Indonesian Journal of Earth Sciences, Vol. 04, No. 1 (2024), A835

P-ISSN: 2798-1134 | E-ISSN: 2797-3549 | DOI: 10.52562/injoes.2024.835

MO.RI Publishing

Indonesian Journal of Earth Sciences

http://journal.moripublishing.com/index.php/injoes

InJoES

| Research Article |

Check for updates

Spatio-temporal Analysis of An Invasive Alien Species, *Vachellia nilotica*, on Rodrigues Island, Mauritius, Using Geographic Information Systems and Remote Sensing Techniques

Reshma Sunkur [1*], John Mauremootoo [2]

[1]*Department of Environment, Science and Social Sustainability, School of Sustainable Development and Tourism, University of Technology, Mauritius, La Tour Koenig, Pointe aux Sables, Mauritius*

[2]*InSpiral Pathways, Bristol, United Kingdom*

* *Correspondence: sunkurr@umail.utm.ac.mu*

Received: 13 October 2023 / Accepted: 31 January 2024 / Published: 10 February 2024

Abstract: Invasive alien species (IAS) constitute a large and growing environmental and socio-economic problem. Tropical islands, one of the richest habitats in the world, are especially vulnerable to invasions because of their island-specific flora and fauna. The aim of this study is thus to assess the viability of monitoring IAS distributions on small tropical islands using Geographic Information Systems (GIS) and remote sensing techniques, focusing on the invasive plant species *Vachellia nilotica* on the island of Rodrigues as a case study. Freely available satellite images are used to conduct the analysis with resulting classified maps having accuracy levels in the high 70s. The results reveal a significant increase in Vachellia coverage from 2013 to 2023 especially along the coasts while the simulation for 2033 indicates an inward migration from coasts to the central plateau which could have severe repercussions on the native vegetation and human activities. Given the high invasive potential of Vachellia, the present findings can support conservation actions and decision making and even support community participation in managing this IAS. In the broader context, the study demonstrates the potential of GIS and remote sensing as cost-effective tools for monitoring certain invasive plant species.

Keywords: remote sensing, GIS, modeling, Mauritius

INTRODUCTION

Invasive alien species (IAS) are non-indigenous species that adversely affect, economically, environmentally or ecologically, habitats where they have been introduced, either accidentally of deliberately, outside their normal past or present distribution (Masters & Norgove, 2010). By nature, IAS can rapidly invade suitable areas through exponential growth and swift dispersal thus putting all ecosystem types at risk. Such biological invasions are driven by intentional human activities such as transport and trade, agriculture, and land use change; and unintentionally when invaders hitchhike on human-mediated pathways (Chong et al., 2021; Seebens et al., 2021). Invasive alien species can have devastating impacts on the local biodiversity, ecosystem functions, economy and human health of the invaded regions (Lourenço et al., 2021). Today, such biological invasions are among the leading drivers of biodiversity loss and species extinctions around the world (Gentili et al., 2021).

Tropical regions contain the vast majority of the world's biodiversity and are also subject to high levels of human activity, but most countries in these latitudes only have limited institutional and financial resources to respond to conservation threats (Barlow et al., 2018) leading to a neglect in managing biological invasions (Chong et al., 2021). Tropical islands especially are one of the most biologically diverse and productive habitats on Earth but face serious ecological threats including biological invasions. Their particular vulnerability to biological invasions is due to their distinctive ecosystems, island specific 'disharmonic' flora and fauna which increases the risk of species extinction (Masters & Norgove, 2010).

It is now widely acknowledged that species mapping and species distribution models are increasingly becoming important tools to support management and decision making (Villero et al., 2017). The Convention on Biological Diversity emphasizes the need to use scientific and technical information such as species mapping to guide decisions related to biodiversity conservation and management (Timmermans & Kissling, 2023). In this regard, remote sensing has long been used for IAS mapping with

Lourenço et al. (2021) stating that today, using high resolution imagery, even invasive alien plants alongside roads can be accurately mapped thus reducing the cost and time of extensive field surveys. Bolch et al. (2020) assert that as technological progress has been made in the field of remote sensing, current technologies such as hyperspectral imaging spectroscopy coupled to advances in image processing algorithms can provide consistent monitoring records to support IAS control efforts.

At this point, only one study exists on the application of remote sensing techniques to map invasive alien species in Mauritius by Koerner et al. (2022) where the authors investigated different approaches to classify *Psidium cattleianum* (strawberry guava, known as Chinese guava in Mauritius) using machine learning techniques. However, no work has been undertaken so far on the application of GIS coupled to remote sensing approaches to assess cover change spatially and temporally. The aim of this study was to map the spatial cover change of the highly invasive species *Vachellia nilotica* (L.) P.J.H.Hurter & Mabb. (Piquant Loulou) on Rodrigues Island, Republic of Mauritius, using freely available satellite images. The study uses an innovative GIS based methodology founded on the machine learning algorithm Random Trees to map the spatial distribution of Vachellia for the years 2013 and 2023 and applies the MOLUSCE plugin to simulate the potential future coverage in 2033. The rationale behind the study is to establish whether freely available resources and tools can be used to monitor IAS distributions on small tropical islands as a basis for improved management. The present study reveals a distinctive increase in the spatial coverage of Vachellia during the period 2013 to 2023, especially along the coasts while the predicted simulation shows an inward migration of Vachellia towards the central plateau. This study demonstrates the potential for low-cost, practical, accurate, and repeatable IAS distribution measurements over time, thus providing consistent monitoring records to support management. Because of its ubiquity, these Vachellia distribution estimates are of little help in informing spatial management priorities. However, through the monitoring of spatial change, these estimates can help to evaluate treatment effectiveness. The invasion maps and data also fulfil a valuable stakeholder awareness raising and advocacy function as they vividly illustrate the historical and current extent of the issue and the future prognosis in the absence of systemic management.

Case Study

Rodrigues, centred on coordinates 19°43'S and 63°25'E, is a volcanic island located in the south western Indian Ocean approximately 700 km east of Madagascar and 600 km of Mauritius Island (Figure 1). Rodrigues forms part of the Mascarene Islands together with Mauritius and Reunion and is the smallest island of the three with an area of 108 km^2. Before its discovery Rodrigues teemed with remarkable endemic species including the large flightless Solitaire bird (*Pezophaps solitaria*). But human settlement on the island quickly led to the extinction of a number of unique species such as giant tortoises, reptiles, snails, butterflies and angiosperms (Florens, 2013). Rodrigues has a native angiosperm flora of 150 species with 72 Mascarene endemics and 47 single island endemics (Baider et al., 2010) which are threatened by several factors such as habitat destruction, fragmentation but the most important being IAS which can reach extreme densities in even the best preserved areas (Strahm, 1993; Florens, 2008; Florens, 2013).

Vachellia nilotica (previously classified as *Acacia nilotica*) with common names like Babul, Gum Arabic tree, prickly acacia, and Piquant Loulou in Mauritius and Rodrigues, is a tree native to Africa and the Indian subcontinent. It is a pioneer species that grows very fast in dry regions, especially near abundant water sources like rivers with cattle, goats and other herbivores helping to disperse seeds (Carter, 1994). Vachellia grows well in dry conditions with a mean annual rainfall of 250-1500 mm and a mean annual temperature of 15-28°C but it can withstand daily temperatures of 50°C (CABI, 2022). It can quickly invade grass and savannah habitats, woodland, cleared land on roadsides and seasonally flooded plains near creeks and streams. Invasion of exotic plant species in Rodrigues has been facilitated by extensive forest clearance and degradation (Kueffer & Mauremootoo, 2004). Vachellia was introduced in Rodrigues in the mid-1970s as part of reforestation programmes; in less than 10 years, the tree became widespread across the island with dispersal aided mainly by grazing animals. Today, Vachellia has become a major nuisance to the general population; inhabitants who inadvertently walk on its thorns can get their legs amputated if they are subject to other diseases while the tree itself is spreading at an alarming rate to the risk of choking out remnant native species. Vachellia thickets can be seen on mountain tops, in pastoral areas and is actively spreading in urban regions. Vachellia invasion in Rodrigues is an example of an IAS which stands out spectrally from its surroundings thus allowing for interclass separability using remote sensing techniques as compared to many ecosystems which are invaded by multiple IAS which compete with native vegetation thus enhancing canopy complexity making remote sensing analysis quite challenging. Rodrigues thus provides a unique opportunity to spatially and temporally map such a biological invasion using remote sensing techniques in the island context.

