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Authors: Cristobal Cayetano[1], Emma Sullivan[2], Peter Miller[3], Daniel Clewely[4], Lota Creencia[5]
Affiliations: Western Philippines University, College of Fisheries and Aquatic Sciences[1], Remote Sensing Group, Plymouth Marine Laboratory[2]
Orcid ids: 0000-0002-0779-5534[1]
Contact e-mail: cris.cayetano@gmail.com

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4 July 2022

The Editor-in-Chief
UCL Open Environment

Dear Editor,

Greetings!

We are pleased to submit our manuscript entitled "Multi-spatiotemporal Analysis of the Changes in Mangrove Forests in Palawan, Philippines: Predicting Future Trends Using Support Vector Machine Algorithm and Markov Chain Model" to be reviewed and considered for publication in the UCL Open Environmental journal as an original RESEARCH ARTICLE.

We are currently in the era of amazing technological advancement and the rising field of remote sensing has been of great importance especially when monitoring over large geographical areas. Mangrove conservation using remote sensing is not just an interesting research idea but also of great significance since we can now learn from this ecosystem without even going through the complex structure of the forest. It would be our honor to share this amazing knowledge especially in the local and global contexts since this research serves as a baseline study for Palawan.

The mangroves in Palawan has a wide reputation nationally, being as a diverse ecosystem with at least 50% of the entire mangrove species in the Philippines can be found in Palawan. Given all the current implementing environmental policies (e.g., Strategic Environmental Plan for Palawan through the Environmentally Critical Area Networks Project, Mangrove Swamp Reserve of 1981, UNESCO Biosphere Reserve in 1991), the mangroves in the province is still susceptible to anthropogenic pressures and climate change. This research makes a vital component on how to properly integrate landscape management initiatives to conserve and protect the remaining mangrove covers in Palawan by understanding the changes in areal extent and projecting the future changes of this unique ecosystem.

Currently, there is a dearth of information about the extent of changes in mangrove assemblages in the province. Especially, the future projection involving different models has not just been integrated in other previous works. Thus, this research is crucially important not just in the local context but also in the global scenario.

We confirm that this manuscript is our original work and has not been previously published or submitted simultaneously for publication elsewhere. Also, this is to certify that all authors have agreed to the content of the paper and shall not be withdrawn once under consideration for publication. Further, there is no conflict of interest among the authors involved in this research, including:

Cristobal B. Cayetano: (Main Author)
Emma Sullivan: (co-Author) Peter I. Miller: (co-Author)
Daniel Clewely: (co-Author) Lota A. Creencia: (co-Author)

Thank you for considering our manuscript.

Respectfully,

CRISTOBAL B. CAYETANO
Lead Author
WESTERN PHILIPPINE UNIVERSITY, College of Fisheries and Aquatic Sciences
Address: STA. MONICA HEIGHTS, PUERTO PRINCESA CITY, PALAWAN
Email address: cris.cayetano@gmail.com
Mobile number: +63966-965-3337 ORCID No.

Multi-Spatiotemporal Analysis of Changes in Mangrove Forests in Palawan, Philippines: Predicting Future Trends Using Support Vector Machine Algorithm and Markov Chain Model

Cristobal B. Cayetano*[1], Emma Sullivan[2], Peter I. Miller[2], Daniel Clewely[2] and Lota A. Creencia[1]

[1] College of Fisheries and Aquatic Sciences, Western Philippines University, Sta. Monica, Puerto Princesa City, Palawan, Philippines

[2] Remote Sensing Group, Plymouth Marine Laboratory, Prospect Place, Plymouth PL4 7QP, UK

***Corresponding Author – cris.cayetano@gmail.com**

ABSTRACT

Multi-temporal remote sensing imagery can be used to explore how mangrove assemblages are changing over time and facilitate critical interventions for ecological sustainability and effective management. This study aims to explore the spatial dynamics of mangrove extents in Palawan, Philippines, specifically in Puerto Princesa City (PPC), Taytay, and Aborlan, and facilitate future prediction for Palawan using the Markov Chain model. The multi-date Landsat imageries during the period 1988–2020 were used for this research. The Support Vector Machine algorithm was sufficiently effective for mangrove feature extraction to generate satisfactory accuracy results (>70% *Kappa coefficient* values; 91% average overall accuracies). In Palawan, a 5.2% (2,693 ha) decrease was recorded during 1988–1998 and an 8.6% increase in 2013–2020 to 4,371 ha. In PPC, 95.9% (2,758 ha) increase was observed during 1988–1998 and 2.0% (136 ha) decrease during 2013–2020. The mangroves in Taytay and Aborlan both gained an additional 2,138 ha (55.3%) and 228 ha (16.8%) during 1988–1998 but also decreased from 2013 to 2020 by 3.4% (247 ha) and 0.2% (3 ha), respectively. However, projected results suggest that the mangrove areas in Palawan will likely increase in 2030 (to 64,946 ha) and 2050 (to 66,972 ha). This study demonstrated the capability of the Markov Chain model in the context of ecological sustainability involving policy intervention. However, since this research did not capture the environmental factors that may had influenced the changes in mangrove patterns, it is suggested the addition of Cellular Automata in future Markovian mangrove modelling.

Keywords: Change detection, Image classification, Landsat, Land use/land cover, Markov Chain Model, Spatial dynamics, Support Vector Machine

1. INTRODUCTION

Mangroves are a group of complex trees and shrubs that naturally inhabit the intertidal zones of the coastal tropical and subtropical regions (Brown et al. 2006; Mukherjee et al. 2014). Although they can tolerate a wide range of salinity, from hypersaline exceeding 100 parts per thousand to lower salinities of 2 parts per thousand (Ball and Pidsley 1995), they cannot compete reproductively with other terrestrial plants because the latter have a better adaptation to a higher-elevation environment (Liang et al. 2008). Mangrove forest is one of the most important coastal ecosystems because it provides bio-productivity, *e.g.*, timber and fuelwood (Walters et al. 2008), protection from natural hazards and regulation of natural phenomena, *e.g.*, flood, storm erosion, and salt intrusion, (Mendoza and Alura 2001; Brown et al. 2006; Macintosh 2010; Giri et al. 2011), serves as a nursery and habitat ground for biodiversity, *e.g.*, breeding and spawning (Nagelkerken et al. 2002; Nagelkerken et al. 2008; Honda et al. 2013), provisioning of socio-economic and cultural importance, *e.g.*, livelihood, ecotourism, recreation, and aesthetic (Camacho et al. 2011; Sarhan and Tawfik 2018), and help mitigate climate change, *e.g.*, carbon sequestration (Camacho et al. 2011; Dixon et al. 2019).

There are about 65 mangrove species around the world (Kandasamy and Bingham 2001), of which at least 50% currently grow in the Philippines (Primavera et al. 2004). According to the Food and Agricultural Organization (FAO 2022), Asia has more extensive mangrove forests than any other continent. The Philippines is considered one of the top biodiversity "hot spot" countries in the world (Myers et al. 2000). The Palawan Council for Sustainable Development Staff (PCSDS 2015a) initially reported 27 mangrove species in Palawan. About 22.23% (56,261.3 ha) of the remaining mangrove forests in the Philippines are found in Palawan (Long and Giri 2011). However, the ability of this ecosystem to colonize and maintain its spatial setting is increasingly being affected by anthropogenic disturbances (Thomas et al. 2017). Consequently, mangrove forest cover in the Philippines has decreased from approximately 500,000 ha in 1918 to about 120,000 ha by the end of 1995 (Primavera 2000; Dodd and Ong 2008). Primavera (2000) reported that the two main contributing factors for this decline are raw product overexploitation and coastal land use conversions (*e.g.*, agriculture, residential settlements, industrial, and aquaculture). Although the recent estimates from the Department of Environment and Natural Resources (DENR 2013) suggest an increase in mangrove extent in 2003 (to 247,362 ha), this estimate is still much lower than the estimated cover area a century before.

