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Habitat Categorization and Vegetation Mapping of Kumana National Park, Sri Lanka

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ABSTRACT

Remote sensing constitutes a broad and influential discipline that has assumed a significant role in vegetation mapping on a global scale in recent years. The availability of an accurate vegetation map assists future ecological studies and the management of protected areas. This study was conducted to identify and map the available habitats in Kumana National Park (KNP), Sri Lanka. We utilized multiple environmental covariates obtained via field surveys and remote sensing techniques for the initial categorization of habitats based on principal component analysis. Vegetation maps for KNP were generated by applying multiple classification algorithms to Sentinel 2 multispectral satellite imagery. The maximum likelihood classification (MLC) model generated the most accurate and detailed vegetation map for KNP, which was verified with ground truth data (overall accuracy of 93%; Kappa, 87%). The study's findings furnish precise insights into the vegetation cover of KNP, thereby augmenting knowledge on the spatial distribution of habitats to support the future work of researchers and park managers. This map offers significantly improved resolution and spatial detail compared to previous maps. It also increased the number of identified habitat types from four to six. These findings can be used to identify critical areas for both terrestrial and aquatic fauna within KNP and support habitat conservation and management strategies in the park.

1. INTRODUCTION

Vegetation is an attribute that describes the land use on Earth (Roy et al., 2015). Remote sensing has been important in vegetation mapping for the past few decades (Langley et al., 2001; Raynolds et al., 2019; Schindler et al., 2021; Mucsi and Bui, 2023). Past studies have been conducted to evaluate National Park vegetation to assess the land cover (Brown de Colstoun et al., 2003; Jiménez and Díaz-Delgado, 2015; Martinez del Castillo et al., 2015; Urban et al., 2018). These vegetation maps categorize the different types of vegetation that play a vital role in managing natural resources (Xiao et al., 2004), evaluating land use changes and management (Beuchle et al., 2015) and contributing to the conservation measures by generating remote sensed vegetation maps (Rose et al., 2015). The main goal of vegetation categorization is to group plant communities assumed to be similar, making it easier to describe the vegetation patterns in a particular geographic area. Traditional methods such as field surveys, literature studies, map interpretation, and collateral and supplementary data analysis are ineffective for acquiring vegetation cover when compared to novel remote sensing techniques due to the long-time consumption and frequently high cost (Xie et al., 2008). Moreover, the development and availability of various land use classification algorithms and models have made remote sensing techniques more versatile in this aspect (Otukei and Blaschke, 2010; Rodriguez-Galiano et al., 2012; Lyons et al., 2018; Mercier et al., 2019).

Remote sensing-based vegetation classification can be identified as the most effective method for generating habitat maps for larger protected areas where ground access is often restricted. There are several remote sensing approaches initiated for habitat

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mapping in Sri Lanka (Dahdouh-Guebas et al., 2000; Nandasena et al., 2023), and this technology has been utilized for forest management and monitoring since (Jewell and Legg, 1993). However, only a handful of studies are available where in-depth analyses have been conducted regarding the vegetation classification and habitat mapping using remote sensing methods restricted to several protected areas, such as Wilpattu (Sandamali and Welikanna, 2018), Maduru Oya (Jayasekara et al., 2021), Horton Plains (Jayasekara et al., 2021) and Udawalawe (Perera et al., 2021) governed by the Department of Wildlife and Conservation (DWC) Sri Lanka. Furthermore, we have observed a lack of remote sensing tools utilization for identifying the types of vegetation in national parks located in the eastern and southern regions due to the unavailability of ground-truth observed data for verification. While Jayasekara et al. (2021) have comprehensively illustrated a vegetation map for Maduru Oya, a dry zone national park located near the border of eastern and Uva provinces we observed that detailed vegetation/habitat maps are not available for the national parks located in eastern and southern regions of the island. This motivated us to map the vegetation in Kumana National Park (KNP) located in the south-eastern dry zone of Sri Lanka utilizing remote sensing techniques.

Kumana National Park is a protected area under the Department of Wildlife Conservation and is ranked sixth in terms of park area. Previously, Kasige et al. (2020) have identified several habitat types (Water bodies, Forests, Grasslands, Bare lands, and Coastlands) in KNP to determine the habitat cover change over 15 years using NDVI data. However, our preliminary ground observations suggested that the map generated by Kasige et al. (2020) needs further improvements to illustrate the complex vegetation of KNP supported by ground reference data. NDVI is a method mostly used for vegetation categorization as well as the healthiness of vegetation (Mtibaa and Irie, 2016). The current study incorporated the NDVI to identify the photosynthetic (Healthy) vegetation inside the park. Furthermore, we incorporated the ground reference data, and composites of high-resolution multispectral satellite bands to conduct advanced vegetation mapping and classification.

Two main types of classifications can be identified in environmental land use mapping: unsupervised and supervised classification (Wu, 2018). The Maximum Likelihood Classification (MLC) algorithm is an effective model for the supervised classification technique (Ali et al., 2018; Navin and Agilandeeswari, 2019). However, vegetation mapping through Random Forest (RF) (Mohammadpour et al., 2022), k-Nearest Neighbours (kNN) (Sun et al., 2018) and Support Vector Machine (SVM) (Shi and Yang, 2015) have been identified as other alternative machine learning algorithms (Thanh Noi and Kappas, 2017). Forest-based classification is a multiple raster regression model that analyses multiple rasters such as NDVI along with satellite images while other applications are available as single raster models in ArcGIS Pro (ESRI, Redlands). As per the previous literature available for KNP, the previous identification of vegetation types was based on an unsupervised iso-cluster method (Kasige et al., 2020).