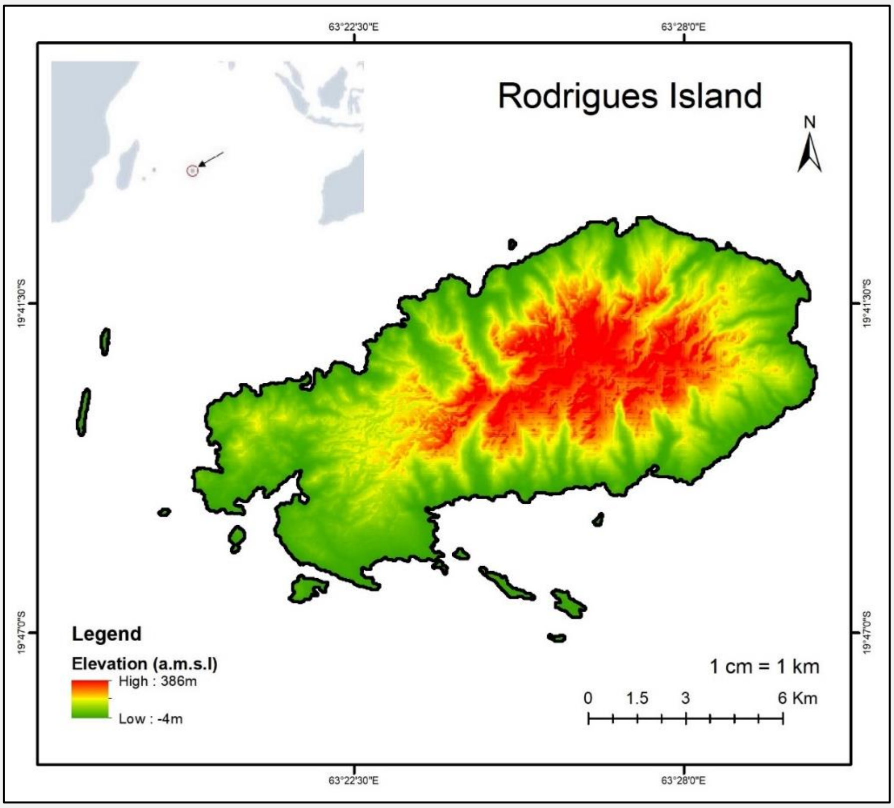

Figure 1. Study site, Rodrigues Island with its location in relation to Africa and its mean height.

METHOD

Figure 2 summarizes the method applied to pre-process the satellite images, carry out the classification exercise and simulate the future prediction of Vachellia in Rodrigues. The detailed analysis is listed below.

Data Collection

GPS coordinates of Vachellia were gathered randomly in Rodrigues using the mobile survey tool ODK Collect v2022.2.3 with default positional accuracy of 5 m from 09 May 2022 to 12 May 2022 at Vachellia monotypic stands. Additional points were gathered by an expert survey where expert botanists identified Vachellia from Google Earth Pro at an observer height of 400 m m.a.s.l based on identifiable crowns, shadowing and colour. All data collected were converted into shapefiles using ArcMap Desktop (ESRI, Redlands, California). Since historical data sets of Vachellia cover were not available for 2013, Google Earth Pro was used to conduct the mapping process for the year 2013, the earliest year where the spectral signature of Vachellia is identifiable on satellite imagery.

Remote Sensing Analysis

Image Pre-processing

Sentinel 2A MSI Level 2A images taken on 01 June 2023 were retrieved from the European Space Agency Copernicus Open Access Hub with a minimum cloud cover. SPOT 5 (Satellites Pour l'Observation de la Terre) images dated 01 March 2013 with minimum cloud cover were acquired through the CNES's Spot World Heritage Programme (CNES, 2023). From the Sentinel image, ten bands were selected for the analysis namely B2, B3, B4, B5, B6, B7, B8, B8a, B11 and B12. In order to increase the spatial resolution of the images, the 20 m bands were resampled to 10 m using the nearest neighbour resampling technique in ArcGIS (version 2.8.4, ESRI California) for all the bands have the same resolution. For the SPOT image, the 4 bands (B1, B2, B3 and B4) were used. All images were then projected to UTM

41S which preserves the area measure and where the pixels are addressable in terms of map coordinates instead of pixel and line numbers (Richards & Jia, 2006).

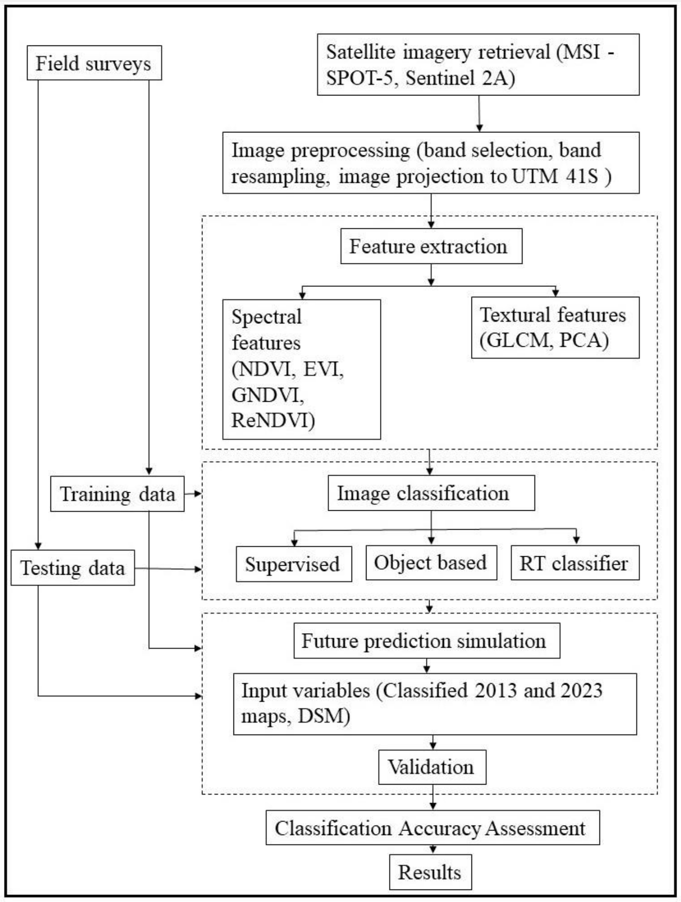

Figure 2. Flowchart explaining the methodology applied to pre-process the satellite images, extract relevant spectral features, classify the images and carry out the future prediction simulation until the results were obtained.

Vegetation Indices

The high-resolution images of Sentinel-2A and SPOT-5 allow the extraction of different features based on the sensitivity of the optical features to biomass. Vegetation indices provide valuable information on the health and density of vegetation cover and are especially important in land cover classification where they help differentiate between different land cover types due to their unique spectral signatures. Four commonly used spectral vegetation indices in IAS studies were thus calculated namely:

a) NDVI (Normalized Difference Vegetation Index) which is one of the most widely used indices to characterise canopy growth (e.g. Dvoreckiy et al., 2022) and calculated based on multispectral information as a normalized ration between the red and near infrared bands (Xue & Su, 2017):

$$NDVI = (B8 - B4) / (B8 + B4) \quad (1)$$

b) EVI (Enhanced Vegetation Index) (e.g. Ouko et al., 2020) which corrects for soil and atmospheric effects that influence NDVI under natural conditions (Liu & Huete, 1995) and is more sensitive in areas with dense vegetation:

$$EVI = 2.5 * (B8 - B4) / (B8 + 6B4 - 7.5B2 + 1) \quad (2)$$

c) GNDVI (Green Normalized Difference Vegetation Index) (e.g. Dube et al., 2022) which estimates photosynthetic activity in vegetation, determines water and nitrogen uptake into the canopy and is more sensitive to variation in chlorophyll content than NDVI (Gitelson et al., 1996):

$$GNDVI = (B8 – B3) / (B8 + B3) \quad (3)$$

d) ReNDVI (Red Edge Normalized Difference Vegetation Index) (e.g. Xu et al., 2023) which capitalizes on the sensitivity of vegetation red edge to small changes in canopy foliage content, senescence and gap fraction (Gitelson & Merzlyak, 1994; Sims & Gamon, 2002):

$$ReNDVI = (B6 – B5) / (B6 + B5) \quad (4)$$

For SPOT-5 images, bands within the same wavelength as Sentinel bands were used for the analysis as is customary.