Mangrove ecosystems form a complex structure, making extensive *in-situ* sampling difficult to do. However, remote sensing techniques provide a convenient tool to map, assess, and monitor the mangroves over large areas and can be used to detect change over time (Lucas et al. 2002; Komiyama et al. 2008; Heumann 2011a; Suratman 2014). In the Philippines, the utilization of remotely-sensed satellite data (*e.g.*, Long and Giri 2011) has been incorporated into policy formulation and enforcement. However, mangrove-related projects in the country remain relatively scarce with only a few national and local mapping efforts focused on the classification and detection of changes in the mangrove's extents, notably from nominal years of 1990-2010 (Long et al. 2014) and 2003-2013 (Pagkalinawan and Ramos 2013). In spite of the low utilization of mangrove remote sensing in the Philippines and the absence of projected data about how the remaining mangroves in the country will respond to the impacts of climate change, mitigating and controlling the magnitude of climate change's impacts on mangrove ecosystems has increased in scientific interest in Southeast Asian countries (Koh and The 2019). Additionally, although the mangroves of Palawan have been protected under the direct human inventions through the International Union for Conservation of Nature (IUCN) protected area Category I-IV (Long and Giri 2011) and 1992 Republic Act No.7611, commonly known as the Strategic Environmental Plan for Palawan Act (SEP Law, FAO 2021), this unique ecosystem remains under threat due to climate change and associated rising sea levels (Gilman et al. 2008; Giri et al. 2011).

Several land use/land cover (LULC) techniques have been developed and utilized for the last three decades, which primarily aim to investigate the spatiotemporal changes of LULC patterns using satellite data to assist in ecological management and decision-making (Lillesand et al. 2015). The parametric (*e.g.*, maximum likelihood classifier, Bolstad and Lillesand 1991) and nonparametric (*e.g.*, artificial neural networks, Benediktsson et al. 1990) classification algorithms can handle complex classification tasks (Ma et al. 2019). To perform the classification using a supervised classification technique training samples must be extracted, which can be time consuming when using multi-temporal Landsat imagery. Unsupervised classification techniques have also been used to map mangrove extent and change over time, for example using vegetation indices (e.g. Normalized Difference Vegetation Index, Mangrove Vegetation Index; Almahasheer et al. 2016; Conopio et al. 2021) and clustering and threshold techniques (e.g. Otsu 1979). The Markov Chain model (Gagniuc 2017; Yang 2020) is one many prediction techniques that are able to assess the LULC changes and make a projection of these changes in the future (Coppedge et al. 2007; Kanjirappuzha et al. 2010; Adhikari and Southworth 2012; Adegbola et al. 2021). Understanding the patterns of change in mangrove geographic distribution and projecting the range of shifts in the future will link the science to policy and decision-making processes for biodiversity conservation and management (Worthington et al. 2020).

Through the Global Challenges Research Fund (GCRF) Blue Communities[1] (BC), as part of its integrated Project 7 which focuses on describing patterns of changes in the environment through Earth observation satellites, this research aims to: (1) develop a mapping approach to investigate the changes in mangrove extents in Palawan using multi-temporal Landsat imagery during the years, 1988, 1993, 1998, 2003, 2008, 2013, 2018, and 2020; (2) determine the areal extent of change in mangrove forests in Palawan including the three case study areas of GCRF BC from 1988 to 2020; and (c) implement change projections of the mangrove forests in Palawan for 2030 and 2050 using a Markov Chain model.

2. MATERIALS AND METHOD

2.1. Study Area

Palawan is a long and narrow island province in the Philippines (09°30'N and 118°30'E) with an approximate total area of 1,489,626 ha and is located at the western portion of the archipelago (Figure 1; PCSD 2010; PCSDS 2015a). Its almost 2,000 km coastline is one of the longest shorelines in the country and accounts for about 1,780 islands. The South China Sea borders the western coast while the Sulu Sea and the Malaysian Sabah Island borders the eastern and southern sides of Palawan (Carandang et al. 2013). The island is comprised of 23 municipalities, one urbanized city (Puerto Princesa), and 433 small villages called "Barangay" (PSA 2009).

Palawan is known as the Philippines' "last ecological frontier" due to its rich culture and biodiversity (Sandalo and Baltazar 1997). As per Presidential Proclamation No. 2152 of 1981, all mangrove forest areas in the province are protected as Palawan was declared a Mangrove Swamp Forest Reserve (PCSD 2010; PCSDS 2015a). In 1991, Palawan was designated as a biosphere reserve under the Man and the Biosphere Programme (MAB) of the United Nations Educational, Scientific, and Cultural Organization (UNESCO). The following year, the 1992 SEP Law assisted the MAB's declaration in the sustainability of Palawan's biological and cultural diversity. In succeeding years of recognizing the biodiversity richness of the province, two out of nine UNESCO World Heritage Sites in the Philippines are found in Palawan: the Puerto Princesa Subterranean River National Park (inscribed in 1999) and the Tubbataha Reefs Natural Park (inscribed in 1993, 2009; Sandalo and Baltazar 1997).

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[1] https://www.blue-communities.org

Mangroves form one of the components of the coastal and marine ecosystem in the Philippines (Naz 2013). Of the provinces in the Philippines, Palawan has the largest remaining mangrove extents (56,261.3 ha; Long and Giri 2011). Mangroves are susceptible to various effects of climate change such as sea-level rise (Ward et al. 2016). Therefore, adoption of various climate change adaptation interventions such as the national framework strategy on climate change (CCC 2021) and the development of the Philippine exposure map on climate change (The Climate Reality Project 2016) have been of great importance for the identification of vulnerable areas of Palawan that are the most susceptible to climate change.

202

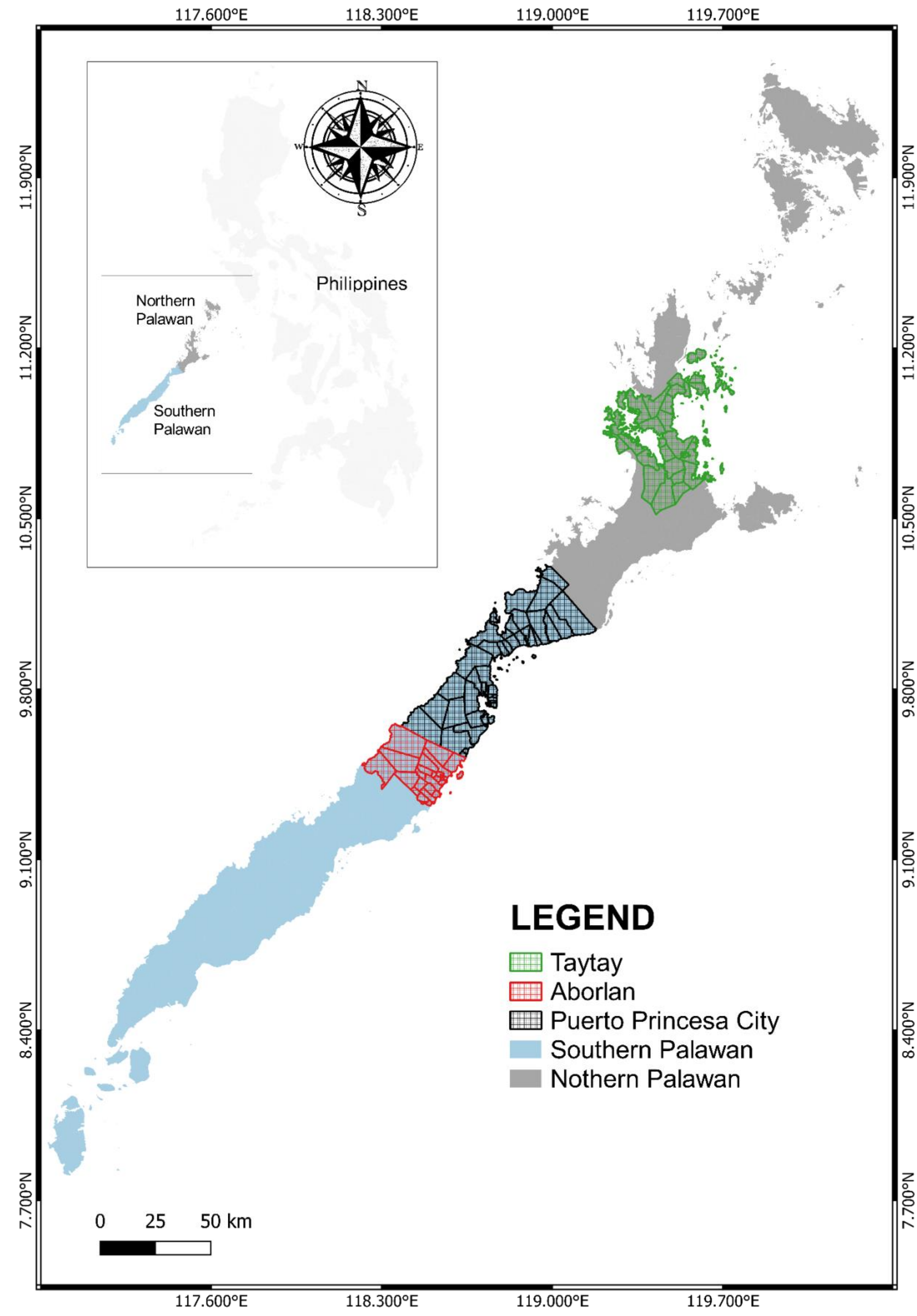
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Figure 1. A map of Palawan, Philippines highlighting the southern and northern divisions and three of the GCRF BC's case study areas – Puerto Princesa City and the municipalities of Taytay and Aborlan.

