-2 is a high spatial resolution (10–60 m) sensor with a temporal resolution of five days, which is usually higher due to its image acquisition angle adjustment capability, hence making the sensor a key tool for large-scale mapping, especially in resource scares zones (Sibanda et al., 2015). It is also the first optical sensor to have the red-edge bands, which is known to increase the sensitivity of vegetation and its spectral response. The use of satellite data with a wider width and unique spectral characteristics such as those of Sentinel-2 may improve the detection and prediction of the geographic distribution of *L. camara*. The integration of RS data in Species Distribution Models (SDMs) has improved the estimation of the likelihood of species occurrence in areas (Kozak et al., 2008; Rocchini et al., 2015). The spectral reflectance characteristics provided by RS offer SDMs species information that is distinct, supporting models to distinguish between suitable and unsuitable areas that cannot be distinguished solely from topographic and bioclimatic factors (Gallien et al., 2012).

SDMs have been introduced as tools that can aid in understanding and predicting current and future species invasion. SDMs are a fixed portrayal of habitats that are suitable for species distribution (Bateman et al., 2012). They are mainly based on the correlation between the occurrence of species and ecological features, whereby their functionality is built on the establishment of relations between a species identified range and selected environmental variables. Thereafter, the relationship is used to detect other areas that may be inhabited by the species of interest (Beaumont et al., 2008). The spatial distribution of IAPs species has previously been modelled using different SDMs. The majority of SDMs use presence and absence data. However, there has been a limitation concerning acquiring absence data (Phillips et al., 2006). Hernandez et al. (2006) noted that the Maximum entropy (Maxent) model was the best modelling method when compared to Multivariate distance (DOMAIN), GARP and Envelope model (BIOCLIM). It was anticipated that Domain, GARP and Bioclim performed poorly due to the small sample sizes. In a study by Wisz et al. (2008), it was found that Boosted decision trees (GBM) and multivariate adaptive regression splines (MARS) which are a rapid application of a Generalized Additive Models (GAM: BRUTO) performed exceptionally well and superior to other techniques, especially when dealing with a larger sample size. The Rule and DOMAIN sets determined by genetic algorithms as well as open modeller version (OM-GARP) were some of the foremost performers when considering smaller sample sizes. However, they produce average results with bigger sample sizes. Additionally, the Maxent entropy was found to be less sensitive to different sample sizes and was the best model to predict species distribution with the use of both large and small sample size.

The Maxent entropy model is an SDM with great potential for identifying invasive species distribution. It is a correlative approach that has been identified among the best SDM for present-only data analysis (Ficetola et al., 2007). This method requires present-only data and a low number of locations to construct models. It has a higher performance when compared to other present-only models, due to its sensitivity to spatial errors that are related to low data (Phillips et al., 2006). Furthermore, it allows the usage of both continuous and categorical variables. Its regularization procedure makes it prone to overfitting as it compensates for small occurrence data (Merow et al., 2017; Phillips et al., 2006).

However, there has been considerable level of success documented in modelling the spatial spread of *L. camara*. However, there are still shortcomings in understanding the factors affecting its versatility of invasions that occur in new environments. As such, mapping of *L. camara* alone is not enough, as it does not explain why the species is occurring in those regions; hence, there is need to incorporate environmental variables in the RS of *L. camara* in Savannah rangelands. This study thus sought to determine the influence of environmental variables in the spatial variability of *L. camara* in savannah ecosystems, utilizing the Maxent algorithm in concert with remotely sensed data derived from the Sentinel-2 satellite data.