Texture Feature Analysis

Texture is one of the most important characteristics to identify objects on a satellite image. Principal Component Analysis (PCA) was conducted on ArcMap to remove redundant spectral data from the multiband dataset subdivided into smaller datasets retaining essential spectral information only. Estornell et al. (2013) remark that PCA has been successfully applied to Landsat images where the first three principal components (PC1, PC2 and PC3) grab over 90% of the data in the original seven bands. Wiegleb (1980) state that with certain options, PCA is ecologically appropriate especially in analysing spatio-temporal change as illustrated by Lasaponara (2006). Four textural variables namely mean, entropy, energy and homogeneity were obtained using the Gray Level Co-Occurrence Matrices (GLCM) which is one of the earliest methods for texture extraction following Haralick et al. (1973) and is widely applied today in remote sensing image analysis. The GLCM approach basically analyses spatial relations between pairs of pixels (Humeau-Heurtier, 2019). SNAP (SeNtinel Application Platform) Desktop implementation version 9.0.0 was used to refine these spectral features. The GLCM statistical approach with a window size of 9x9 based on the size of the study area, a probabilistic quantizer and quantization levels of 32 and ALL angle were used to derive the: (1) mean which uses the frequency of occurrence of neighbouring pixels to weigh the pixel value; (2) entropy measures the degree of disorder of the GLCM; (3) energy measures the textural uniformity of the image; (4) homogeneity measures the level of homogeneity showing high values when the same pairs of pixels are identified.

Land Cover Classes

Class definition was generalized with emphasis on Vachellia cover. As a result, land cover classes chosen were: a) Vachellia picked up by its specific spectral signature; b) settlements representing houses, buildings and built infrastructure; c) water bodies for lakes, reservoirs and ponds; d) barren representing bare land, bushes and pastures; and e) forest which represent trees other than Vachellia. Congalton (1991) suggested the use of at least 50 samples per class for accuracy assessment and to increase the sample size the larger the land area and spectral variation. This resulted in 2020 samples for Vachellia, 3 for water (water bodies are scarce on Rodrigues), 1000 for settlements, 980 for forest and 899 for land totaling 4902 samples for Sentinel image processing and 1458 Vachellia, 5 water, 686 settlements, 560 forest and 800 land or a total of 3509 samples for SPOT.

Classification Analysis

Each image was then stacked in ArcMap resulting in a 26 band or feature composite image (including 10 spectral bands, four vegetation indices, four GLCM features each in PC1, PC2 and PC3) for the Sentinel 2A image and 12 feature composite images for the SPOT-5 image. Supervised classification was conducted according to object-based classification type using the Random Trees classifier on ArcMap Pro. The Random Trees algorithm uses multiple decision trees that are trained using small variations of the same training data and where the majority vote of the trained trees decides on the output class. Random Trees uses the Leo Breiman's Random Forest Algorithm a commonly used machine learning algorithm for vegetation classification (ESRI, 2018). A maximum of 50 trees of was chosen with a maximum tree depth of 30m and a maximum number of samples of 1000 per class. Segment attributes selected were active chromaticity colour, mean digital number and standard deviation.

Accuracy Assessment

Accuracy assessment of the classification was based on the Stratified Random Strategy, a widely used statistical approach, which create points that are randomly distributed within each class and where each class has a number of points proportional to its relative area. For each class, error mask images where pixels were incorrectly classified was calculated in a confusion matrix. Kappa analysis was conducted to check the spectral signatures of the surveyed data based on the confusion matrix. The Kappa coefficient assesses classification performance by measuring the overall statistical agreement of an error matrix taking into consideration non-diagonal elements (Cho, 2021). A Kappa value of 1 represents full agreement while a value of 0 reflects no agreement. Training and testing data was then resampled based on a 70% training and 30% testing split to obtain the best results as recommended by Gholamy et al. (2018). The dataset was resampled 10 times each time calculating the Kappa to obtain overall mean accuracy.

Future Prediction Simulation

To predict the future potential coverage of Vachellia, the MOLUSCE (Modules for Land-Use Change Simulation) plugin in QGIS 2.18.15 was used. MOLUSCE is widely used in land cover change studies such as the works of Mazumder et al. (2021) and Kayet et al. (2022) and has been applied to IAS distribution studies such as the work of Silvestre et al. (2019). MOLUSCE contains a set of algorithms to predict land use changes such as Artificial Neural Network (ANN) Multilayer Perceptrons (MLPs), Logistic Regression (LR), Weight of Evidence (WoE) plus validation based on Kappa values. An initial raster and a final raster are input into the plugin; the modeling stage creates a model that predicts land use changes between these two rasters based on transition potentials in current land use and condition of factors or on general patterns (NextGIS & AAS, 2014).

Input Variables

The classified 2013 and 2023 maps were used as inputs for the modelling and a 30m DSM (Digital Surface Model) acquired through the JAXA portal, resampled to 10m and re-projected to UTM 41S zone was input as spatial variables.

Transition Maps

Class statistics and transition matrix tables were calculated between the initial and final raster data sets to create a change map of the different classes. This map was then input to model transition potential for 2033. The ANN method was applied to the modeling using 1000 randomly chosen samples. ANNs are neural computation systems based on the functioning of the human brain. Several types of ANN have been developed based on different learning processes with MLP with a backpropagation (BP) algorithm often used for supervised learning (Park & Lek, 2016). MLPs have been extensively implemented in ecological studies, remote sensing and GIS data analysis and habitat suitability evaluation (Park & Lek, 2016). The neighbourhood selected was 1px, learning rate of 0.100, maximum iterations of 1000, 10 hidden layers and momentum of 0.050.

Cellular Automata Simulation

Cellular automata (CA) simulation was then conducted based on the results of the ANN-MLP analysis. CA is a widely used bottom-up modelling approach that implements Tobler's First Law ('everything is related to everything else, but near things are more related than distant things') into simulation modelling where the status of a cell in the next process is based on its current status and its neighbours (Wolfram, 2002). CA are powerful tools to understand land use changes and their underlying dynamics especially when combined with ANN (Muhammad et al., 2022). The neural network learning curves for the ANN method shows whether the training and validation datasets are suitably representative. They indicate how the behaviour of a neural network is improved as the number of training samples increases and its relationship with the complexity of neural networks (Murata et al., 1992).

Validation

Finally, validation of the simulated map was undertaken using the 2023 map as reference map and a number of iterations of 5.

RESULTS & DISCUSSION

Ground Truth-ing

Vachellia cover has increased significantly on Rodrigues Island during the period 2013 to 2023 based on visual observations and analysis of historical images (Figure 3). Ground truthing samples were taken from large dense monotypic stands and it was observed that during the period 2013 to 2023, these stands had been increasing in size. In forested areas in the highlands, considered mixed classes, the spectral signature of Vachellia was distinctly observable especially where the canopy is open. But it is worth to note that given the limited ground truth samples, the credibility of the classified images could have been affected. While the aim of the present study was to investigate if freely available remotely sensed images could be used to spatially map Vachellia distribution, it is of utmost importance that future studies consider a large enough sample size for the study area and appropriately distributed over the study site for more accurate results. The model, and hence the results, can be refined with more ground truth data which decreases the risk of misinterpreting and misclassifying land cover types.

Image Classification and Change Analysis

The classified images revealed a distinctive increase in spatial coverage of Vachellia during the period 2013 to 2023. Areas of high concentration were on the west of coast of Rodrigues, the north and north-east regions and along almost all of the coastal strips. Patches were identified all over the island, even within forested regions. It was observed during this time period that monotypic stands increased in size and the number of Vachellia patches across the islands increased, often in previously barren land. Layer masks were applied to display only Vachellia spatial cover from 2013, 2023 and 2033 (Figure 3). The overall Vachellia coverage for 2013 was 30.2km^2, 57.3km^2 for 2023 and 70.6km^2 for 2033. These figures equate to 26.6%, 50.4%, and 62.1% of the total area of Rodrigues respectively.

At this point it is worth to note that the results obtained reflect the data that was input, that is, the limited ground truth samples that were available at the moment of the analysis and coordinates obtained through visual analysis and expert knowledge which could have introduced subjectivity in the analysis. Likewise, the use of two different types of satellite images namely SPOT and Sentinel could also have affected the analysis. With this successful pilot study, for more accurate and homogenous results it would be better that future studies rely on actual ground truth data (with the cooperation of local authorities, fellow researchers and scientists) and use the same type of satellite imagery to decrease classification errors. The resulting maps would then be reliable tools for decision making and to direct resources for managing Vachellia and even for the conservation of native species.

The total area of the study site was 113.68km^2 (the main island of Rodrigues at 108 km^2 and the remainder being its offshore islets) of which 82.83km^2 was classified in 2013 and 86.23% in 2023. The highest percentage change in class cover is seen to be in barren to Vachellia by 28.74km^2 during the study period, followed by barren to barren by 18.7km^2 and Vachellia to Vachellia by 15.36km^2. Since the current study is based on the spatio-temporal change in Vachellia cover, the classification analysis is focused on Vachellia change. In this respect, Vachellia class change of 4.3km^2 can be observed for forest to Vachellia, 3.39km^2 for settlements to Vachellia, 2.46km^2 Vachellia to barren, 4.44km^2 Vachellia to forest, 2.44km^2 Vachellia to settlements, 0.01km^2 Vachellia to water body and 0.01km^2 water body to Vachellia (Table 1). A general decrease in 7km^2 to 0.01km^2 is noted for the rest of the classified classes.