2.2. Pre-Processing the Landsat Sensor Data

The multi-temporal resolution and multi-spectral Landsat 4-5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) images in multiple years between 1988 and 2020 were used for this study (Supplementary Information Table S1). A total of 20 scenes for TM (for years 1988, 1993, and 1998), 18 scenes for ETM+ (for years 2003, 2008, and 2013), and 11 scenes for OLI (for years 2018 and 2020) were sourced using the Semi-automatic Classification Plugin (SCP) version 7.9.0 Matera in Quantum Geographical Information System (QGIS) version 3.22.1 Białowieża.

To normalize various conditions across the multitemporal and multispatial Landsat datasets, it is imperative that Landsat data undergoes pre-processing routines to enhance the quality and remove various radiometric and geometric errors in each image (Gordon 1987; Lillesand and Kiefer 1994; Bruce and Hilbert 2006; Young et al. 2017). Thus, radiometric calibration and atmospheric correction were employed for this study.

The 2018 OLI Level-2 data were used as the reference image to apply geometric correction to the satellite images in each epoch. The parameters of this transformation function were derived from a spread of 200 Ground Control Points (GCPs) which were uniformly chosen from distinct topographic features throughout the target image. To match with the original pixel size of the Landsat data, all images were resampled to a ground resolution of 30 x 30 m and reprojected to WGS 84 UTM datum. The Root Mean Square Error (RMSE) of 0.25 pixel was calculated and was deemed enough to facilitate accurate LULC change detection analysis (Dai 1998). Throughout these processes, the Nearest Neighbour resampling algorithm was employed to maintain geometric integrity across all the images.

Following geometric correction was the radiometric correction (Bruce and Hilbert 2006). Upon checking the image noise (*e.g.*, dropouts and bit errors) for TM and ETM+ images using the Environmental Systems Research Institute's (ESRI's) ArcGIS version 10.7.1, a correction was not necessary. The next process of radiometric calibration involved the conversion of the signal of the quantified energy from multispectral brightness values or digital numbers (DNs) into Top-of-Atmosphere (TOA) reflectance units. In particular, this process involved two steps: (a) the conversion of DNs to spectral radiance (L_λ) and (b) the transformation to TOA reflectance (ρ_λ) as corrected for illumination variabilities (*i.e.*, sun angle and Earth-sun distance) within and between scenes (Bruce and Hilbert 2006; Schroeder et al. 2006; Young et al. 2017; USGS 2019). For the TM and ETM+ data, the Equations (Eq 1), (Eq 2), (Eq 3), (Eq 4), and (Eq 5) were applied, respectively:

$$L_\lambda = DN\ x\ G\ +\ B \qquad \text{(Eq 1)}$$

where L_λ corresponds to the radiance measured at the sensor bandwidth for each band ($Wm^{-2}sr^{-1}\mu^{-1}$); *DN* is the digital number value; *G* and *B* are the (Gain) slope and (Bias) intercept of response functions, calculated as follows:

$$B\ =\ L_{min} - (L_{max} - L_{min}/Q_{max} - Q_{min})\ x\ Q_{min} \qquad \text{(Eq 2)}$$

$$G\ =\ (L_{max} - L_{min}/Q_{max} - Q_{min}) \qquad \text{(Eq 3)}$$

where L_{min} and L_{max} are the lowest and highest radiance measured by a detector in $mWcm^{-2}sr^{-1}$, as reported by TM and ETM+ metadata files; L_{min} – $(L_{max}\ L_{min})$ correspond to the minimum and maximum values of *DN* for TM and ETM+ sensors, ranging from 1 to 255. The TOA reflectance (ρ_λ) calculation for each band applied on a pixel-by-pixel basis for each scene in each epoch and the output reflectance values were scaled to an 8-bit data range, this can be calculated as:

$$\rho_\lambda = \frac{(\pi\ x\ L_\lambda\ x\ d^2)}{E_{o\lambda}\ x\ os\theta_s} \qquad \text{(Eq 4)}$$

where *d* is the Earth-sun distance correction; L_λ is the radiance as a function of bandwidth; $E_{0\lambda}$ is the mean solar exoatmospheric irradiances and θ_s is the solar zenith angle. Following the corrections of sensor gains and offsets spectral band solar irradiance and solar zenith angle, and after the topographic normalization implementation, was the application of absolute atmospheric correction and relative correction. The removal of additive path radiance (*Lp*) was calculated using (Eq 5) based on the dark-object subtraction (DOS) 1% technique (Chavez 1988; Song et al. 2001; Richards 2013). The DOS assumes that the lowest reflectance value for dark objects across the image is 1% and any values greater than zero can be attributed to the additive effects of haze (Jensen 1996; Bruce and Hilbert 2006; Kanjirappuzha et al. 2010). The relatively constant errors removal was implemented using the formula:

$$L_p = L_{min} + \left[\frac{(L_{max} - L_{min})}{255}\right]\ x\ DN_{min} - 0.01\ x\ [(E_{o\lambda}\ x\ cos\theta_s x\ T_z) + E_{down}]\ x\ \frac{T_v}{\pi} \qquad \text{(Eq 5)}$$

where L_p is the path radiance; the DN_{min} adopted the histogram technique (Chavez 1988) allowing the haze DN value to be automatically calculated from the DN frequency histogram of the image; T_v and T_z are assumed equally in state thereby downward diffusion of radiation at the surface (E_{down} = 0) is absent (Chavez 1988).

2.3. Spectral Bands Selection

In LULC classification, different land cover classes may respond to different ranges of wavelengths, and not all spectral bands are useful for the analysis. Consequently, it is imperative to appropriately identify the useful ranges of wavelength since the procedure increases class discrimination (Mausel et al. 1990). Chen et al. (2013) made an assumption that the low reflectance of mangroves in the short wavelength infrared (SWIR) region of the EM spectrum was due to the weak-scattering signal of the intercellular structure of the leaves. Unsurprisingly, the low reflectance of the mixed mangrove assemblage with the surrounding mud and water could further reduce the reflected radiance of mangroves in general. Therefore, they used the Jeffries-Matusita distance technique to calculate the spectral separability among the LULC classes. This technique was adopted for this research and was conducted using the *spatialEco* package version 1.3–7 in R programming software (Bhattacharyya 1943; Kailath 1967; Bruzzone et al. 1995).

The Jeffries-Matusita criterion measures the distance between the means of each class feature and the distribution of values around the means, giving a measure of spectral separability between the features of the class, and thus able to determine the quality of the target class samples (Bruzzone et al. 1995, Ghoggali and Melgani 2009). Values range from 0 to 2, where 2 indicates high separability while the lower values indicate a possible misclassification of the classes (Richards and Jia 1999). In the latter case, distances registered below the threshold of 1 were removed from the prioritized band image. Additionally, we have considered the Jeffries-Matusita values between 1.7–1.9, as good class separability (Jensen 1996). In this study we combined the equivalent bands of each sensor to give an overall distance for the colour band. The generated results for the Jeffries-Matusita distance calculation indicate that the highest levels of separability between the mangrove vegetation and non-mangrove vegetation classes were observed for bands 5–4–3 for TM and ETM+ and 6–5–4 for OLI (Table 1). Thus, the band combination of SWIR1–NIR–Red was selected as the most appropriate band for the entire image classification.

Table 1. Spectral separability results using the Jeffries-Matusita distance technique to isolate the differences between the mangrove vegetation and non-mangrove areas for each band of TM, ETM+, and OLI sensors.