2 | MATERIALS AND METHODS

2.1 | Study area

This research was carried out in the communal area of Bushbuckridge and Kruger National Park (Figure 1). Bushbuckridge is located between the Drakensberg escarpment and the Kruger National Park, which is close to the Sabie-Sand Game. Rainfall is approximately 1200 mm per annum in the western region to 500 mm in the eastern region, while the average yearly temperature is roughly 22°C. The terrain is characterized by flat to undulant surfaces. The thin sandy lithosol is the dominant soil type in the area with low-lying areas having different soil types. The standard vegetation is mainly the open extensive grasslands and deciduous forests. The utmost livestock found in the area is domesticated animals, such as cattle and goats, while the agricultural activities include crop planting. The

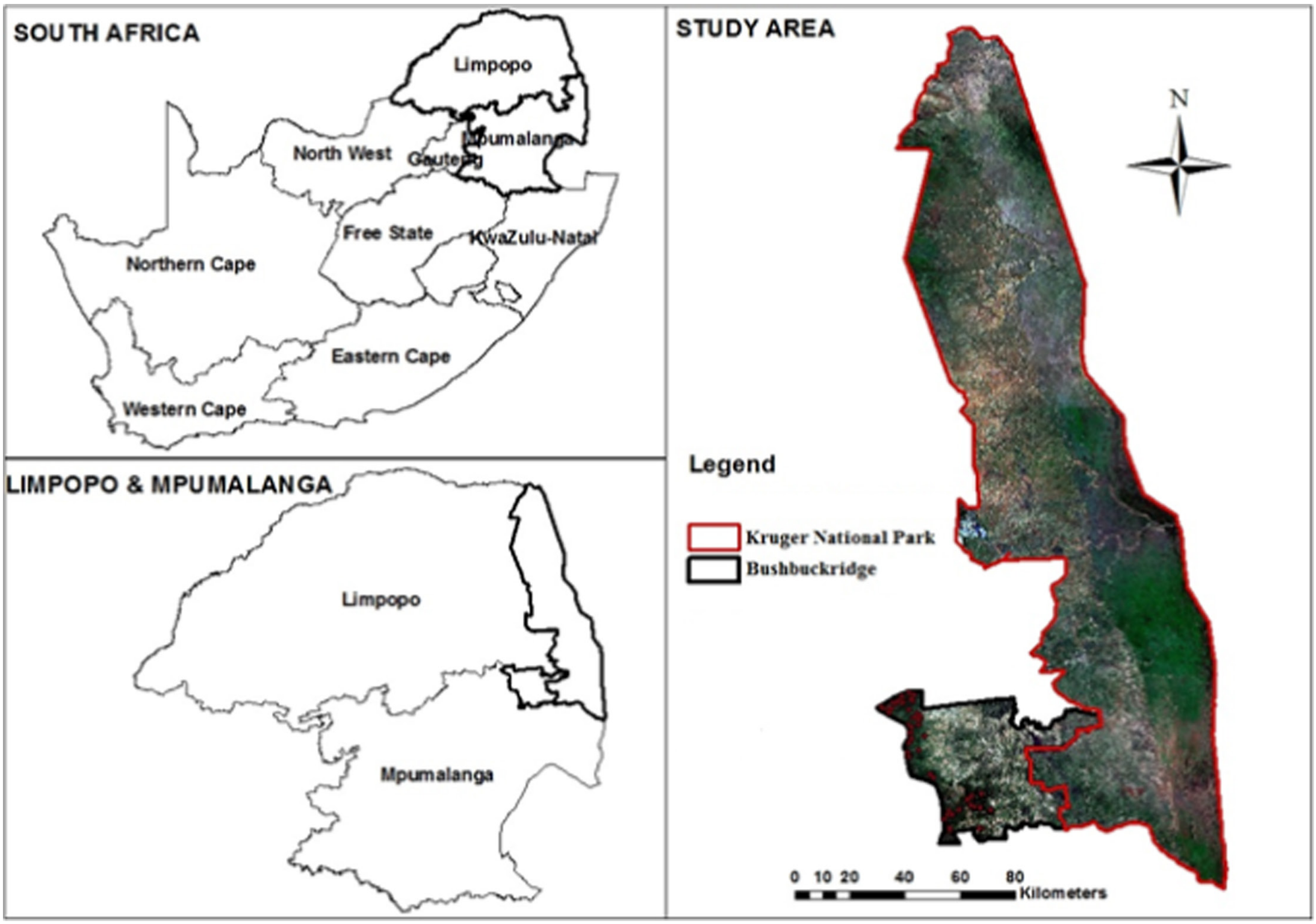

FIGURE 1 Location map of the study area

Kruger National Park is one of the largest in the world (19,485 km^2) and is located along the eastern part of Mpumalanga and Limpopo provinces in South Africa. It is about 65 and 360 km in width and length, respectively. The region is characterized by subtropical climate type with hot and humid summer days. Rainy season begins around September all through to the month of May.