This spread of Vachellia in Rodrigues is a major concern as it has severe impacts on the local community and ecosystem. The island is already water stressed because of its sharp topography and lack of water storage capacities; Vachellia's spread into watersheds could worsen water supplies (Kueffer & Mauremootoo, 2004). Likewise, as Vachellia gains more ground, it will considerably decrease land accessibility to cattle for grazing (Kueffer & Mauremootoo, 2004). Eventually, it will also form denser monospecific stands that limit the regeneration of native species, compete with native species for resources and space and increase soil nitrogen availability in Rodrigues. The present maps are thus helpful in visualizing where management efforts should be concentrated especially near native forests and urban areas. They can assist in water resource management near watersheds as well, identify critical habitats for restoration and monitor changes thus promoting sustainable IAS management practices in the island context.

Predicted Simulation for 2033

The simulation conducted showed a general increase in Vachellia cover for 2033 using the ANN-CA approach especially an inward migration of Vachellia from the coasts towards the central plateau. Results from the neural network learning curve as shown in Figure 4 indicate a good model fit with both the training and validation datasets decreasing to a point of stability in a coherent manner and the two learning curves having a minimal gap suggesting that the training and validation dataset are representative of the model. Hence, using the data that was available, the model is representative of the future distribution of Vachellia within the next 10 years under a business as usual scenario, that is with no management intervention. Again, a note of caution is added that the future spatial distribution of the IAS is only representative of the limited ground truth samples and expert knowledge and that the model can become more accurate and reliable with more reliable ground truth data.

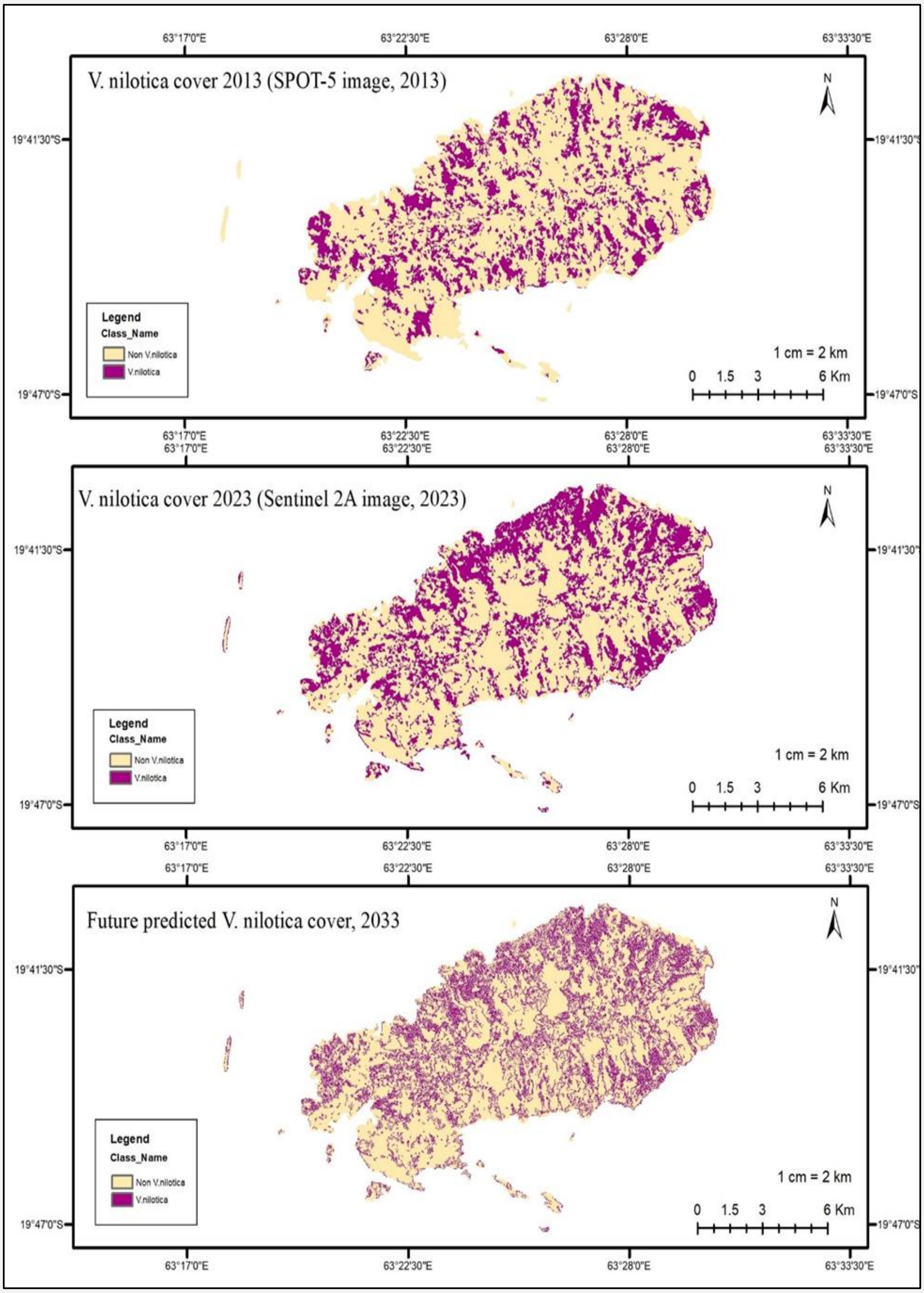

Figure 3. Classified maps for the periods 2013 based on SPOT-5 image, 2023 based on Sentinel 2A image and future predicted map for 2033; purple color depict Vachellia distribution in Rodrigues whereby an increase in coverage can be noted from 2013 to 2023 and from 2023 to 2033.

Accuracy Assessment

Overall accuracy was in the 80s and 70s when assessed with validation data using the RF classifier (Table 2). Kappa values of 0.7 and above are considered to be very good agreement between observed and expected accuracy (Landis & Koch, 1977).

The 2013 SPOT-5 image had an overall Kappa value of 0.83, Sentinel 2A a Kappa of 0.79 and the simulated map a Kappa of 0.78. The confusion matrix showed where misclassifications occurred by the producer and the user during the modelling process. For the SPOT image, the main confusion in modelling was between settlements and barren classes, barren with settlements, forest and Vachellia classes and Vachellia and forest classes. For the Sentinel image, the main confusion in modelling was between Vachellia and forest classes.

For the simulated 2033 map, the Kappa value was 0.98 using the ANN method with overall accuracy of –0.00385, and a minimum validation overall error of 0.00443. When the simulated map was validated with the 2023 classified image, the Kappa value was 0.90, with a 93.4% correctness, 0.94 Kappa (histo) and 0.96 Kappa (loc).

Table 1. Area change for the classified features between 2013 and 2023

Classified feature	Change (2013-2023)	Area change (sq km)	Change - Vachellia
Barren	Barren - Barren	18.7	-
	Barren - Forest	1.81	-
	Barren - Settlements	4.15	-
	Barren - Vachellia	28.74	+28.74
	Barren - Water body	0.07	-
Forest	Forest - Barren	3.66	-
	Forest - Forest	7.7	-
	Forest - Settlements	1.5	-
	Forest - Vachellia	4.3	+4.3
	Forest - Water body	0.01	-
Settlements	Settlements - Barren	7.88	-
	Settlements - Forest	2.38	-
	Settlements - Settlements	4.31	-
	Settlements - Vachellia	3.39	+3.39
	Settlements - Water body	0.07	-
Vachellia	Vachellia - Barren	2.46	-2.46
	Vachellia - Forest	4.44	-4.44
	Vachellia - Settlements	2.44	-2.44
	Vachellia - Vachellia	15.36	0
	Vachellia - Water body	0.01	-0.01
Water body	Water body - Barren	0.18	-
	Water body - Forest	0.01	-
	Water body - Settlements	0.07	-
	Water body - Vachellia	0.01	0.01
	Water body - Water body	0.02	-
	Total	113.67	27.09

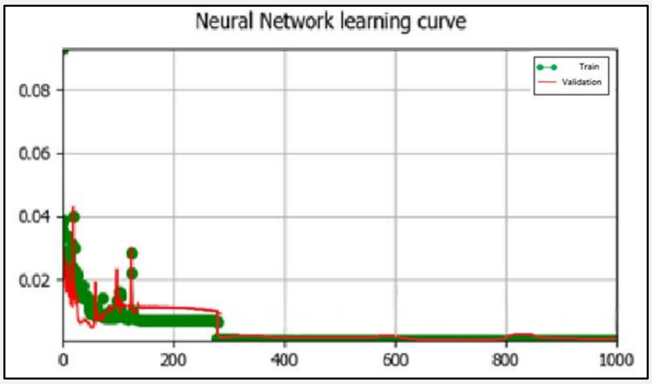

Figure 4. Neural network learning curve based on the ANN-MPL simulation.