The present study aims to categorize the vegetation of KNP with the highest possible spatial accuracy. We aim to assess the applicability and accuracy of multiple classification algorithm models to generate a detailed vegetation map for the area. Due to the in-depth remote sensing analysis and comprehensive ground truth assessment and verification, we are convinced that the results of our research would be valuable from both a remote sensing and ecological perspective.

2. METHODOLOGY

2.1 Study area

The study was conducted from August 2022 to March 2023, for 8 months in KNP located in Ampara district along the southeast coast of Sri Lanka (Figure 1). The KNP was previously designated as Yala-East National Park in 1970, and the present name was declared in 2006 (Krishan et al., 2020). The park spreads over an area of 35,665 ha (357 km^2). KNP borders Kumbukkan Oya from the south and Panama-Kudumbigala sanctuary from the north (Krishan et al., 2020). The Kumana National Park belongs to the dry zone of Sri Lanka which has an altitude of the ranges from sea level to 90 meters. The vegetation of the park is mainly dry mixed evergreen forest (Figure 2), scrublands, and dunes (Krishan et al., 2020). The dry season in Kumana generally runs from February to September and the wet season runs from October to December while the mean annual temperature is 27.30°C and the area receives 1,300 millimeters of annual rainfall (MoMD&E, 2016).

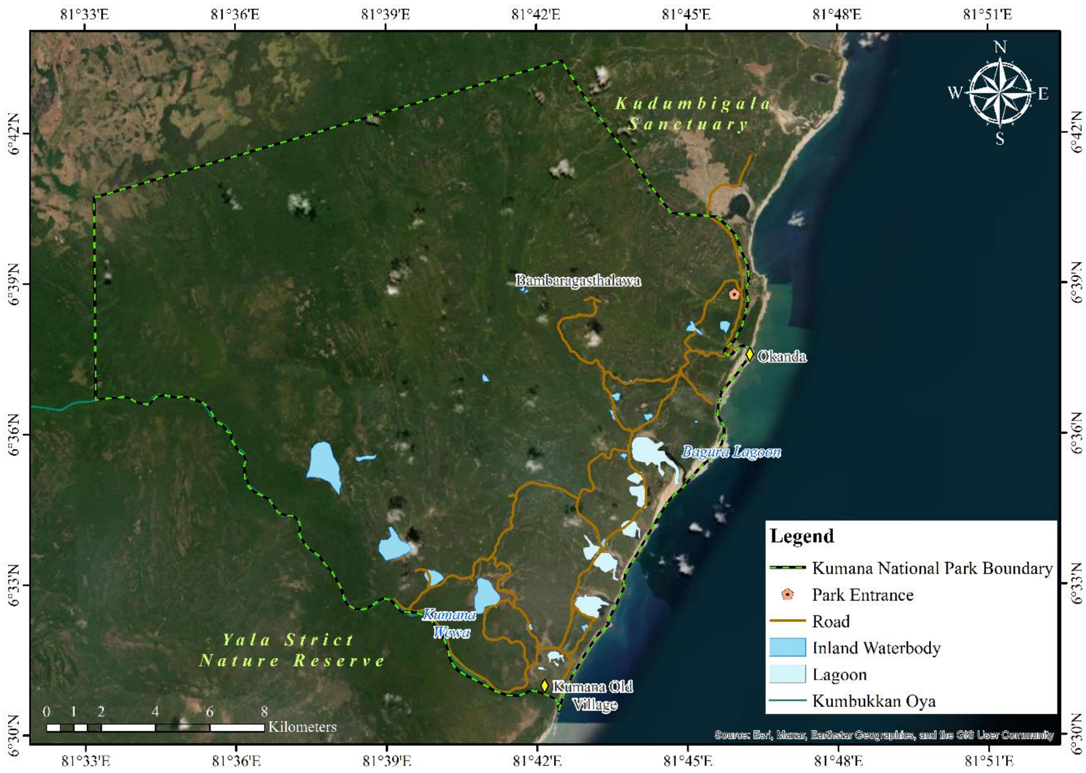

Figure 1. General map of the Kumana National Park

Figure 2. View of Kumana National Park from the Bambaragasthalawa rocky mountain. Tropical dry mixed evergreen forest habitats with rocky clusters are clearly visible

2.2 Survey for the habitat categorization

A preliminary survey was conducted based on the available literature (Gunatilleke and Gunatilleke, 1990; Gunatilleke et al., 2008; Kasige et al., 2020) to identify the nomenclature used for the vegetation types of the region. With the aid of online ArcGIS (Esri, Redlands, USA) base maps, the general borders of the major vegetation types were created on a physiognomic basis (Dias et al., 2004). Sampling quadrats of 10×10 m were selected randomly within larger 2×2 km^2 plots ensuring the representation of different habitat types within the KNP. Most of the sampling was conducted within the eastern region of the park due to the limitations in ground accessibility. We traversed the area by 4×4 vehicles and ground trekking up to six km to establish 90 quadrats. At each quadrat, the environmental parameters were obtained in a standard manner following the methods explained in Table 1. Principal component analysis (PCA) in R version 4.3.3 (R Core Team, 2024) was performed to create clusters of similar vegetation/land cover types.