2.1.1 | Field data collection

Field data were collected in July 2017, following a systematic sampling procedure. Stratified random transects were generated in a GIS environment. The generated points were then uploaded on a Trimble Juno 3B, hand-held GPS. Subsequently the points were used to locate the sampling sites on the field. Specifically, a quadrant within the 30–40 transect after every 10-m interval was used. Eighty sample points were generated using field data and then divided into 70% for model training and 30% for model validation. The GPS captured coordinates were presented in a table format using Microsoft Excel Version 4.0. The GPS was then imported into a GIS environment and overlaid on the study area GIS layer. For purposes of compatibility with Maxent, the measured the *L. camara* GPS points were changed to comma-separated values (csv) and used for the modelling of potential vulnerable areas.

2.2 | Image acquisition and processing

The freely accessible Sentinel-2 imagery was used in this study. A cloudless satellite dataset of Sentinel-2 covering the study area was downloaded from Sentinel Copernicus data hub. The acquired images coincided with field data collection. Sentinel-2 is a multispectral sensor that was launched on the 23 June 2015. It comprises of two indistinguishable satellites, namely Sentinel-2A and Sentinel-2B. The satellite is characterized by a high temporal resolution with five-day return intervals. The satellite collects data at 10 m (blue, green, red and near infrared 1) and 20 m (red edge1 to 3, close infrared-2, short waves infrared 1 and 2), respectively. For this study, bands 1, 9 and 10 were excluded due to the course spatial resolution of 60 m. Atmospheric correction of the acquired images was carried out with the aid of a toolbox called Sen2cor within the Sentinel Application Platform (SNAP) tool Version 4.0.

2.3 | Topographic indices

To model the occurrence and distribution of *L. camara*, the 30-m digital elevation model (DEM) from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) was used. Specifically,

TABLE 1 Model scenarios with selected environmental inputs

Model scenario	Variables	No. of variables
Model 1	Aspect, elevation, slope, TPI, TWI	5
Model 2	Bands 2, 3, 4, 5, 6, 7, 8, 8a, 11, 12	10
Model 3	Bios 01, 02, 05, 06, 07, 12, 13, 14, 17	9
Model 4	GNDVI, NDVI, RVI, TVI	4
Model 5	Aspect, elevation, slope, TPI, TWI, bands 2, 3, 4, 5, 6, 7, 8, 8a, 11, 12	15
Model 6	Aspect, elevation, slope, TPI, TWI, bios 01, 02, 05, 06, 07, 12, 13, 14, 17	15
Model 7	Aspect, elevation, slope, TPI, TWI, Bands 2, 3, 4, 5, 6, 7, 8, 8a, 11, 12, Bios 01, 02, 05, 06, 07, 12, 13, 14, 17, GNDVI, NDVI, RVI, TVI	28

the DEM was used to derive the Topographic Wetness Index (TWI), slope, aspect elevation and Topographic Position Index (TPI). These topographic indices have been demonstrated in the literature as having significant influence on vegetation growth patterns and distribution as they influence the net radiation and soil moisture distribution and availability (Shoko et al., 2019). Before modelling, the DEM was preprocessed to eliminate imperfections associated with the data. DEM pre-processing was conducted in a GIS environment, using the spatial analyst extension tool. The DEM-based surface terrain variables, i.e. elevation, aspect and slope, were extracted using the surface extension spatial analyst tool. On the other hand, the TWI, which is a hydrological index that determines the variability in soil water conditions, was derived using the hydrological spatial analyst (Shoko et al., 2019). The DEM-derived *L. camara* model input parameters were standardized to the same resolution as that of remotely sensed derived vegetation indices, using nearest neighbour resampling technique in a GIS environment. Resampling of the DEM variables and remotely sensed variables was meant to ensure their compatibility and consistency in mapping and modelling of *L. camara*.