Table 2. Accuracy assessment of the Sentinel and SPOT image based on the confusion matrix

SPOT-5 Image, 2013								
Class	W	S	B	F	V	Total	U_Accuracy	Kappa
Water	5	0	0	0	0	5	1	0
Settlements	0	18	4	1	1	24	0.75	0
Barren	0	4	257	4	4	269	0.732	0
Forest	2	0	3	93	8	106	0.877	0
V. nilotica	0	3	3	18	80	104	0.769	0
Total	7	25	267	116	93	508	0	0
P_Accuracy	0.714	0.72	0.962	0.802	0.860	0	0.892	0
Kappa	0	0	0	0	0	0	0	0.829
Sentinel 2A Image, 2023								
Class	W	S	B	F	V	Total	U_Accuracy	Kappa
Water	2	0	0	0	0	2	1	0
Settlements	0	35	4	0	0	39	0.897	0
Barren	0	18	215	3	6	242	0.888	0
Forest	0	0	1	66	8	75	0.88	0
V. nilotica	0	2	4	28	118	152	0.776	0
Total	2	55	224	97	132	510	0	0
P_Accuracy	1	0.636	0.959	0.680	0.894	0	0.855	0
Kappa	0	0	0	0	0	0	0	0.786

W: Water; S: Settlements; B: Barren; F: Forest; V: V. nilotica

The Efficacy of Remote Sensing to Identify and Map *Vachellia nilotica* in Rodrigues

The risks posed by invasive alien species have spatial and temporal contexts as it is unreasonable to assume an IAS will be present in all places at all times (Venette, 2015). In this regard, remote sensing techniques have proved to be successful in mapping invasive alien plant species due to: a) contrasting phenology of IAS compared to native species; b) distinct physiological, biochemical and structural traits of IAS from native species; and c) prevalence of known IAS in the study area (Gholizadeh et al., 2022). Phenology based approaches are founded on remotely sensed data where IAS are spectrally distinct from surrounding native species. As a case in point, the flowering season of Vachellia, usually from June to September, creates a distinct spectral signature on remotely sensed images making identification and separation from other species easy. This is exemplified in the study of Paz-Kagan et al. (2019) who took advantage of the phenological flowering stages of invasive Acacia trees observable on hyperspectral imaging and multispectral earth observation data to map their distribution in the coastal plain of Israel. Nonetheless, it is important to note that phenology-based approaches require distinct phenology of the target IAS from the surrounding native components and the availability of fine imagery for observations (Gholizadeh et al., 2022). Spectral responses of plants are also affected by their physiological, biochemical and structural traits making them distinguishable from other canopies and features on remote sensed images. For example, Masemola et al. (2020) exploited the canopy chlorophyll content, nitrogen concentrations and leaf area index of invasive Australian Acacia species in South Africa to map their spatial distribution and severity of invasion using Sentinel-2-time series images. Spectral identification of this nature is critical in canopies where native species have similar phenologies, but the success of this approach depends largely on the availability of hyperspectral data with fine resolution to identify plant physiology and biochemistry remotely (Gholizadeh et al., 2022). Ultimately, IAS detection on remote sensed images is dependent upon their spatial abundance within a region or whether they form homogeneous patches large enough to match the spatial resolution of the images (Gholizadeh et al., 2022).

This study was feasible because of this characteristic of Vachellia in Rodrigues where the species has been established for a long time and formed monotypic stands across the western, and south eastern coasts. While fine resolution images in the range of 2.5-5m are ideal (but quite expensive and not always available cloudy-free as tropical areas are generally very cloudy) to pick up the spectral signature of individual species in small areas such as nature parks or specific locations, the 10m resolution images used proved to be effective in grasping the spatial distribution of Vachellia over the large scale of the whole island. Monotypic stands were distinctly visible on both Sentinel-2A and SPOT-5 images translating into effective classified classes with the RF classifier. Likewise, extraction of vegetation indices (NDVI, EVI, GNDVI and ReNDVI) and spectral features (PCAs mean, entropy, energy and homogeneity) from the images refined the maps to the extent that the spectral signature of Vachellia became distinguishable from the surrounding alien and native species. Model confusion as reflected in the confusion matrix arose mainly from settlements and barren classes due to their almost similar spectral signature and between Vachellia stands and forests as the spectral signature tends to converge because of elevation. While Kappa values generally show good agreement, the accuracy of the maps can be increased by reclassifying the different classes to the appropriate ones, a time-consuming process, and running the model until a better accuracy level is reached. It is interesting to note that when the feature mask is applied, Vachellia becomes distinguishable in forested canopies suggesting the accuracy of the training data used for Vachellia. The results obtained in this study are in line with visual observations from Google Earth and a forestry map created by CIRAD using SPOT-6 imagery, 2013 (CIRAD, 2019).

Simulated Projected Extent with MOLUSCE

Managing Vachellia invasion appropriately in Rodrigues can benefit from knowledge on the future potential coverage of the tree. Prediction in itself is a controversial topic in ecology with many ecologists arguing that the quality of ecological predictions is too low or not accurate sufficiently often and suggesting how predictions can be improved to yield better results (Elliott-Graves, 2019). To be sure, making predictions about how any system will behave over time and when exposed to different environmental variables is difficult. However, there is a demand for predictive studies so as to understand the possible impacts of phenomena such as IAS, climate change, habitat fragmentation, etc.

MOLUSCE has been widely used to analyse spatio-temporal land cover change and predict future patterns for e.g. Muhammad et al. (2022), Abbas et al. (2021), Kamaraj & Rangarajan (2022) with Sajan et al. (2022) even classifying lychee as a separate class in a land use study in India. The ANN-CA algorithms embedded in the MOLUSCE plugin are powerful tools to analyse spatio-temporal data and make future predictions. The validation process uses a reference dataset that compares the validity of the change map to the reference data, which in this case yielded a very high Kappa value. MOLUSCE's strength is based on Tobler's First Law which refers to the importance of distance in geography as the most important variable that governs the influence of one entity relative to another. By analysing the relative distance of raster cells to each other within the 10-year scale in the present study, the CA model is able to predict the future spatial extent of these cells relative to each other in another 10-year period (2033). Variables such as distance to rivers and roads can be used as additional variables to refine the simulation process (Hudjimartsu et al., 2017) and analyse their correlation with future trends of Vachellia but since Rodrigues is quite small with few roads and no major rivers, only DSM, which is assumed to undergo minor changes by 2033, was used as spatial variable in the study.

The Need for Risk Maps

Spatio-temporal maps as presently produced reflect the spatial and temporal extent of IAS within an area of concern and reflect the underlying models of factors that characterise the course of invasion and its potential impacts on the structure and function of ecosystems (Venette et al., 2010). These authors further point out that risk maps can be powerful tools to help managers and stakeholders effectively manage and mitigate invasion risks and/or inspire critical thought as to the results of data, models and theory related to invasions. For instance, Hudjimartsu et al. (2017) used a Generalized Linear Model (GLM) to model the distribution of Vachellia in Baluran National Park, Indonesia, where invasions could potentially disrupt the savannah ecosystem with ripple effects on food chains. With the looming threat of climate change on IAS distribution including Vachellia, it is expected that these species will colonize new environments putting natural, societal and economic systems at risk. By using SDMs with climatic data, future predictions of the potential spread of species can be conducted such as the work by Sutomo & van Etten (2017) that modelled the potential future spread of Vachellia across the tropical environment of Indonesia under current and future climate conditions for policy makers to consider best practices to handle invasions.