Table 1. Environmental covariate and the standard method

Environmental parameter	Abbreviation	Standard method
Canopy cover (%)	CC	CC was calculated by photo point analysis using TinEye Online Color Extractor and eCognition software package
Litter cover (%)	LC	LC was estimated by obtaining the litter cover inside 1×1 m^2 quadrats ocularly within a 10×10 m^2 plot
Litter depth (cm)	LD	LD was measured with a metal ruler within multiple 1×1 m^2 quadrats and averaged
Horizontal visibility (%)	HV	HV was measured ocularly by visualizing an object 30 m far from the observer in the habitat and the visibility was ranked numerically from 1 to 10 10=Maximum 0=Minimum
Ground vegetation cover (%)	GV	GV was estimated by observing the ground vegetation less than 10 cm (<10 cm) height within 10×10 m^2 quadrats ocularly and averaged.
Rock availability (%)	RA	RA was estimated ocularly by observing the rocks in the selected location using 10×10 m^2 quadrats ranked 0 -10 0=Minimum 10=Maximum
Canopy height (m)	CH	CH was measured using a Rangefinder and ranked 0 -10 0=Minimum 10=Maximum

2.3 Generation of the vegetation map using different classification models

Atmospherically corrected SR (Surface reflectance) satellite images from the Sentinel 2A dataset were used to determine the spatial distribution of habitat/vegetation types of the study site. The images were obtained from the Copernicus Open Access Hub database (https://scihub.copernicus.eu/) for the NDVI and vegetation analysis. Google Earth Engine (GEE) geospatial processing service in the Google Cloud Platform was used to filter the satellite images captured from January 1, 2018 to December 31, 2023. Cloud and cirrus correction were obtained using the "maskS2clouds" function in GEE. The mosaic function in Google Earth Engine (GEE) was used to combine multiple images into a single image using the filtered image collection with low cloud cover for the corresponding period. A multiband composite image was generated including the spectral bands B1, B2, B3, B4, B5, B6, B7, and B8. The generated multispectral composite image was downloaded from the GEE and further analyzed in Arc GIS Pro (ESRI, Redlands). Different band combinations such as 4,3,2 (True color), 8,4,3 (False color infrared), 5,4,3 (Color Infrared-Vegetation), 5,6,4 (Land/water), etc. were utilized to identify and gather detailed information about the vegetation and water areas (Mtibaa and Irie, 2016; Simonetti et al., 2014). The Normalized Difference Vegetation Index (NDVI) was used to assess the healthiness of the vegetation and greenness (Chlorophyll content). NDVI was determined using the formula: (NIR - Red)/(NIR + Red) where NIR and Red are the near-infrared and red bands respectively (Mtibaa and Irie, 2016).

Before image classification, training samples were created using the ground observation taken from January 2023 to March 2023. The supplementary training data was obtained utilizing ArcGIS base map imaginary data (Esri, Digital Globe) for inaccessible areas and outside the eastern region of the park. Five different classification functions namely, Maximum Likelihood Classification (MLC), Random Forest (RF), k-nearest Neighbour (kNN), Support Vector Machine (SVM), and Forest Based Classification (FBC) algorithm were carried out (da Silveira et al., 2022) ArcGIS Pro 3.2. The software extrapolated the given ground truth data and used the supervised classification algorithm to create complete land cover/vegetation cover maps of KNP. Post-classification processing was conducted on the classified images using the tools majority filter, boundary clean, region group, and nibble for the noise removal and smoothing of the generated maps. ArcMap area calculation option in ArcGIS Pro 3.2 was aided to estimate the area of each habitat category. The overall framework for the vegetation mapping is illustrated in Figure 3.

2.4 Accuracy assessment of generated maps

The forecasted outcomes were compared to ground reference data as part of an accuracy assessment. Observations collected on the ground and base-map imagery were used to verify the accuracy of the map. Arc Map was used to build the error matrix and calculate the Kappa coefficient (κ) (Abbas and Jaber, 2020), and the accuracy of generated maps using different models was compared to select the most accurate classification model.

$$\text{Kappa coefficient } (\kappa) = \frac{(\text{TS} \times \text{TCS}) - \Sigma(\text{Column Total} \times \text{Row Total})}{(\text{TS} \times \text{TS}) - \Sigma(\text{Column Total} \times \text{Row Total})} \times 100 \quad (1)$$

(While; TS=total samples; TCS=total corrected samples)