TM Bands	ETM+ Bands	OLI Bands	Band Name	Jeffries-Matusita
1	1	2	Blue	0.51
2	2	3	Green	0.75
3	3	4	Red	1.63
4	4	5	NIR	1.86
5	5	6	SWIR 1	1.91
6	6	10	Thermal	0.72
7	7	7	SWIR 2	1.25

2.4. Cloud Patching Process, Stacking, Mosaicking, and Masking

Clouds and cloud shadows have a significant effect on the satellite sensors' spectral bands reflectance values (Zhu and Woodcock 2012) and degrade the quality of the sensors' data (Li and Roy 2017). Therefore, the Landsat database was searched for the clearest satellite images of the study area with the lowest cloud cover. However, for images where clouds are present, more than one scene from the same epoch was acquired to facilitate the cloud patching process using the Fmask algorithm (Zhu and Woodcock 2012; Zhu et al. 2015). The selection of different eras was based on the availability of quality data. Thus, the year 2021 was excluded from the potential list of options because most of the data available was poor in quality. All the selected bands were stacked together and created a seamless mosaic of the study area. The ocean areas were masked out using the Normalized Difference Vegetation Index (NDVI) with a threshold of cut-off of 0.5 (Chen et al. 2013).

2.5. Image Classification and Change Detection Analysis

To delineate the mangroves of Palawan, this study used the Support Vector Machine Classifier (SVM) algorithm. This linear supervised non-parametric statistical learning theory has been proven effective in LULC research (Mountrakis et al. 2010; Shi and Yang 2015; Campomanes et al. 2016; Madanguit et al. 2017; Talukdar et al. 2020). The SVM-based classifier requires a training sample and one of the advantages of this technique is that it can generalise well from a limited amount of training data compared to alternative methods (Mountrakis et al. 2010). This algorithm uses successive executions of a process until it generates the probabilistic estimates for known and unknown classes. In this entire procedure, the Bayesian minimum-error decision rule is adopted (Wang 2005; Press et al. 2007; Thomé 2012).

The overall accuracy results of SVM depend on the kernel used as well as the chosen kernel's parameters and methods (Huang et al. 2002). We chose the parameters Gamma (G) in Radial Basis Function (RBF) kernel and the C hypermeter in SVM to control error, using the cross-validation (CV) optimization technique (Zhang et al. 2018; Buitre et al. 2019). We set the default threshold values of 0.091 for G and 100 for penalty parameter C to gain lower bias and penalize incorrect classification heavily (Heumann 2011b; Campomanes et al. 2016). The RBF kernel formula (Eq 6) is shown below:

$$K(x, x') = exp\ (-g||x - x'||^2), g > 0 \qquad \text{(Eq 6)}$$

where, $||x - x'||^2$ is the squared Euclidean distance between two data points, x and x'; g is the user-defined gamma. Across the series of Landsat data, we created two spectral classes including (a) mangrove vegetation, *i.e.*, intertidal halophytic forests both natural and rehabilitated, and (b) non-mangrove areas, *e.g.*, rivers, estuaries, lakes, sea, tidal mudflats, agricultural areas, grassland, high- and lowland forests, bushes, residential and industrial areas in rural and urban regions, aquaculture ponds, salt pans, etc. A random sampling technique was used to select a minimum of 400 pixels for each spectral class. For all the classified Landsat images, the total mangrove areas were quantified.

Assessing the accuracy of multi-decadal mangrove change is challenging due to the limited availability of *in-situ* reference datasets in the time period of interest (Liu et al. 2018). In this work, the accuracy of mangrove classification was assessed using government data derived from the 2010 historical record of the National Mapping and Resource Information Authority (NAMRIA). The training mangrove forest polygons were validated through the established testing samples and the accuracy was assessed using the producer's accuracy, the user's accuracy, the overall accuracy, and the kappa coefficient values (Congalton 1991). This study produced >86% overall accuracy results by which the definite mapping identification of different land use/land cover categories generated valid results (Weng 2010). Furthermore, the *Kappa* analysis for this study generated results >70%, which qualify them as significant covariates (Manonmani and Suganya 2010).

Upon completing the rigorous pre-processing, image classification, and validation procedures, we conducted the change detection for Palawan and the three case study areas of GCRF BC, using the SCP version 7.9.0 Matera in Quantum in QGIS version 3.22.1 Białowieża, to determine the magnitude of changes in mangrove vegetation and non-mangrove classes, and the trends of these changes across three time periods (1988–1998, 1998–2008, and 2008–2020).

2.6. Mangrove Change Projection

A Markov Chain is a stochastic process that describes the likelihood of changing one state to another (Serfozo 2009; Arsanjania et al. 2013) through the implementation of neighborhood rules (Aitkenhead and Aalders 2009; Serfozo 2009). The Markovian process has been implemented in many LULC studies due to its efficiency in future land use prediction (Coppedge et al. 2007; Kanjirappuzha et al. 2010; Adhikari and Southworth 2012; Hua 2017; Abdulrahman and Ameen 2020; Faichia et al. 2020). In mangrove forest spatial classifications, the integration of the Markov Chain model (Chen et al. 2013) and its cross-functional application with Cellular Automata (Mukhopadhyay et al. 2015; Abdulrahman and Ameen 2020) have been considerably growing.

In statistical terms, the Markov Chain Modelling can effectively make a prediction of the changes in LULC based on the calculation of the transition probabilities of one system at time t_2 with the state of the system at time t_1 according to the specific year (Houet and Hubert-Moy 2006; Kanjirappuzha et al. 2010; Murugesan et al. 2012; Kumar et al. 2014). The transition probability matrix (Omar 2014) is one of the descriptive tools generated in the process where the mangrove areas transitional matrix derived from different mangrove classes (Mukhopadhyay et al. 2015). The Markov processes used in this study are expressed in equations (Eq 7), (Eq 8), and (Eq 9):

$$v_{t2} = M v_{t1} \qquad \text{(Eq 7)}$$

where the input LULC proportion column vector corresponds to v_{t1} and the output vector to v_{t2}; M is an $m \times m$ transition matrix for the time interval $\Delta t = t_2 - t_1$. The development of the probability transition matrix (p_{ij}) can be calculated using as follows:

$$n_i = \sum_{j=1}^{q} n_{ij} \qquad \text{(Eq 8)}$$

$$p_{ij} = n_{ij} / n_i \qquad \text{(Eq 9)}$$

where n_{ij} is the number of pixels of class i from the first date (current state) that were changed to class j in the second date (next period); cell n_i is in the change detection matrix by row marginal frequency; q is the total number of classified classes; p_{ij} is the land-cover probabilistic transition matrix. We have conducted three projections using the Markov Chain model. The first one was the mangrove projection for 2013 using the 1988-1993 datasets. In the second and third projection scenarios, we chose the years 2013–2020 datasets to predict the spatial changes of mangroves for the years 2030 and 2050. Using the IDRISI Environment version 17.00, the Markov Chain transition probability matrix was generated.

2.7. Model Validation of the Markovian Process

We validated the model by comparing the simulated mangrove and non-mangrove areas in 2013 with the observed data in the 2013 ETM+ map. The output was tested with observed values using the Pearson's Chi-squared χ^2 test to examine the appropriateness of the model:

$$\chi^2 = \sum \frac{(O - E)^2}{E} \quad \text{(Eq 10)}$$

where *O* represents the simulated value (1988–1993) and *E* is the actual value of the transition matrix (2013–2020). The calculated χ^2 is compared with the χ^2 from the table at alpha-level of 0.05 with degrees of freedom $(2–1)^2$. The land-use change analysis is compatible with the hypothesis of data independence if the computed χ^2 is smaller than the tabled-value χ^2.

The entire methodological process of mangrove classification and predictive modeling underwent three major processes: (1) Raw data and pre-processing, (2) Image classification and change detection, and (3) Mangrove change projection (Figure 2).