2.4 | Vegetation indices

Sentinel-2 data were used to generate four vegetation indices, namely Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1973), Transformed Vegetation Index (TVI) (Deering, 1975), Ratio Vegetation Index (RVI) (Baret & Guyot, 1991) and Green Normalized Difference Vegetation Index (GNDVI) (Gitelson & Merzlyak, 1998). The NDVI was derived using the red and near-infrared bands to evaluate changes in the phenology of vegetation, which therefore uses the utmost absorption and reflection, and reflectance of the chlorophyll. Additionally, the TVI is used in the elimination of negative values as well as the transformation of NDVI histograms to an ordinary distribution (Deering, 1975; Mróz & Sobieraj, 2004). The RVI is based on the principle that leaves absorb more red wavelengths than infrared light. The RVI is sensitive to vegetation and have a significant relationship with plant biomass; as such, it is mostly used for estimating and monitoring vegetation (green) biomass (Xue & Su, 2017). The GNDVI is an index of plant and one of the most generally utilized indices to assess canopy variation in biomass (Gitelson & Merzlyak, 1998). The selected spectral indices were informed by their performance in vegetation mapping as reported in the literature (Dube et al., 2014, 2018; Shoko et al., 2018).

2.5 | Bioclimatic data

Current climate data layers generated through the interpolation of average monthly data using the splining techniques were obtained. Bioclimatic variables were derived as raster grid format of a 30 arc-seconds spatial resolution from the current WorldClim climatic conditions database (http://www.worldclime.org/). The bioclimatic variables used in this study were derived from the monthly temperature and rainfall data to produce variables that are biologically relevant. These climatic datasets are an average of long-term measurements (30 years of data) and contain grids of rainfall, temperature and derived bioclimatic summary variables (Hijmans et al., 2005). The variables were categorized into temperature and soil moisture. As such, all other variables were resampled to a 30 m spatial resolution and projected to the Universal Transverse Mercator (UTM). This was meant to enhance compatibility with topographic variables. To ensure that all variables match, the variables were converted from raster format to American Standard Code for Information Interchange (ASCII) to ensure their compatibility with the Maxent algorithm for easy implementation (Jarnevich & Reynolds, 2011).

2.6 | Modelling *L. camara* distribution

Freely available maximum entropy (Maxent) model was downloaded from (http://biodiversityinformatics.amnh.org/open_source/maxent/). The remaining model parameters were set to default replication of one, with 500 iterations, using cross-validation. The advantage of Maxent is that it has the ability to use presence-only data incorporated with interactions amongst categorical and continuous data (Ficetola et al., 2007). Furthermore, the Maxent algorithm is developed to improve on detection of the probability distribution; hence, the method is less likely to be influenced by the number and spatial error of sample size (Hernandez et al., 2006). To reduce model overfitting, regularization multipliers were set to four (Ndlovu et al., 2018). The clog-log output format was used due to its ability to predict the area of moderately high invasion when compared to the logistic output (Kumbula et al., 2019). During the model training, the Maxent entropy algorithm also performs a jackknife test, which is key in assessing the relative importance of predictor variables that explain the spatial distribution of the species, including the unique information provided by each variable (Phillips & Dudík, 2008). This method was thus used to analyse the effects of environmental variables on model results to indicate influential variables as it can estimate parameters and adjust the deviation without assumptions of distribution probability (Kumbula et al., 2019). A summary of different modelling scenarios adopted in this study is detailed in Table 1.