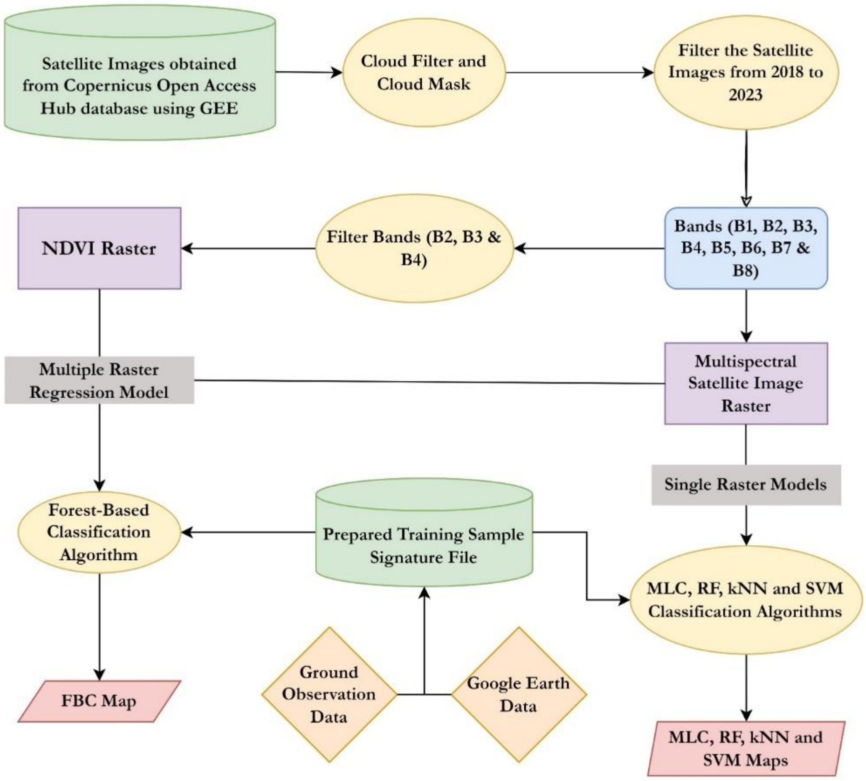

Figure 3. Overall research framework for the vegetation mapping analysis

3. RESULTS AND DISCUSSION

3.1 Habitat categorization of KNP

The principal component analysis (PCA) clustered five vegetation types in KNP namely: Tropical dry-mixed evergreen forest, Tropical thorn forest (Scrubland), Dry riverine forest, Seasonal grassland, and Rocky outcrops (Figure 4(b)). The tropical dry mixed evergreen forests are dominated by *Manilkara hexandra* ('Palu') and *Drypetes sepiaria* ('Veera') while *Diospyros quaesita* ('Kalu Madiriya') and *Diospyros ovalifolia* ('Kunumella') were also present in this habitat. The tropical thorn forest comprised of thorny shrubs such as *Dichrostachys cinerea* ('Andara'), *Bauhinia racemosum* ('Mila'), *Salvadora persica* ('Maliththan'), *Carissa spinarum* ('Heen Karaba'), and *Ziziphus oenoplia.* ('Heen Eraminiya'). *Terminalia arjuna* ('Kumbuk') was dominant in the dry riverine forest whereas tiny clusters of *Walsura trifoliolata* ('Kiri Koon') and *Drypetes sepiaria* ('Veera') were located along with the riverbanks and the adjacent area (Table 2). Most of these dry riverine forests get flooded during the rainy season. Seasonal grasslands and bare land areas are profoundly located around the water bodies of the park. Most of these areas are swamped occasionally and temporal shifts can be observed turning them into either seasonal grasslands or bare lands based on the rainfall and water levels. Rocky outcrops were identified as areas with a mosaic distribution of rocks within the forest clusters including several rocky mountain areas that emerge above the generally plain surrounding forested landscape. The vegetation of these habitats was like the tropical dry mixed evergreen forests and tropical dry thorn forests (Figure 5).

Table 2. Prominent plant species of each forest habitat types located in KNP

Forest habitat type	Prominent plant species	Plant family	Local name (*'In Sinhala'*)
Tropical dry mixed Evergreen forest	*Manilkara hexandra*	Sapotaceae	Palu
	Drypetes sepiaria	Putranjivaceae	Veera
	Diospyros quaesita	Ebenaceae	Kalu Madiriya
	Diospyros ovalifolia	Ebenaceae	Kunumella
Tropical thorn forest	*Dichrostachys cinerea*	Fabaceae	Andara
	Bauhinia racemosum	Fabaceae	Mila
	Salvadora persica	Salvadoraceae	Maliththan
	Carissa spinarum	Apocynaceae	Heen Karaba
	Ziziphus oenoplia	Rhamnaceae	Heen Eraminiya
Dry riverine forest	*Terminalia arjuna*	Combretaceae	Kumbuk
	Walsura trifoliolata	Meliaceae	Kiri Koon

According to the loading plot (Figure 4(a)) the canopy height, litter cover, and horizontal visibility were the significant contributing factors to shape the structure of tropical dry-mixed evergreen forests. The tropical dry-mixed evergreen forest and scrublands are composed of several shared features, but the two habitats can be distinctly identified. The ground vegetation and canopy cover negatively influenced the tropical thorn forest (Scrublands). The dry riverine forest cluster was separated via litter depth and the canopy height. Seasonal grasslands indicated a low canopy cover and litter cover with a high horizontal visibility. Rock availability exhibited a positive influence on the determination of rocky outcrops.

(a)