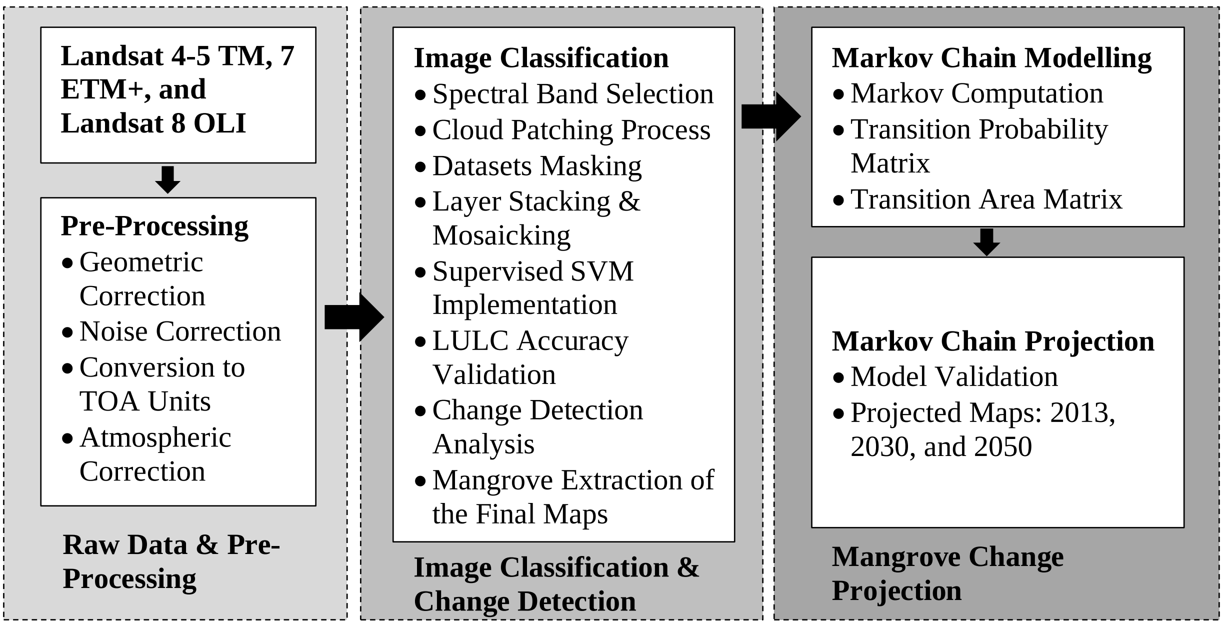


Figure 2. Schematic diagram of change detection and projection of mangrove forests in Palawan using the Landsat imageries and Markov Chain model.

3. RESULTS

3.1. Spatiotemporal Distribution of Mangroves and Comparison with the Previous Records

Our mapping classification resulted in two major classes, the mangrove forests and non-mangrove areas. We have presented in Figure 3 the spatiotemporal distribution of mangroves in Palawan within the span of 32 years, particularly the time periods of 1988, 1993, 1998, 2003, 2008, 2013, 2018, and 2020. We observed that mangrove forests in Palawan were generally concentrated around the coastal boundaries, particularly in estuarine fringes, bays, riverbanks, and margins between land and sea. Based on this study and the previous records, the mangrove forests cover in Palawan were still relatively high compared with the other provinces in the Philippines (*e.g.*, Long and Giri 2011).

The largest mangrove concentrations in Palawan were found in the eastern part of the island. These mangroves form dense and continuous stands in Puerto Princesa City, Bataraza, Balabac, and Brooke's Point in the south, and in the municipalities of Taytay, Coron, Busuanga, Culion, El Nido, Aracelli, and Dumaran in the north. In Puerto Princesa City, the greatest concentration of mangroves are generally found in Puerto Princesa Bay, Honda Bay, Ulugan Bay, and Turtle Bay.

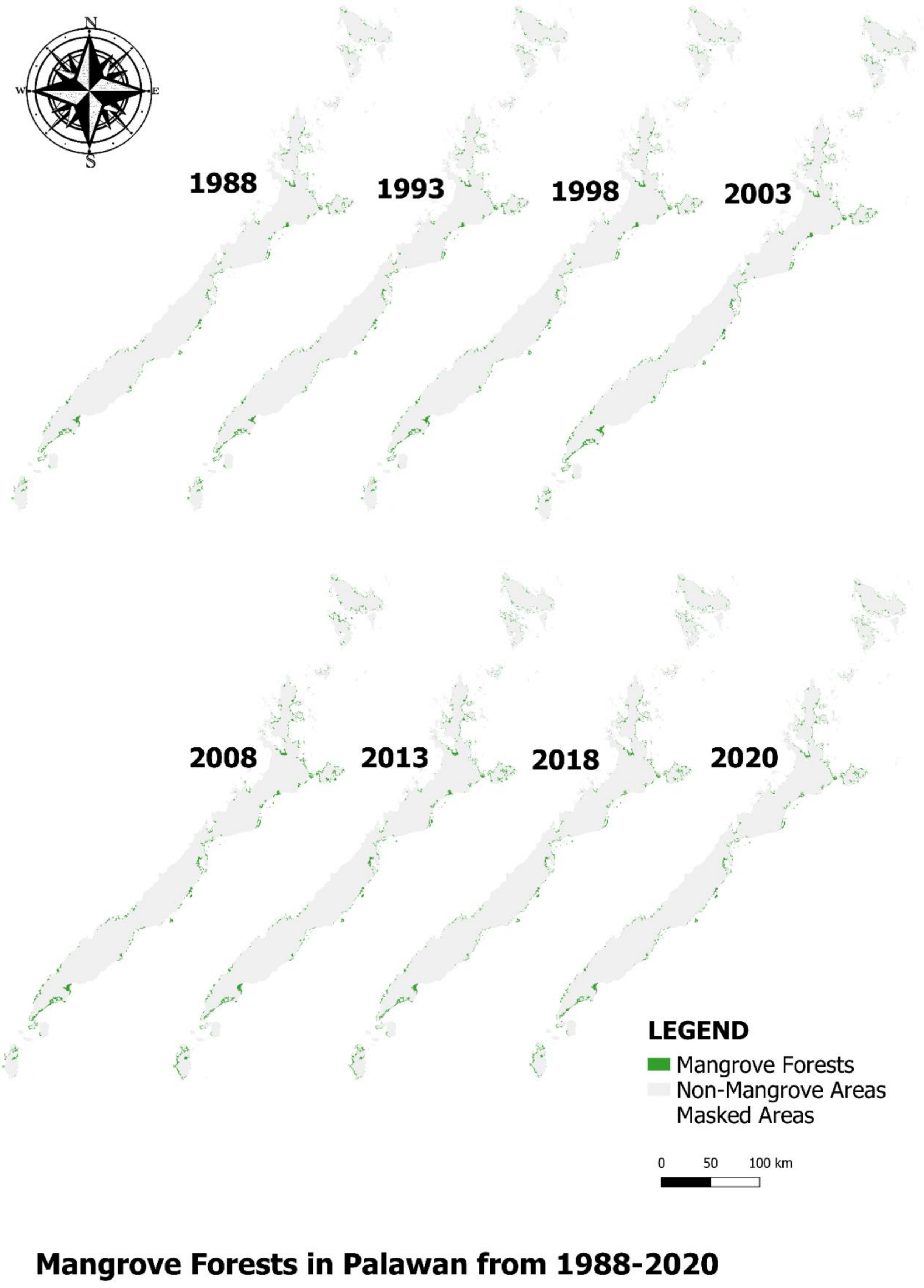
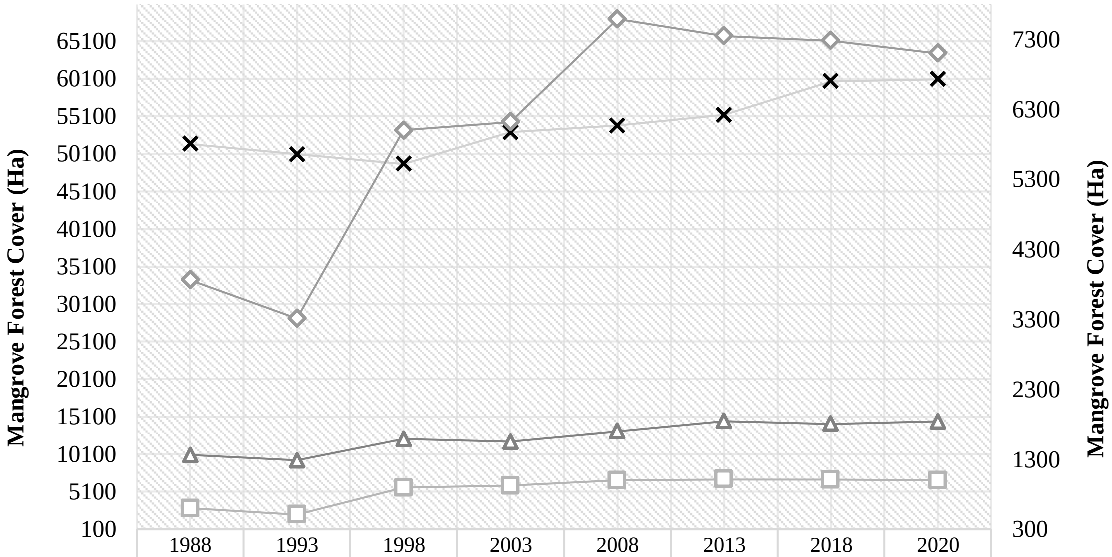


Figure 3. Spatiotemporal distribution of mangroves in Palawan in a span of 32 years from 1988 to 2020.