2.7 | Model evaluation

To evaluate the models performance and accuracy, the AUC, which is a threshold-independent measure of accuracy, the TSS and Cohen's Kappa, which are threshold-dependent measures of accuracy, were used. The AUC tests the agreement between the observed species presence and the estimated distribution, indicating whether the classifier (Phillips et al., 2006) correctly ordered the probability of presence (sensitivity) versus absence (specificity). An AUC value of 0.5 shows that model predictions are not better than random; <0.5 worse than random; 0.5–0.7 poor performance; 0.7–0.9 reasonable/moderate performance; and >0.9 high performance (West et al., 2016). Kappa has been used to measure the model performance. However, it has been highly criticized for dependence on prevalence (Allouche et al., 2006). As such, the TSS has been presented as an alternative measure of accuracy as it corrects this dependence while retaining the advantages of Kappa. Furthermore,

TABLE 2 Evaluation results for all model scenarios

Model scenarios	AUC	TSS	KAPPA
Model 1	0.924	0.667	0.338
Model 2	0.906	0.621	0.328
Model 3	0.925	0.751	0.397
Model 4	0.854	0.549	0.295
Model 5	0.952	0.773	0.401
Model 6	0.928	0.698	0.367
Model 7	0.955	0.765	0.387

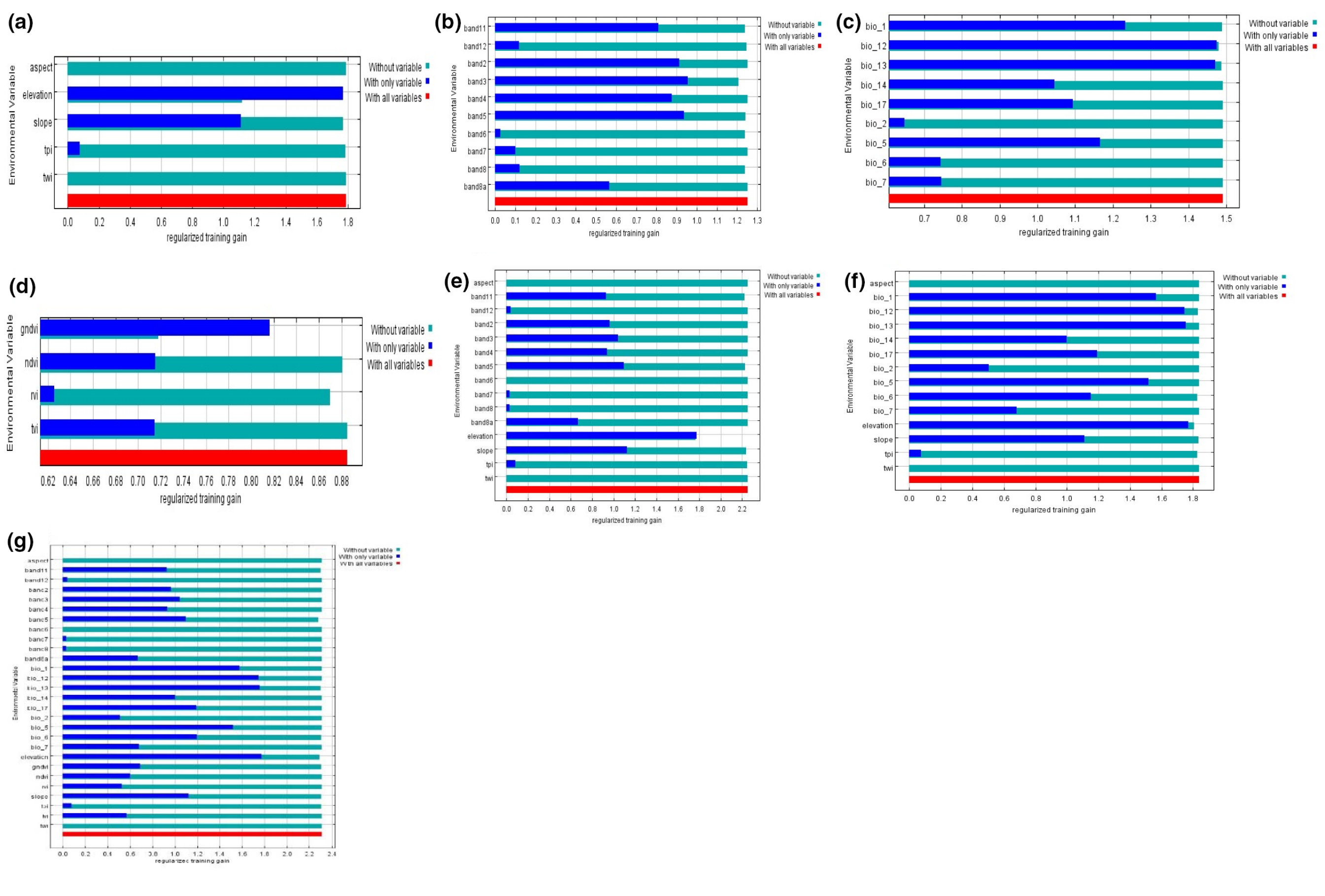

FIGURE 2 Jackknife test of variable importance (a) topographic variables, (b) sentinel bands, (c) bioclimatic variables, (d) selected vegetation indices, (e) topographic variables and sentinel bands, (f) topographic and bioclimatic variables, (g) composite of all variables