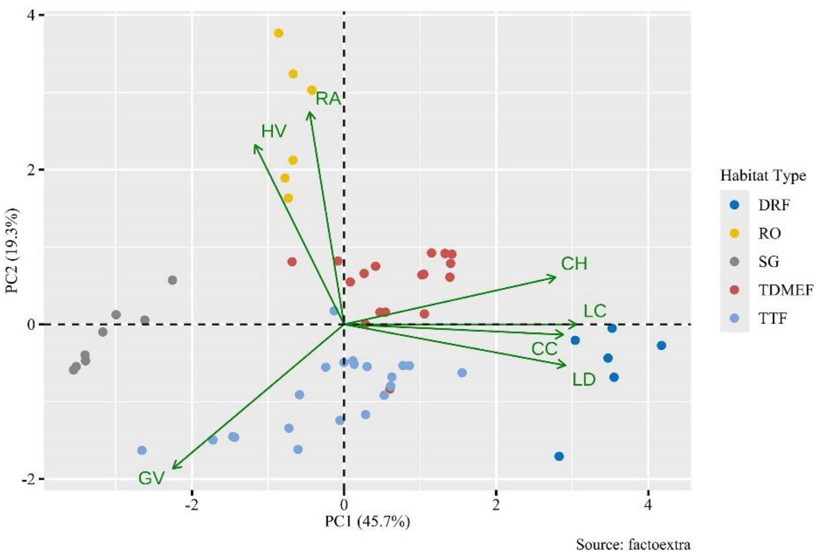

Figure 4. (a) Loading plot and (b) Score plot of PCA conducted for KNP through a field survey [*TDMEF - Tropical Dry Mixed Evergreen Forest, SG - Seasonal Grassland and DRF - Dry Riverine Forest, TTF - Tropical Thorn Forest, RO - Rocky Outcrops]

(b)

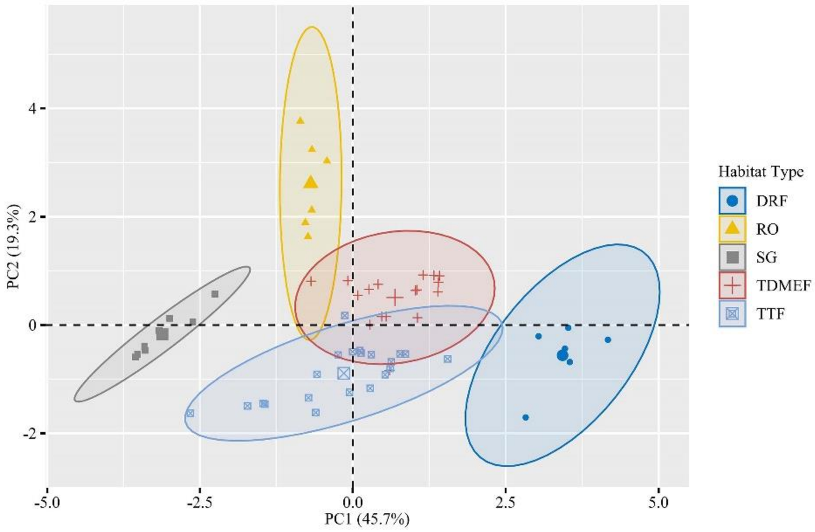

Figure 4. (a) Loading plot and (b) Score plot of PCA conducted for KNP through a field survey [*TDMEF - Tropical Dry Mixed Evergreen Forest, SG - Seasonal Grassland and DRF - Dry Riverine Forest, TTF - Tropical Thorn Forest, RO - Rocky Outcrops] (cont.)