The classified maps from 1988–2020 showed that the largest area of mangroves in Palawan was recorded in 2020 (60,033.8 ha) while the year 1998 (48,745.3 ha) had the least extent (Figure 3). The lower total area calculated for 1998 is likely due to misclassification as a result of minor cloud patches, especially in the northern part of Palawan. Our estimate for this year, however, does not deviate too far from the estimates in 1993 (50,045.3 ha) and 2003 (52,961.5), respectively.



	1988	1993	1998	2003	2008	2013	2018	2020
Palawan	51438.2	50045.3	48745.3	52961.5	53877.2	55302.4	59774.9	60033.8
Puerto Princesa City	2876.3	2056.3	5634.2	5922.7	6621.4	6738.1	6709.4	6601.8
Taytay	3865.1	3311.5	6003.4	6120.8	7591.8	7351.5	7285.1	7103.6
Aborlan	1363.4	1287.7	1591.8	1553.4	1697.6	1842.5	1803.2	1839.7

Figure 4. Composite representation of area statistics of mangroves in Palawan, Puerto Princesa City, Taytay, and Aborlan.

In consideration of the funder of this study, we also separately quantified the mangrove extents in Puerto Princesa City, Aborlan, and Taytay. Two of the GCRF BC's smaller geographical case study areas (barangay) were located in Aborlan municipality while Puerto Princesa City and Taytay municipality both had four case study locations each. Among these three major boundaries, Taytay had the largest mangroves cover followed by Puerto Princesa City and Aborlan (Figure 4). The mangrove areas in Taytay showed an increase since 1988 (3,865.1 ha) and peaked in 2008 (7,591.8 ha) before the trend showed a gradual decrease until the most recent estimate, in 2020 (7,103.6 ha). Similarly, the mangroves in Puerto Princesa City also exhibited a pattern of increase from 1988 (2,876.3 ha) and reached the highest records in 2008 (6,621.4 ha) and 2013 (6,738.1 ha) before the total estimates dropped. Unlike the two previous locations, the mangrove forests in the municipality of Aborlan demonstrated an increasing trend from 1993 (1,287.7 ha) to 2020 (1,839.7 ha). However, the total mangrove area in Aborlan accounts for only about <25% and <30% of the overall mangrove forest covers in Taytay and Puerto Princesa City, respectively.

One of the most challenging aspects of classifying the non-mangrove areas in this study was the areal immensity of Palawan. The largest estimate for non-mangrove areas was recorded in 1998 at 1,375,197.7 ha (Figure 5). Mainly, the non-mangrove areas identified were highland and lowland forests, agricultural areas, and built-up areas (*e.g.*, residential and industrial areas in rural and urban localities). A trend of decrease in non-mangrove areas was evident from 1998 to 2020 (1,363,909.2 ha). The smallest change, at approximately 250 ha, was recorded between 2018 (1,364,168.1 ha) and 2020.

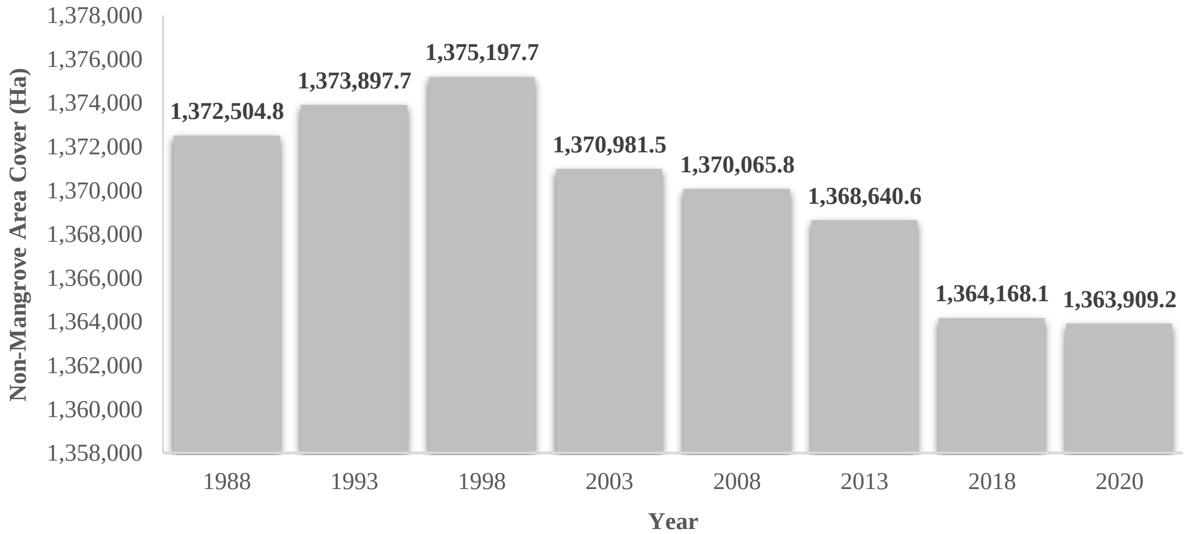


Figure 5. Estimated total cover of non-mangrove areas in Palawan.

To visualize the mangrove forests extents in Palawan across the different time periods, which used different techniques and resources, the result of this study particularly for the years 2020, 2018, and 2013 were presented along with other previous estimates. As shown in Figure 6, our estimates for the total areal extent of mangrove forests in Palawan are similar to other estimates from 1992–2015, except for the estimate of Songcuan et al. (2015) at only 43,000 ha which was the lowest among all the gathered data. In the 1990s, the earliest records of mangrove estimates were obtained by the Japan Forest and Technology Association (DENR-JAFTA 1992-2000) and NAMRIA. Our current estimate for 1993 (50,045.3 ha) was quite lower compared with the previous records of DENR-JAFTA (1992-2000) and NAMRIA at 50,602 ha and 51,346 ha, respectively. However, our estimate for 1998 (48,745.3 ha) had about 5% margin with the NAMRIA's record (51,346 ha). In 2005, the PCSDS utilized the Satellite Pour I'Observation de la Terre (SPOT) satellite sensor to delineate the extent of mangroves in Palawan and generated approximately 58,400 ha. Based from the mangrove data extraction made by Richter et al. (2022) from the Global Mangrove Watch (GMW), in accordance with the same mangrove areal estimates that were originally created by Bunting et al. (2018), the GMW figures from 2007–2010 had a very slight difference with the 2008 estimate (53,877 ha) for this study. Unsurprisingly, among all the references cited in this study, NAMRIA recorded the highest estimates at 63,532 ha in 2010 (FAO 22) which was higher than the GMW data in the same year (53,731 ha) and even higher than our most recent estimate for 2020. Our current study revealed a minor difference in the increase of mangrove forests, showing at least 59,774.2 ha in 2018 and 59,9925.8 ha in 2020, respectively (Figure 6). Surprisingly, the mangrove forests assessment of Long and Giri (2011) revealed a sudden decrease in mangrove areas in just a year span. Our estimates for 2013 at 55,302.4 ha had a minor margin of difference with the approximation obtained by Long and Giri (2011).