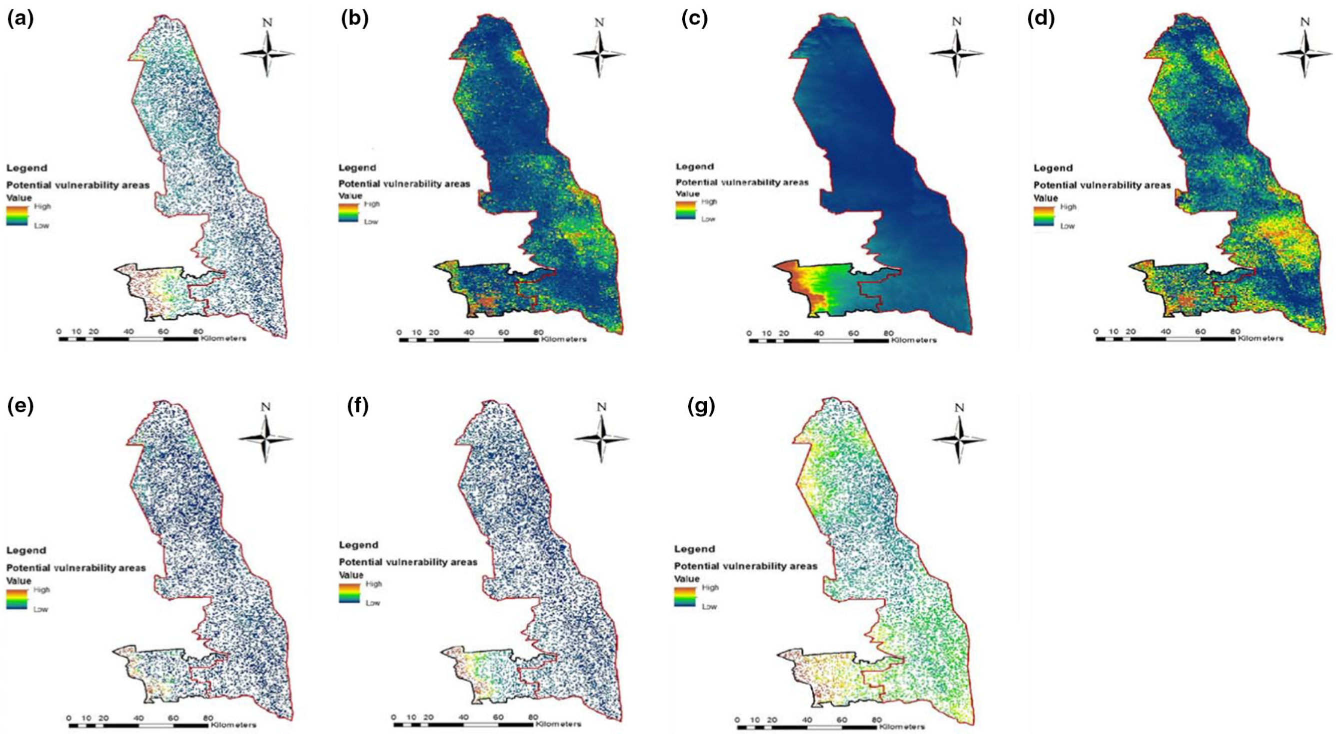

FIGURE 3 Spatial distribution of *Lantana camara* as predicted by Maxent where the following variables were used for each model: (a) topographic variables, (b) sentinel bands, (c) bioclimatic variables, (d) selected vegetation indices, (e) topographic variables and sentinel bands, (f) topographic and bioclimatic variables, (g) composite of all variables

the error matrix was used to derive specificity, sensitivity, Kappa and TSS values using background samples as absence data. The 10-percentile threshold value was used to evaluate classification accuracy.

3 | RESULTS

3.1 | Model accuracy

The results in Table 2 show the derived AUC, TSS and Kappa values. The model that used all variables achieved the highest predictive accuracies and had the highest performance, attaining an AUC of 0.96, a TSS of 0.77 and a Kappa of 0.39. On the other hand, the model developed based on indices alone achieved the lowest accuracies, yielding an AUC of 0.854, a TSS of 0.549 and a Kappa 0.30.

The results in Figure 2 show the jackknife test of variable importance. The findings ranked elevation as the overall most influential variable in predicting areas most vulnerable to the invasion of *L. camara*. As observed in Models 1 (a), 5 (e), 6 (f) and 7(g), elevation is the environmental variable with the highest gain, when it is used in isolation, and it therefore, appears to have the most useful information on the spread of *L. camara*. Furthermore, it is also the only environmental variable with the highest mean decrease in accuracy omitted from the model. The use of Models 3 (c) and 4 (d) depicted bio 12 (mean annual rainfall) and GNDVI as standalone yielded the highest gain and leads to poor model performance omitted, whereas Model 7 (g) depicted band 5 (vegetation red edge) as the most important variable.

3.2 | Spatial distribution of *L. camara*

The integration of multi-source data (environmental and remotely sensed variables) successfully predicted the spatial distribution of *L. camara* in both the protected and unprotected areas. Figure 3a–g shows the predicted potential habitats suitable for *L. camara* occurrence. The warm colours illustrate high level of invasion while cooler colours illustrate low level of invasion. The results from all the predictive models indicated that invasion is more likely to occur in the communal area of the study area that is Bushbuckridge, specifically in moisty areas. Although invasion is taking place in the protected area, the level of invasion is lower. For example, Figure 3a, c, e, f shows that *L. camara* invasion is more pronounced in the communal lands of Bushbuckridge when compared to the protected area. However, the results in Figure 3a and d demonstrate that the protected area (Kruger National Park) has isolated patches of invasion by *L. camara* occurrence with great occurrence noted in the northern part of the park and central parts. Further, dry areas within the protected area have low levels of invasion while the areas that have moister have some invasion taking place, specifically the central eastern part of the protected area. Overall, the distribution maps seem to be in agreement with the areas that are most vulnerable to the invasion of *L. camara*.