Implications of findings

GIS, coupled to remote sensing techniques, have proved to be effective tools to monitor plant community change, whether it be native or invasive. But in the context of island ecosystems, the present methodology and results have very important implications. Island nations generally lack the financial resources associated with high resolution satellite images (such as 50cm resolution imagery for more accurate analysis) and modeling software, ecological modeling knowledge and human expertise to conduct such works. The present methodology thus filled in this gap by using medium resolution images and GIS software that is licensed to research bodies with QGIS being open source. GIS provides a userfriendly interface with snippets on the use of different tools and algorithms at each stage of the classification and simulation process. It does not require coding knowledge but instead provides tools that are already embedded with machine learning algorithms. By combining different machine learning techniques like RF for classification and ANN-MPL and CA for projected simulations, the ensemble model utilized in this study produced promising results for analysing the spatio-temporal distribution of Vachellia, which can also be substituted for other target species. For instance, the same methodology can be applied to monitor mangroves, rare species, riparian vegetation or roadside species over different time scales. One of the greatest challenges that islands face is the lack of historical data as baseline and for comparison purposes. With such maps, baselines can be created and used to enhance future studies on the spatio-temporal distribution of target species not only island wise but to larger extents as well. With rising human population and international trade, environmental change is inevitable, especially in the introduction and spread of IAS globally with unfortunate repercussions on local communities and associated ecosystem functioning. Thus, it is crucial to improve biodiversity change detection so as to create more effective policies to better manage species and communities and help advance conservation strategies (Pinto-Ledezma & Cavender-Bares, 2020). Such data can be used by local governments, organizations and research bodies to enhance ecological studies while spatial distribution maps can be crucial tools to inform the general public of local threats such as the thorny Vachellia and thus support community participation in managing Vachellia.

In the broader context, the present study adds to the ongoing research in biogeography and conservation management. As the number of invasions increase globally due to increased travel and climate change, many countries are moving towards more holistic approaches to improve conservation strategies (Tamburello & Litt, 2023). Given the elevated costs associated with IAS control and management as well as the limited feasibility of such activities, large scale coordination is key to managing invasions and preventing large scale ecological disruption (Couch et al., 2023). Species mapping and future prediction as carried out in this study support early detection of IAS in all types of environments thus enabling rapid response actions; detailed maps further facilitate more efficient and effective control measures and prioritize conservation areas for native species. Eppinga et al. (2023) further state that such types of maps can then serve as basis to understand pathways of invasion and even model invasive spread taking into consideration different climate change regimes to support climate change adaptation plans.

Study Limitations and Future Research

This study was mainly limited by the lack of ground truth data for Vachellia for both the present and 2013. Future studies should incorporate more ground truth data to validate and enhance the accuracy of the classification process possibly with the cooperation of other researchers.

Classification was based mainly on expert knowledge and visual interpretation using Google Earth Pro. Also, Sentinel 2A images were not available for the period 2013 which was why SPOT-5 imagery was chosen for the analysis. It should be noted that though both Sentinel and SPOT images were resampled to 10m resolution, re-projected to the same coordinate system and analysed in the same manner, the difference in band composition between these two images could have introduced errors in classifications. Thus, future studies could look into additional spectral indices or image processing techniques to improve the distinction between similar spectral signatures. While it is common to run a model 10 times to increase model performance, a better Kappa value and hence better classification could have been made if more attempts had been made to train the model. Similarly, MOLUSCE allows for validation of data using a reference dataset which generally is another classified map produced within the study period (2017/2018 in this case). Due to the lack of ground data and map maker availability time, the 2023 map was used to test the validity of the simulation output. The number of training iterations for the model can be increased in future studies to make the results more accurate and a separate, accurately classified map for validation purposes can be used to test the model's predictions more effectively.

Another important error that arose during the classification process was the similar spectral signature of different classes especially barren with settlements and forests with Vachellia. From an ecological standpoint, it would be better to have feature classes related to tree species within the area instead of land cover classes as used in the present study. It is thus suggested for future research to include more feature classes in order to better segregate spectral details in different classes. In the same way, it is advised to prepare another classified map within the study period for use as reference dataset when using MOLUSCE. Support Vector Machine (SVM) classifier is also a powerful classifier used in supervised learning models for classification and quite effective in high dimensions for small and complex datasets. It would be worth analysing model performance using SVM or carry out a comparison analysis between different classifiers such as the work by Koerner et al. (2022). This could also help in determining the most effective method for such studies. The study also did not take into consideration spatial variables that could affect Vachellia distributions such as temperature and water availability from rivers. It would be beneficial for management purposes to examine the relationship between these different variables and Vachellia cover both in the present and future conditions as well as understand the factors driving their spread.

CONCLUSION

Biological invasions are now a looming threat to the world's biodiversity that has pushed several species to extinction in the past, a scenario which is expected to worsen in the future. Consequently, it is crucial to find innovative ways to manage such invasions especially on tropical islands which are ecologically fragile with limited resources to manage and control IAS. The present study thus used GIS coupled to remotely sensed data to analyse the spatio-temporal distribution of *Vachellia nilotica*, a highly invasive species on Rodrigues Island. Freely available MSI Sentinel 2A and SPOT-5 images were used for the analysis. Through four vegetation indices and spectral feature extraction, composite maps of both Sentinel and SPOT were classified using the RF classifier which yielded an accuracy level of 0.78 for Sentinel 2A and 0.82 for SPOT-5. Five classes were selected for the classification exercise and the datasets were split into 70% training and 30% testing data. Because of the distinct spectral signature of Vachellia mainly due to its monotypic stands, separability with other classes was straightforward to the extent of being distinguishable even within forested areas when feature masks were applied. To further investigate on the potential future distribution of Vachellia, the MOLUSCE plugin was used to simulate future trends for 2033 based on an ANN-CA model and validated against the Sentinel 2A map with an accuracy level of 0.98.

The analysis was conducted using GIS tools, which are founded on machine learning algorithms, from pre-processing to future projection thus demonstrating the efficiency of GIS in modeling species distribution at both present and future levels. This study demonstrates the potential for low-cost, practical, accurate, and repeatable IAS distribution measurements over time, thus providing consistent monitoring records to support management. However, one of the most important limitations of the study was the lack of ground truth samples to train and validate the model. While the aim of the study was to pilot test the use freely available satellite images and GIS to map IAS island wise, future studies must ensure a large enough ground truth sample to refine the results. Such outputs are key in informing management strategies to control an IAS like Vachellia in island ecosystems such as Rodrigues and support conservation actions, policies and even in engaging community participation. Likewise, for better results, the same types of satellite images can be used to decrease classification errors and other classification techniques such as SVM can be used for comparative purposes.

In the broader context, such spatio-temporal maps enhance IAS management, helping to prioritize conservation actions and divert resources more effectively. Vachellia in Rodrigues is an example of an invasive plant which stands out spectrally from its surroundings. The methodology applied in this study can be used to model and predict the spatial distribution of other plant species such as native species, rare species, mangroves, etc. as a trend interpolation approach. By adding more data to the analysis such as rivers, temperature etc. the spatial relationship between different variables can be analysed and modeled.

Funding

This work was supported by the Global Environment Facility (GEF) Trust Fund through the United Nations Development Programme (UNDP) - GEF Project ID 9553.

Disclosure Statement

The authors report there are no competing interests to declare.

Data Availability

The satellite images used in this study are open access: SPOT-5 images can be downloaded through the CNES portal at https://regards.cnes.fr/user/swh/modules/60 and Sentinel 2A images can be downloaded through the ESA portal at https://sentinels.copernicus.eu/ . The software used to carry out the study are detailed throughout the manuscript. All GPS coordinates of Vachellia collected for this study can be made available upon request.

REFERENCES

Abbas, Z., Yang, G., Zhong, Y., & Zhao, Y. (2021). Spatiotemporal Change Analysis and Future Scenario of LULC using the CA-ANN Approach: A Case Study of the Greater Bay Area, China. *Land, 10*(6), 584. https://doi.org/10.3390/land10060584

Baider, C., Florens, F. V., Baret, S., Beaver, K., Matatiken, D., Strasberg, D., & Kueffer, C. (2010). Status of Plant Conservation in Oceanic Islands of the Western Indian Ocean. In *Proceedings of the 4th global botanic gardens congress* (Vol. 2, pp. 1-7). Dublin: National Botanic Gardens of Ireland. [pdf] Retrieved from https://www.researchgate.net/publication/252932769 [Accessed 19 March 2023]

Barlow, J., França, F., Gardner, T. A., Hicks, C. C., Lennox, G. D., Berenguer, E., Castello, L., Economo, E. P., Ferreira, J., Guénard, B., Leal, C. G., Isaac V., Lees, A. C., Paar, C. L., Wilson, S. K., Young, P. J., & Graham N. A. (2018). The Future of Hyperdiverse Tropical Ecosystems. *Nature, 559*(7715), 517-526. https://doi.org/10.1038/s41586-018-0301-1

Bolch, E. A., Santos, M. J., Ade, C., Khanna, S., Basinger, N. T., Reader, M. O., & Hestir, E. L. (2020). Remote Detection of Invasive Alien Species. In Jeannine Cavender-Bares, John A. Gamon, & Philip A. Townsend (Eds.), *Remote Sensing of Plant Biodiversity* (pp. 267-307). Springer Link. https://doi.org/10.1007/978-3-030-33157-3