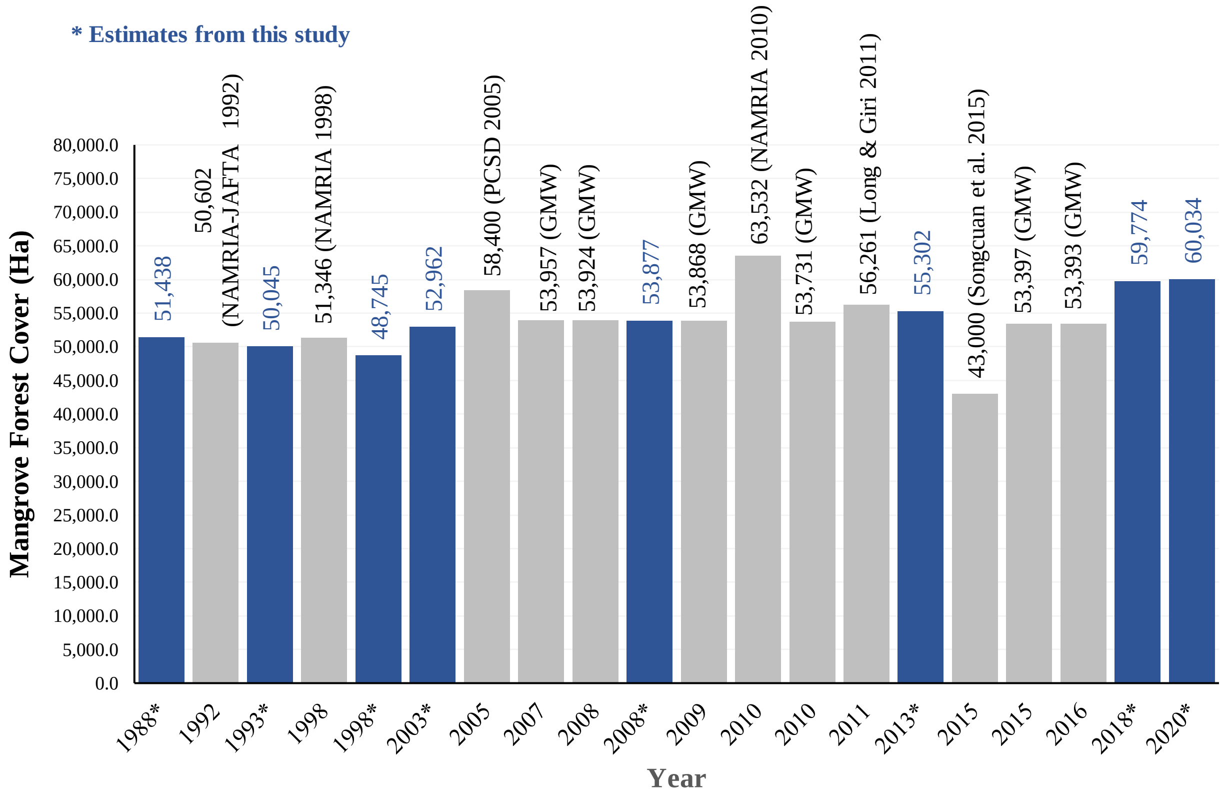


Figure 6. Representation of mangrove forest areas in Palawan based on the previous estimates and the results of this study.

The result of mangrove forest covers we obtained in 1993 (1,287.7 ha) for Aborlan was comparably lower than the estimation made by Venturillo (2016) in 1992 (1,494.8 ha). However, a small gap in the estimated values was determined between the work of Venturillo (2016) in the same period and this study in 1998 (1,591.8 ha; Table 2). Additionally, this study estimated the mangrove forests in

Aborlan in 2008 at about 1,676.6 ha which was higher than the GMW data (1,341.3 ha). Although the interval of years was relatively small between 2010 to 2013, the assessment made by Jansen (2017) in 2010 at 1,202 ha was distinctly lower than the estimates from GMV (Bunting et al. 2018) and our result for 2013 (1,842.5 ha). Unsurprisingly, from the time periods 2013 to 2018, the GVM data for 2015 and 2016 (Bunting et al. 2018) are similar when in fact variations in areal changes were evident in between 2013, 2014, and 2016. However, all the assessments reported for Aborlan revealed a similar pattern where mangrove forests cover increased from inclusive time periods 1992, 1993, 1998, 2010, 2013, 2014, and 2016.

Table 2. Comparison of mangrove forest areas in Taytay, Aborlan, and Puerto Princesa City based on the previous estimates and the results of this study. The '*' symbol denotes the estimates from this study. The GMW estimates were sourced from Richter et al. (2022) and are based on the measurements by Bunting et al. (2018).

Year (Reference)	Mangrove Forest Cover (Ha)		
	Puerto Princesa City	Taytay	Aborlan
1992 (Venturillo 2016)	-	-	1,494.8
1993	-	-	1,287.7
1998	5,634.2*	-	1,591.8*
2003	5,922.7*	-	-
2003 (Pagkalinwan & Ramos 2013)	3,201.8	-	-
2007 (GMW)	5,839.8	6,727.1	1,340.7
2008 (GMW)	5,835.7	6,714.2	1,341.3
2008	6,621.4*	7,591.8*	1,697.6*
2009 (GMW)	5,816.3	6,713.2	1,341.3
2010 (Jansen 2017)	4,020.0	1,578.0	1,202.0
2010 (GMW)	5,773.3	6,715.5	1,341.3
2013 (Pagkalinwan & Ramos 2013)	4,577.2	-	-
2013	6,738.1*	7,351.5*	1,842.5*
2014 (Venturillo 2016)	-	-	1,866.8
2015 (GMW)	5,754.8	6,601.0	1,337.2
2016 (Jansen 2017)	5,668.0	3,905.0	1,655.0
2016 (GMW)	5,754.8	6,601.0	1,337.2
2018	6,601.8*	7,103.6*	1,740.3*
2020	6,601.8*	7,103.6*	1,839.7*

In the municipality of Taytay, our estimated result obtained in 2008 has close margin of difference from the GMW data. However, our estimates for 2013 (7,351.5 ha) and 2018 (7,103.6 ha) unsurprisingly differed significantly from the data gathered by Jansen (2017) in 2010 (1,578 ha) and

2016 (3,905 ha; Table 2). Similar interpretation goes on the data by Jansen (2017) in 2010 and from the GMW report in the same year where the former generated a very low estimate (1,578 ha) against the latter figure of 6,715.5 ha.

In 2003, Pagkalinawan and Ramos (2013) estimated the total mangrove forests extent in Puerto Princesa City at 3,201.8 ha. It was lesser than our calculated results for 1998 (5,634.2 ha) and 2003 (5,922.7 ha), respectively (Table 2). On separate assessments, Jansen (2017), Bunting et al. (2018), and Pagkalinawan and Ramos (2013) recorded 4,020 ha, 5,773.3 ha, and 4,577.2 ha of mangrove forests in 2010 and 2013. We obtained a relatively higher estimate in 2013 (6,738.1 ha) compared with Pagkalinawan and Ramos (2013) in the same year. We only observed an almost 100 ha difference between the estimates of Jansen (2017) in 2016 and the quantified extent made by Bunting et al. (2018) in the same year. However, between 2016 and 2020, an almost 1,000 ha difference was observed between the previous and current estimates.

3.2. Accuracy Assessment

Using the 2010 LU/LC NAMRIA map as our ground reference data, the mangrove classification accuracies for years 1988, 1993, 1998, 2003, 2008, 2013, 2018, and 2020 were generated. The comparative accuracy measurements yielded satisfactory agreements across all the years. The highest and lowest overall accuracies and *Kappa coefficient* values for the mangrove forest class were produced in 2020 (92.90% and 0.91) and 1993 (86.66% and 0.73) classification maps, respectively (see Supplementary Information). The highest and lowest user's accuracy in the classification of mangrove forest features were generated in the years 2003 (95.76%) and 1993 (86.04%). These suggest the commission errors of 4.24% and 13.96%, in which the pixels identified in the map as mangrove forest class actually represent an incorrect class based on a reference image. On the other hand, the generated producer's accuracy quantifies the probability that a pixel was classified as something other than that class. The year 2013 yielded the highest producer's accuracy (6.73% omission error) and the eras of 1998 and 1993 were at the lowest rank (11.80% and 11.56% omission errors). We presumed that the low overall accuracy and *Kappa coefficient* values generated for 1993 were due to the poor satellite image quality. During this period, the cloud covers in two of the six scenes (refer to the Supplementary Informations Table 1: WRS Path 116/Row 052 and WRS Path 118/Row 054) made marginal spectral confusion between different features. Generally, our classifications only produced <15% commission and omission errors for both mangrove forest and non-mangrove area classes (see Supplementary Information).

3.3. Mangroves Change Detection

We carried out change detection analysis for mangroves in Palawan by comparing multiple years in discrete intervals (*e.g.*, 10–year gap, 7-year gap). The results of the change detection statistics within the four-time periods (1988–1998, 1998–2008, 2008–2018, 2013–2020) showed that the mangrove extents in the Palawan dramatically increased for the last 32 years (Figure 4, Table 3). The periods with the greatest change in mangrove forest extents in Palawan were recorded in 2008–2018 and 1998–2008, showing at least 10.95% (5,897.7 ha) and 10.53% (5,131.9 ha) increase since the time periods 1998 to 2018 (Table 3, Figure 7a & 7b). However, we also noted the reduction in mangrove forest cover during the time period 1988–1998 at 5.24% (2,692.9 ha) loss. Although this decrease might imply disturbance in the mangrove ecosystems in the study area, we did not exclude from our conclusion that this figure could be attributed to the spectral confusion of the different classes during the classification stage (see Supplementary Information).