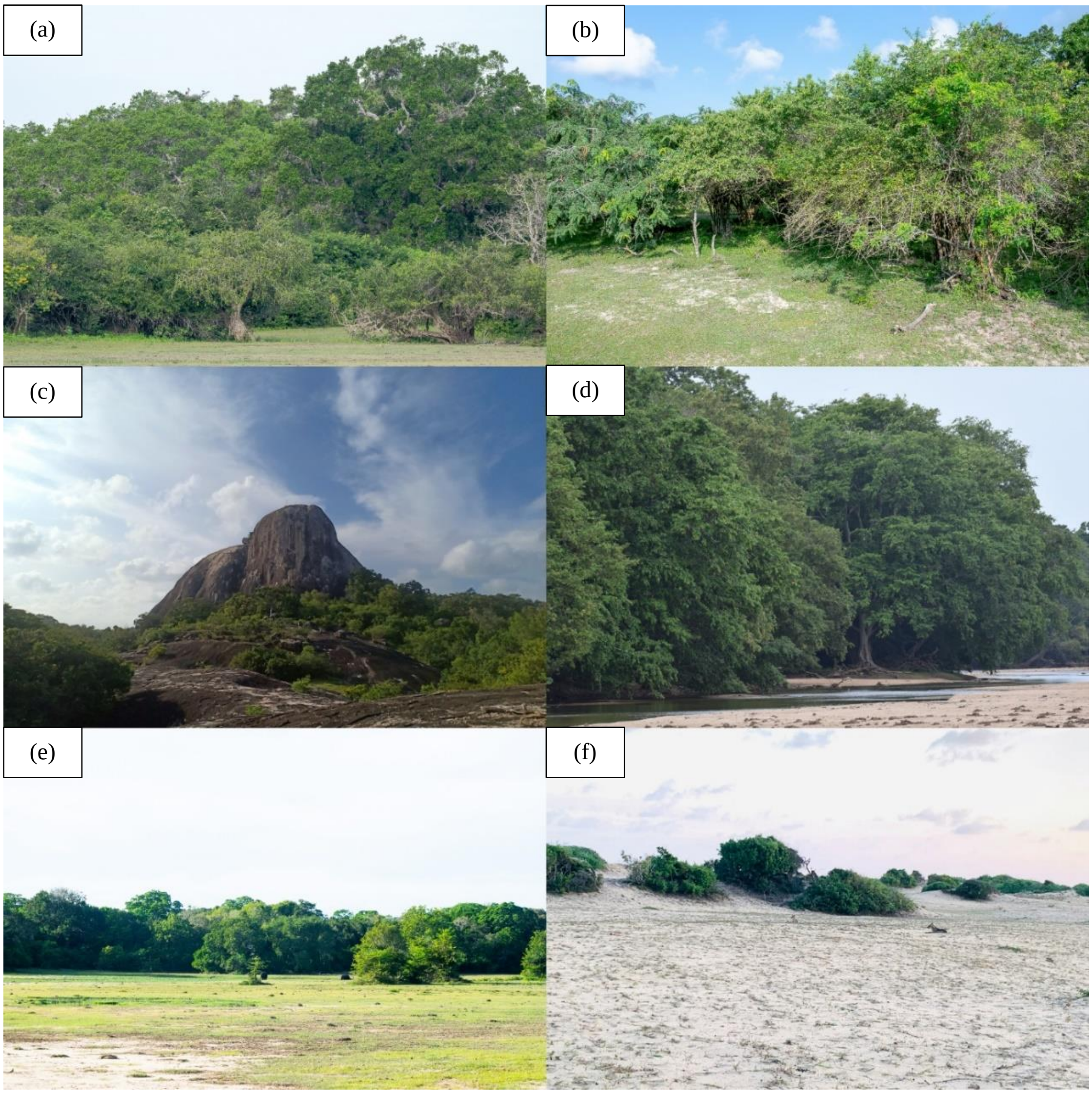

Figure 5. Terrestrial habitats in Kumana National Park; (a) Tropical Dry-mixed Evergreen Forest; (b) Tropical Thorn Forest; (c) Rocky Outcrops; (d) Dry Riverine Forest; (e) Seasonal Grassland; and (f) Sand and Dunes along the coastline

3.2 Generation of classified habitat maps using supervised data

Four post-processed maps were generated through Maximum Likelihood Classification (MLC), Random Forest (RF), k-Nearest Neighbour (kNN), and Support Vector Machine (SVM) classification models. The Forest-Based Classification (FBC) model was not post-processed due the poor accuracy. Five terrestrial habitats and two aquatic habitats were classified in the generated maps. Terrestrial habitats were, namely, Tropical Dry-mixed Evergreen Forests, Tropical Thorn Forests (Scrublands), Seasonal Grasslands, Rocky Outcrops, and Sand Dunes (Figure 5). All seasonal and permanent waterbodies including rivers (Kumbukkan Oya and estuaries) were considered as aquatic habitats. The dry riverine forest area near the Kumbukkan Oya River remained as undefined in the categorized map probably due to the minor proportion of this forest type along a small stretch beside the river. From all the terrestrial habitats, Tropical dry-mixed evergreen forests accounted for an area of 28,562 ha followed by Tropical thorn forests (Scrublands) which covered 5,218 ha. The tropical dry-mixed evergreen forests covered 77.9% of the park followed by the tropical thorn forests, rocky outcrops, and seasonal grasslands covering 14.3%, 1.9%, and 1.3% of the park respectively (Table 4). Waterbodies cover 1.4% of the total park which are situated mostly within the eastern region of the park. Sand dunes and river areas accounted for a relatively smaller area (<1%) (Table 3).

3.3 Accuracy assessment of generated maps

The maximum value of the Kappa coefficient (κ) was achieved for the classified map using the maximum likelihood classification model (MLC) which had an overall accuracy of 91% (Figure 6). Other maps had a lower accuracy with Kappa coefficients less than 0.87 (κ<0.87). Each classified map was visually compared with satellite images obtained from ArcGIS Pro 3.2 imagery data for further verification (Figure 7).

Table 3. Accuracy assessment table for the Maximum Likelihood Classification (MLC) model

	Dry-mixed Evergreen	Tropical Thorn	Rocky Outcrop	Bare/Grass land	Waterbody	River	Sand and Dunes	Total (User)	User Accu (%)
Dry-mixed Evergreen	62	0	0	0	0	0	0	62	100
Tropical Thorn	5	11	0	0	0	0	1	17	64.7
Rocky Outcrop	1	0	6	0	0	0	0	7	85.7
Bare/Grass land	0	0	0	4	0	0	0	4	100
Waterbody	0	0	0	0	4	0	0	4	100
River	0	0	0	0	0	3	0	3	100
Sand and Dunes	0	0	0	0	0	0	3	3	100
Total (Producer)	68	11	6	4	4	3	4	100	-
Producer Accu (%)	91.2	100	100	100	100	100	75	-	91

Table 4. Habitat availability based on vegetation mapping in KNP

Habitat categories in KNP	Area proportion (%)	Area (ha)
Tropical dry-mixed evergreen forest	77.9	28,562
Tropical thorn forest (Scrubland)	14.3	5,218
Rocky outcrops	1.9	692
Bare land and Seasonal grass	1.3	461
Waterbodies	1.4	508
Sand and dunes	0.7	262
River	0.2	68
Total area		35,773