CABI. (2022). *Acacia nilotica (Gum Arabic Tree).* [Online] Available from https://www.cabidigitallibrary.org/-doi/10.1079/cabicompendium.2342 [Accessed 14 May 2023]

Carter, J. (1994). Acacia nilotica: A Tree Legume Out of Control. In Gutteridge, R., & Shelton, H., (Eds.), *Forage tree legumes in tropical agriculture* (pp. 338-351). Wallingford: CAB INTERNATIONAL. ISBN : 9780851988689

Cho, S. M. (2021). Classification of Warm Temperate Vegetations and GIS-based Forest Management System. *International journal of advanced smart convergence, 10*(1), 216-224. https://doi.org/10.7236/IJASC.2021.10.1.216

Chong, K. Y., Corlett, R. T., Nuñez, M. A., Chiu, J. H., Courchamp, F., Dawson, W., Kuebbing, S., Liebhold, A. M., Padmanaba, M., Souza, L., & Andersen, K. M. (2021). Are Terrestrial Biological Invasions Different in the Tropics?. *Annual Review of Ecology, Evolution, and Systematics, 52*, 291-314. https://doi.org/10.1146/annurev-ecolsys-012021-095454

CIRAD. (2019). *Preliminary Study of The Conditions For The Creation Of An Energy Valorization (Bioelectricity) Sector For Woody Biomass In Two IOC Member States: Mauritius (Rodrigues) And Seychelles (La Digue).* Provisional Report, Ref. COI/ENERGIE/SERV/2018/046.

CNES. (2023). *SWH Data Site.* [online] Available from https://regards.cnes.fr/user/swh/modules/60 [Accessed 06 June 2023]

Congalton, R. G. (1991). A Review of Assessing The Accuracy Of Classifications Of Remotely Sensed Data. *Remote Sensing of Environment, 37*(1), 35-46. https://doi.org/10.1016/0034-4257(91)90048-B

Couch, C. E., Peterson, J. T., & Heimowitz, P. (2023). Evaluating the Institutional and Ecological Effects of Invasive Species Prevention Policy: A Case Study from the US Fish and Wildlife Service. *Management of Biological Invasions, 14*(2), 269-288. https://doi.org/10.3391/mbi.2023.14.2.06

Dube, T., Maluleke, X. G., & Mutanga, O. (2022). Mapping Rangeland Ecosystems Vulnerability to Lantana camara Invasion in Semi-arid Savannahs in South Africa. *African Journal of Ecology, 60*(3), 658-667. https://doi.org/10.1111/aje.12951

Dvoreckiy, T. V., Trylis, V. V., & Savytskyy, O. L. (2022). Evaluation of Mass Development of The Invasive Plant Pistia Stratiotes in The Water Bodies of The Left-Bank Flood Plain of The Dnieper River Nearby Kyiv on The Basis of Satellite Data. *Hydrobiological Journal, 58*(4), 18-29. https://doi/10.1615/HydrobJ.v58.i4.20

Elliott-Graves, A. (2019). The Future of Predictive Ecology. *Philosophical Topics, 47*(1), 65-82. https://www.jstor.org/stable/26948092

Eppinga, M. B., Baudena, M., Haber, E. A., Rietkerk, M., Wassen, M. J., & Santos, M. J. (2021). Spatially Explicit Removal Strategies Increase The Efficiency of Invasive Plant Species Control. *Ecological Applications, 31*(3), e02257. https://doi.org/10.1002%2Feap.2257

ESRI. (2018). *Is the Random Trees Classifier equal to Random Forest?* [online] Available at https://community.esri.com/t5/arcgis-spatial-analyst-questions/is-the-random-trees-classifier-equal-to-random/m-p/385927?search-action-id=100522784797&search-result-uid=385927 [Accessed 24 April 2023]

Estornell, J., Martí-Gavilá, J. M., Sebastiá, M. T., & Mengual, J. (2013). Principal Component Analysis Applied to Remote Sensing. *Modelling in Science Education and Learning, 6*, 83-89. https://doi.org/10.4995/msel.2013.1905

Florens, F. B. V. (2008). *Ecologie des forêts tropicales de l ' île Maurice et impact des espèces introduites envahissantes* (*PhD thesis*). Université de La Réunion, Réunion, France.

Florens, F. V. (2013). Conservation in Mauritius and Rodrigues: Challenges and Achievements from Two Ecologically Devastated Oceanic Islands. In Peter H. Raven, Navjot S. Sodhi, Luke Gibson (Eds.), *Conservation Biology: Voices from the Tropics* (pp. 40-50). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118679838.ch6

Gentili, R., Schaffner, U., Martinoli, A., & Citterio, S. (2021). Invasive Alien Species and Biodiversity: Impacts and Management. *Biodiversity, 22*(1-2), 1-3. https://doi.org/10.1080/14888386.2021.1929484

Gitelson, A. A., Kaufman, Y. J., & Merzlyak, M. N. (1996). Use of A Green Channel in Remote Sensing of Global Vegetation from EOS-MODIS. *Remote sensing of Environment, 58*(3), 289-298. https://doi.org/10.1016/S0034-4257(96)00072-7

Gitelson, A. A., & Merzlyak, M. N. (1994). Spectral Reflectance Changes Associated with Autumn *Senescence of Aesculus hippocastanum* L. and *Acer platanoides* L. Leaves. Spectral Features and Relation to Chlorophyll Estimation. *Journal of plant physiology, 143*(3), 286-292. https://doi.org/10.1016/S0176-1617(11)81633-0

Gholamy, A., Kreinovich, V., & Kosheleva, O. (2018). *Why 70/30 or 80/20 Relation Between Training and Testing Sets: A Pedagogical Explanation.* https://scholarworks.utep.edu/cs_techrep/1209/

Gholizadeh, H., Friedman, M.S., McMillan, N. A., Hammond, W. M., Hassani, K., Sams, A.V., Charles, M. D., Garrett, D. R., Joshi, O., Hamilton, R. G., & Fuhlendorf, S. D. (2022). Mapping Invasive Alien Species in Grassland Ecosystems Using Airborne Imaging Spectroscopy and Remotely Observable Vegetation Functional Traits. *Remote Sensing of Environment, 271*, 112887. https://doi.org/10.1016/j.rse.2022.112887

Haralick, R. M., Shanmugam, K., & Dinstein, I. H. (1973). Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics, 3*(6), 610-621. https://doi.org/10.1109/TSMC.1973.4309314

Hudjimartsu, S. A., Herdiyeni, Y., Prasetyo, L. B., & Siswoyo, A. (2017). Prediction of the Spread of Acacia nilotica Invasive Species Using Generalized Linear Models. *Jurnal Manajemen Hutan Tropika, 23*(3), 150-157.

Humeau-Heurtier, A. (2019). Texture Feature Extraction Methods: A Survey. *IEEE Access, 7*, 8975-9000. https://doi.org/10.1109/ACCESS.2018.2890743

Kamaraj, M., & Rangarajan, S. (2022). Predicting the Future Land Use and Land Cover Changes for Bhavani Basin, Tamil Nadu, India, using QGIS MOLUSCE Plugin. *Environmental Science and Pollution Research, 29*, 86337–86348. https://doi.org/10.1007/s11356-021-17904-6

Kayet, N., Pathak, K., Chakrabarty, A., Kumar, S., Chowdary, V. M., & Singh, C. P. (2022). Risk Assessment and Prediction of Forest Health for Effective Geo-environmental Planning and Monitoring of Mining Affected Forest Area in Hilltop Region. *Geocarto International, 37*(11), 3091-3115. https://doi.org/10.1080/10106049.2020.1849413

Koerner, L. M., Chadwick, M. A., & Tebbs, E. J. (2022). Mapping Invasive Strawberry Guava (Psidium cattleianum) in Tropical Forests of Mauritius with Sentinel-2 and Machine Learning. *International Journal of Remote Sensing, 43*(3), 841-872. https://doi.org/10.1080/01431161.2021.2020364

Kueffer, C., & Mauremootoo, J. (2004). Case Studies on the Status of Invasive Woody Plant Species in the Western Indian Ocean. 3 Mauritius (Islands of Mauritius and Rodrigues). *Forest Health and Biosecurity Working Paper, (4-3E).* Record Number : 20123338431

Landis, J. R., & Koch, G. G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biometrics, 33*(1), 159–174. https://doi.org/10.2307/2529310

Lasaponara, R. (2006). On the Use of Principal Component Analysis (PCA) for Evaluating Interannual Vegetation Anomalies from SPOT/VEGETATION NDVI Temporal Series. *Ecological Modelling, 194*(4), 429-434. https://doi.org/10.1016/j.ecolmodel.2005.10.035

Liu, H.Q., & Huete, A. (1995). A Feedback Based Modification of the NDVI to Minimize Canopy Background and Atmospheric Noise. *IEEE Transactions on Geoscience and Remote Sensing, 33*(2), 457-465. https://doi.org/10.1109/TGRS.1995.8746027

Lourenço, P., Teodoro, A. C., Gonçalves, J. A., Honrado, J. P., Cunha, M., & Sillero, N. (2021). Assessing the Performance of Different OBIA Software Approaches for Mapping Invasive Alien Plants along Roads with Remote Sensing Data. *International Journal of Applied Earth Observation and Geoinformation, 95*, 102263. https://doi.org/10.1016/j.jag.2020.102263

Masemola, C., Cho, M.A., & Ramoelo, A. (2020). Sentinel-2 Time Series Based Optimal Features and Time Window for Mapping Invasive Australian Native Acacia Species in KwaZulu Natal, South Africa. *International Journal of Applied Earth Observation and Geoinformation, 93*, 102207. https://doi.org/10.1016/j.jag.2020.102207

Masters, G., & Norgrove, L. (2010). Climate change and invasive alien species. *UK: CABI Working Paper, 1*, 30.