3.3 | Discussion

The study modelled the potential spatial distribution of *L. camara* in savannah ecosystems, using the Maxent entropy model. Results revealed that Bushbuckridge communal lands are more vulnerable to the invasion by *L. camara* when compared to the Kruger National Park. Similar trends have been observed in other studies; for example, Rodgers and Parker (2003) compared two tourist islands (the St. Simons Island and Jekyll Island) and two protected National Wildlife Refuge Islands (the Blackbeard Island and Wassaw Island) to find the island that is the most highly invaded by alien plants. It was found that Alien plant cover was greater in severely disturbed sites than in less disturbed sites on all islands and in both habitats. This is further supported by the work by Lin (2007) who observed that major roadsides of Moorea, French Polynesia, were infested with *L. camara*. It was found that the roadside area covered by *L. camara* was 1.99% whereby the presence was correlated with the roadside habitat type with the highest being in areas of agricultural disturbance. The area covered by *L. camara* was also positively correlated with soil moisture and slope. According to Sharma et al. (2005), disturbed areas such as railway tracks, roadsides and canals are more favourable for the species distribution. This is because the occurrence and spread of IAPs are influenced by the presence of optimal growth conditions and the altered disturbance regimes that are caused by anthropogenic activities increase the performance of the invading species over that of native species (Daehler, 2003). As a result, IAPs are usually invading disturbed areas (Hobbs & Huenneke, 1992). These disturbance decreases the cover and the vigour of competitors, and it increases the resource levels, which, in turn, facilitate invasions (Kneitel & Perrault, 2006).

Results further indicated that some variables highly influence the spatial distribution of *L. camara* while others have no significant contribution. The model developed using all variables yielded the highest predictive accuracies and had the highest performance. The literature reported similar observations when models developed with a composite of various variables performed better than those based exclusively on one set of variables (Buermann et al., 2008; Parra et al., 2004; Parviainen et al., 2013; Saatchi et al., 2008). Furthermore, all the models achieved AUC values of above >0.85. These results are consistent with those of Phillips and Dudík (2008) and therefore indicate that the models were able to predict areas vulnerable to *L. camara* invasion.

In addition, the findings of this study have indicated that the elevation was the only environmental variable with the highest gain, when used as independent model dataset in modelling the distribution of *L. camara*. Our results are in line with those of Ndlovu et al. (2018) and Adeola (2017) whose work demonstrated that elevation explained probability of occurrence ($p > 0.5$). According to Adeola (2017), elevation is a variable that has an influence on the spatial distribution of plant species as well as soil properties. This is supported by the findings of Priyanka and Joshi (2013a,b) who observed the superiority of elevation gradients in accordance with the expected species since *L. camara* flourishes well at lower altitudinal ranges, and as it increases, the species occurrence tends to diminish.

Furthermore, Band 5 (vegetation red edge) derived from Sentinel-2 was depicted as another variable that is important in modelling invasive *L. camara*. According to Delegido et al. (2011), the inclusion of Sentinel-2 red edge bands is important in enabling the detection of subtle green canopy and chlorophyll content. The red edge is important for the prediction of *L. camara* as the sensitivity of its presence to the red-edge bands is in line with the assertion that subtle vegetation changes and characteristics or variations are prominent in some portions of the electromagnetic spectrum (Zhu et al., 2007). Hence, its attributes can be probabilistically determined in terms of the red-edge band reflectance. Vegetation red edge bands contribute to vegetation mapping and offer broader discrimination. Dhau et al. (2017) have stressed the potential of vegetation red edge in vegetation mapping and prediction.

3.4 | Conclusions

The findings of this work demonstrate that communal areas of Bushbuckridge are more likely to be invaded by *L. camara* when compared to the Kruger National Park. Almost 10% of the communal area is more likely to be invaded by *L. camara*, whereas only 7% of the Kruger National Park is anticipated to be invaded. Furthermore, findings of this study revealed that the Maxent-based models performed exceptionally well with AUC scores >0.85. The model developed using all the variables yielded the highest predictive accuracies and had the highest performance. In addition, the results demonstrated that elevation plays a critical role in the spatial distribution of *L. camara* when compared to other variables considered in this study. The findings of this study could assist in conservation planning and management of invasive species and protected areas. Moreover, such information is vital for ecologists, land managers and policy-makers in the monitoring of areas that are vulnerable to the invasion of *L. camara* and where early response mechanisms could be put in place.

CONFLICT OF INTEREST

Authors would like to declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon request.

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