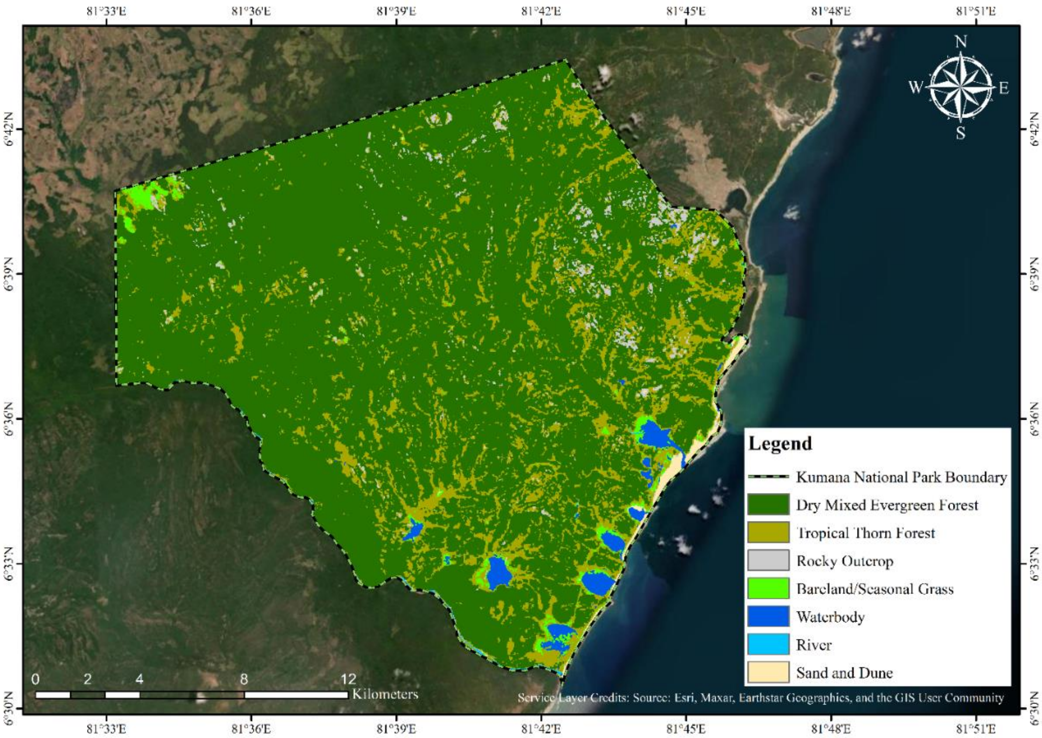

Figure 6. Categorized map using Maximum Likelihood Classification (MLC) model with available habitat types in Kumana National Park

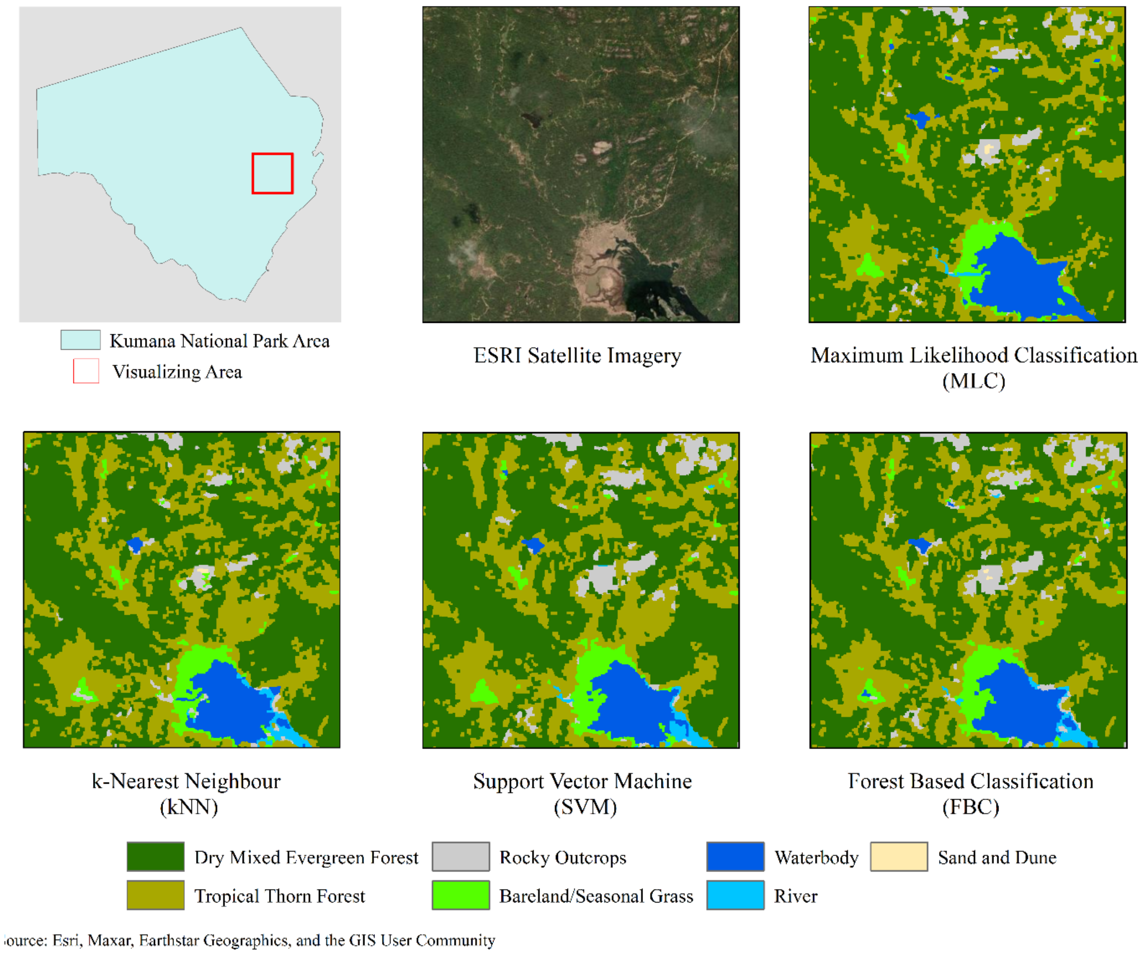

Figure 7. Vegetation maps developed using different models for the Kumana National Park