Mazumder, S., Saha, J., Nandi, G., Naskar, M., Gayen, J., & Datta, D. (2021). Long-term Monitoring of Cropland Transformation in Kolkata Metropolitan Area, India Using Open-source Geospatial Technologies. *SN Applied Sciences, 3*(98), 1-19. https://doi.org/10.1007/s42452-020-04064-4

Muhammad, R., Zhang, W., Abbas, Z., Guo, F., & Gwiazdzinski, L. (2022). Spatiotemporal Change Analysis and Prediction of Future Land Use and Land Cover Changes using QGIS MOLUSCE Plugin and Remote Sensing Big Data: A Case Study of Linyi, China. *Land, 11*(3), 419. https://doi.org/10.3390/land11030419

Murata, N., Yoshizawa, S., & Amari, S. I. (1992). Learning Curves, Model Selection and Complexity of Neural Networks. *Advances in Neural Information Processing Systems, 5.* [pdf] Retrieved from https://proceedings.neurips.cc/paper/1992/hash/b2f627fff19fda463cb386442eac2b3d-Abstract.html [Accessed 19 March 2023]

NextGIS, & AAS. (2014). *Landscape Change Analysis with MOLUSCE - Methods and Algorithms.* GISLAB. [online] Available from https://wiki.gis-lab.info/w/Landscape_change_analysis_with_MOLUSCE_-_methods_and_algorithms [Accessed 07 June 2023]

Ouko, E., Omondi, S., Mugo, R., Wahome, A., Kasera, K., Nkurunziza, E., Kiema, J., Flores, A., Adams, E. C., Kuraru, S., & Wambua, M. (2020). Modeling Invasive Plant Species in Kenya's Northern Rangelands. *Frontiers in Environmental Science, 8*, 69. https://doi.org/10.3389/fenvs.2020.00069
Park, Y. S., & Lek, S. (2016). Artificial Neural Networks: Multilayer Perceptron for Ecological Modeling. In *Developments in environmental modelling* (Vol. 28, pp. 123-140). Elsevier. https://doi.org/10.1016/B978-0-444-63623-2.00007-4
Paz-Kagan, T., Silver, M., Panov, N, & Karnieli, A. (2019). Multispectral Approach for Identifying Invasive Plant Species Based on Flowering Phenology Characteristics. *Remote Sensing, 11*(8), 953. https://doi.org/10.3390/rs11080953
Pinto-Ledezma, J. N., & Cavender-Bares, J. (2020). Using Remote Sensing for Modeling and Monitoring Species Distributions. In Jeannine Cavender-Bares, John A. Gamon, & Philip A. Townsend (Eds.), *Remote Sensing of Plant Biodiversity* (pp. 199-223). Springer Link. https://doi.org/10.1007/978-3-030-33157-3
Richards, J. A., & Jia, X. (2006). Multisource, Multisensor Methods. In John A. Richards & Xiuping Jia (Eds.), *Remote Sensing Digital Image Analysis: An Introduction* (pp. 333-357). Springer Link. https://doi.org/10.1007/3-540-29711-1_12
Sajan, B., Mishra, V. N., Kanga, S., Meraj, G., Singh, S. K., & Kumar, P. (2022). Cellular Automata-Based Artificial Neural Network Model for Assessing Past, Present, and Future Land Use/Land Cover Dynamics. *Agronomy, 12*(11), 2772. https://doi.org/10.3390/agronomy12112772
Seebens, H., Bacher, S., Blackburn, T. M., Capinha, C., Dawson, W., Dullinger, S., Genovesi, P., Hulme, P. E., van Kleunen, M., Kühn, I., & Jeschke, J. M. (2021). Projecting the Continental Accumulation of Alien Species Through to 2050. *Global Change Biology, 27*(5), 970-982. https://doi.org/10.1111/gcb.15333
Silvestre, V. Q., Dillon, M. O., Zevallos, Í. T., Aguilar, M. B., Rios, A. M., Aranibar, D. R., Vera, K. D., & Tubée, D. M. (2019). Impact of Climate Changes and Land Use in the Distribution of Species of Endemic Genera of Asteraceae from Arequipa. *Arnaldoa, 26*(1), 71-96. https://doi.org/10.22497/arnaldoa.261.26105
Sims, D. A., & Gamon, J. A. (2002). Relationships Between Leaf Pigment Content and Spectral Reflectance Across a Wide Range of Species, Leaf Structures and Developmental Stages. *Remote Sensing of Environment, 81*(2-3), 337-354. https://doi.org/10.1016/S0034-4257(02)00010-X
Strahm, W. A. (1993). The Conservation and Restoration of the Flora of Mauritius and Rodrigues. (*PhD Thesis*). University of Reading, Reading.
Sutomo, S., & van Etten, E. (2017). Species Distribution Model of Invasive Alien Species Acacia nilotica for Central-Eastern Indonesia Using Biodiversity Climate Change Virtual Laboratory (BCCVL). *Tropical Drylands, 1*(1), 36-42. https://doi.org/10.13057/tropdrylands/t010106
Tamburello, N., & Litt, M. A. (2023). Multiple impacts of invasive species on species at risk: a case study in British Columbia, Canada. *FACETS, 8*, 1-13. https://doi.org/10.1139/facets-2022-0234
Timmermans, J., & Kissling, W. D. (2022). *Advancing Terrestrial Biodiversity Monitoring with Satellite Remote Sensing in the Context of the Kunming-Montreal Global Biodiversity Framework*. bioRxiv, 2022–04 [online]. Available from https://www.biorxiv.org/content/10.1101/2022.04.25.489356v2 [Accessed 9 August 2023].
Venette, R. C. (2015). The Challenge of Modelling and Mapping the Future Distribution and Impact of Invasive Alien Species. In *Pest Risk Modelling and Mapping for Invasive Alien Species* (pp. 1-17). Wallingford UK: CABI.
Venette, R. C., Kriticos, D. J., Magarey, R. D., Koch, F. H., Baker, R. H. A., Worner, S. P., Raboteaux, N. N. G., Mckenney, D. W., Dobesberger, E. J., Yemshanov, D., De Barro, P. J., Hutchison, W. D., Fowler, G., Kalaris, T. M., & Pedlar, J. (2010). Pest Risk Maps for Invasive Alien Species: A Roadmap for Improvement. *Bioscience, 60*(5), 349362. https://doi.org/10.1525/bio.2010.60.5.5
Villero, D., Pla, M., Camps, D., Ruiz-Olmo, J., & Brotons, L. (2017). Integrating Species Distribution Modelling into Decision-making to Inform Conservation Actions. *Biodiversity and Conservation, 26*(2), 251–271. https://doi.org/10.1007/s10531-016-1243-2
Wiegleb, G. (1980). Some Applications of Principal Components Analysis in Vegetation: Ecological Research of Aquatic Communities. In *Classification and Ordination: Symposium on Advances in Vegetation Science, Nijmegen, The Netherlands, May 1979* (pp. 67-73). Springer Netherlands. https://doi.org/10.1007/978-94-009-9197-2
Wolfram, S. (2002). *A new kind of science* (Vol. 5, p. 130). Champaign: Wolfram media.
Xu, C., Manley, B., & Ye, N. (2023). Mapping Minor Plantation Species for New Zealand's Small-scale Forests using Sentinel-2 Satellite Data. *New Zealand Journal of Forestry Science, 53*(12), 1-22. https://doi.org/10.33494/nzjfs532023x314x
Xue, J., & Su, B. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of sensors, 2017*. https://doi.org/10.1155/2017/1353691