4. DISCUSSION

Our study presents a detailed habitat map for Kumana National Park (KNP), which can be utilized for park management decisions and future ecological research. This map offers significantly improved resolution and spatial detail compared to the previous map by Kasige et al. (2020). By incorporating multispectral data and ground-based surveys, we achieved a higher accuracy level. While Kasige et al. (2020) identified four habitat types, our study identified six: 1) Dry-mixed evergreen forest, 2) Tropical thorn forest, 3) Rocky outcrop, 4) Dry riverine forest, and 5) Seasonal grasslands through PCA analysis. Sand dunes were excluded from the PCA due to their low area percentage.

Despite the PCA identifying the dry riverine forest adjacent to the Kumbukkan Oya River, none of the classification models were able to distinguish it as a unique habitat type. Consequently, this habitat was excluded from our final map due to misidentification with dry-mixed evergreen forest and its relatively low spatial distribution. Our findings contrast sharply with the habitat areas reported for 2019 by Kasige et al. (2020), who noted only 124.43 km^2 of forest cover and 57.80 km^2 of grasslands. In contrast, we identified a forested area of 337.8 km^2, encompassing both dry-mixed evergreen and tropical thorn forests, while grasslands cover only 4.61 km^2. This discrepancy likely arises from our identification of tropical thorn forests as a distinct habitat type and the enhanced clarity achieved through improved spatial resolution and mosaicking of spectral data, resulting in a temporally representative satellite image instead of a single-point NDVI raster.

Our study highlights Google Earth Engine's (GEE) potential for filtering, preprocessing, and raster mosaicking over a time range, which significantly improved the classification's overall accuracy by reducing temporal bias. Accurate habitat classification is crucial for park managers, enabling them to make more informed and effective management decisions.

However, Kumana National Park currently generates significant revenue, largely due to its appeal to tourists interested in its diverse mammalian and avian fauna (SLTDA, 2019). Therefore, our study offers valuable insights for managing the recreational road network and camping sites maintained by the Department of Wildlife Conservation (DWC). We recommend an integrated approach that balances visitor satisfaction with habitat conservation to ensure sustainable tourism within the park. Our findings can assist in spatially identifying areas with high potential for wildlife viewing, while also safeguarding more sensitive and critical habitats. The use of freely available satellite data allowed us to conduct this study cost-effectively (Gil et al., 2011), and the use of remote sensing multispectral products, combined with verification through Google Earth and Arc basemaps, overcame accessibility limitations.

Gunatilleke et al. (2008) observed that most of Sri Lanka's natural forest area is covered by tropical dry mixed evergreen forest. Similarly, we found that approximately 75% of KNP is covered by this forest type, primarily located away from recreational roads and within the park's interior. These forests, characterized by a 12-meter canopy height with prominent species such as *Manilkara hexandra*, *Diospyros quaesita*, and *Diospyros ovalifolia*, provide critical habitats for elusive mammalian species. In contrast, the tropical thorn forests, which are the second-largest habitat type in KNP, feature thorny vegetation and are primarily found near recreational roads and aquatic bodies. This habitat includes species such as *Dichrostachys cinerea* and *Ziziphus* sp., along with other characteristic flora.

The dry riverine forest, although less spatially extensive, is another significant habitat along KNP's southern boundary, nourished by the Kumbukkan River. Dominated by *Terminalia arjuna* (Kumbuk), these forests exhibit a denser canopy near the riverbanks, withstanding seasonal floods and creating a shaded environment with lower ground vegetation than the tropical dry-mixed evergreen forests. Grasslands in KNP, consisting of short seasonal grasses, are primarily located near major water bodies and are subject to seasonal flooding. These grasslands, which are most visible during the dry season, are easily distinguishable in satellite images due to their high ground vegetation cover and lack of a canopy layer. Seasonal grasslands and bare lands with open soil and mudflats cluster together due to similar pixel values.

Initially, we used LANDSAT 9 satellite imagery from the United States Geological Survey (USGS) for vegetation classification. However, due to its low resolution, we opted for Sentinel-2A images from the Copernicus Open Access Hub. Among the various classification models we tested, Maximum Likelihood Classification (MLC), after post-modification, produced the most accurate map, as evaluated using the kappa coefficient. This map accurately depicted the physical features of the area, including forest habitats, rocky outcrops, grasslands, and water bodies. Thus, we propose the vegetation map (Figure 7) for KNP using the MLC algorithm. Despite the availability of newer classification algorithms, the MLC model remains highly competent in achieving high accuracy. We believe our study will support decision-makers and relevant authorities in managing protected areas more effectively.

5. CONCLUSION

The findings of this study offer modern solutions for vegetation categorization in future ecological research. Kumana National Park is predominantly covered by dry mixed evergreen forest, followed by tropical thorn forest, resulting in a substantial forest cover of 92.2%. The habitat map we generated, along with the associated spatial parameters, can be used to identify critical areas for both terrestrial and aquatic fauna within KNP. These findings can be effectively utilized to support habitat conservation and management strategies in the park.

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