Table 3. Changes in mangrove forest distribution in Palawan during (a) 1988–1998, (b) 1998–2008, (c) 2008–2018, and (d) 2013–2020. The percentage of reduction or increase in mangrove extents in each region was quantified based on the calculation used by Chen et al. (2013): $(S_j – S_i)/S_i \times 100$, where S_j and S_i represent the total areas in each categorical class in the *i*th and *j*th time periods. The symbol '▲' denotes the percentage and areal change of increase in mangrove forests while the decrease is denoted by the symbol '▽', respectively.

Time Period	Palawan		Puerto Princesa		Taytay		Aborlan	
	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%
1988-1998	2,692.9 ▽	5.24 ▽	2,757.9 ▲	95.88 ▲	2,138.3 ▲	55.32 ▲	228.4 ▲	16.75 ▲
1998-2008	5,131.9 ▲	10.53 ▲	987.2 ▲	17.52 ▲	1,588.4 ▲	26.46 ▲	105.8 ▲	6.65 ▲
2008-2018	5,897.7 ▲	10.95 ▲	88.0 ▲	1.33 ▲	306.7 ▽	4.04 ▽	105.6 ▲	6.22 ▲
2013-2020	4,731.4 ▲	8.56 ▲	136.3 ▽	2.02 ▽	247.9 ▽	3.37 ▽	2.8 ▽	0.15 ▽

Concurrently, the mangrove forests cover in Puerto Princesa City showed a sharp increase from 1988 to 1998 at about 2,757.9 ha (95.88%). However, unlike the increasing trend in Palawan in 2013–2020, the percentage of change at 2.02% (136.3 ha) in the mangrove forests cover in Puerto Princesa City on the same time period showed a slight decrease. Most of the mangroves in Puerto Princesa City were found in the eastern seaboard of the study area, forming dense and narrow canopies along the riverbanks, estuarine regions, and margins of the bays, particularly in Honda Bay, Puerto Bay, and Turtle Bay. The only notable concentration of mangroves in the western seaboard of Puerto Princesa City was found in Ulugan Bay (Figure 7c).

Similarly, the municipality of Taytay also established an increase from the time periods 1988–1998 and 1998–2008 with the percentage of increase at about 55.32% (2,138.3 ha) and 26.46% (91,588.4 ha), respectively (Table 3). Since 2008, the mangroves in this region suffered a consecutive loss, particularly with the reducing rates of 4.04% and 3.37% in 2008–2018 and 2013–2020, respectively. Despite this decrease, the mangrove extent in Taytay remained relatively higher than Puerto Princesa City and Aborlan (Figure 3). These mangroves were mostly concentrated in Taytay Bay and along the Malampaya Sound area. The thick mangrove assemblages within the inner south-eastern portion of the Malampaya Sound were notable in the classified map. Furthermore, mangroves were seen forming boundaries along the coastlines of smaller and larger islands in Taytay Bay, especially in the north-eastern part of the bay (Figure 7d).

In comparison with the mangrove forests in Taytay and Puerto Princesa City, the municipality of Aborlan only suffered a small loss in mangrove assemblages during 2013–2020 (0.15%, 2.8 ha; Table 3). For the period of 20 years, the mangrove forests cover in Aborlan increased although the extent of expansion was relatively lower than Puerto Princesa City and Taytay. Despite the similarities in the pattern of changes in Palawan, we did not exclude the possibility that the variations in tidal inundation and the time of the data acquisition may influence the estimations. Although we did not exclude the possibility that mangroves can also be found in the western seaboard of Aborlan, for this study we only recorded the mangroves in the eastern seaboard portion. Notably, the small islands of *Puntog* and *Malunot* generally had thick mangrove assemblages (Figure 7e).

There was a clear pattern of change in non-mangrove areas in Palawan from 1988 to 2020. An increasing trend was seen from 1988 to 1998 before a spike of decrease happened. The evidence of decreasing trend continued from 2003 to 2020 (Figure 4). We assumed that these changes incorporate growth in closed-forest areas and the residential, industrial, and agricultural developments in the region. Moreover, we also presumed that tourism growth and infrastructure expansion projects (*e.g.*, construction of national roads or highways) play a critical role in the elaborated expansion of non-mangrove areas in Palawan.

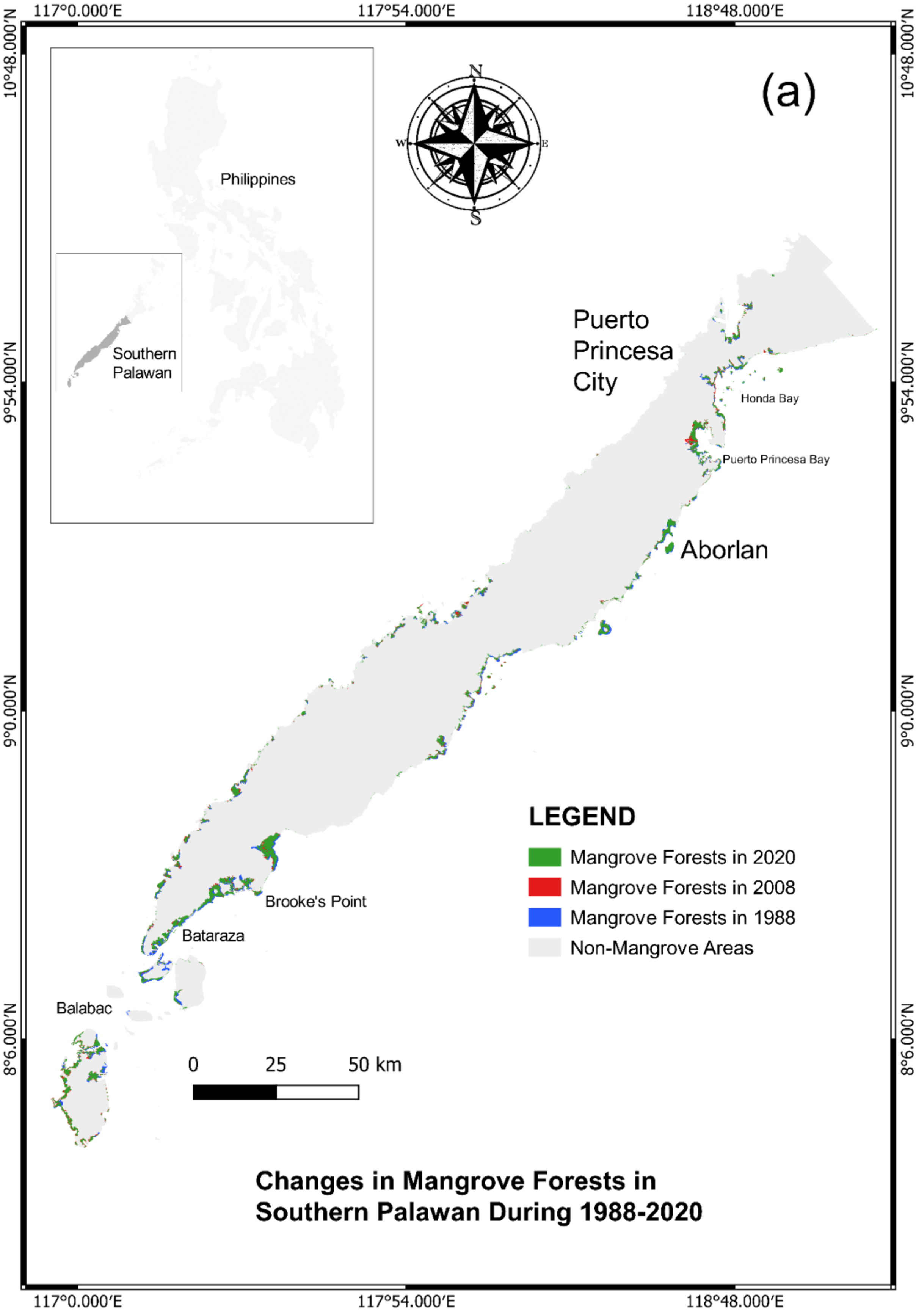


Figure 7. Changes in mangrove forests in Palawan from 1988 to 2020.

631 **Figure 7.** (Continued…)

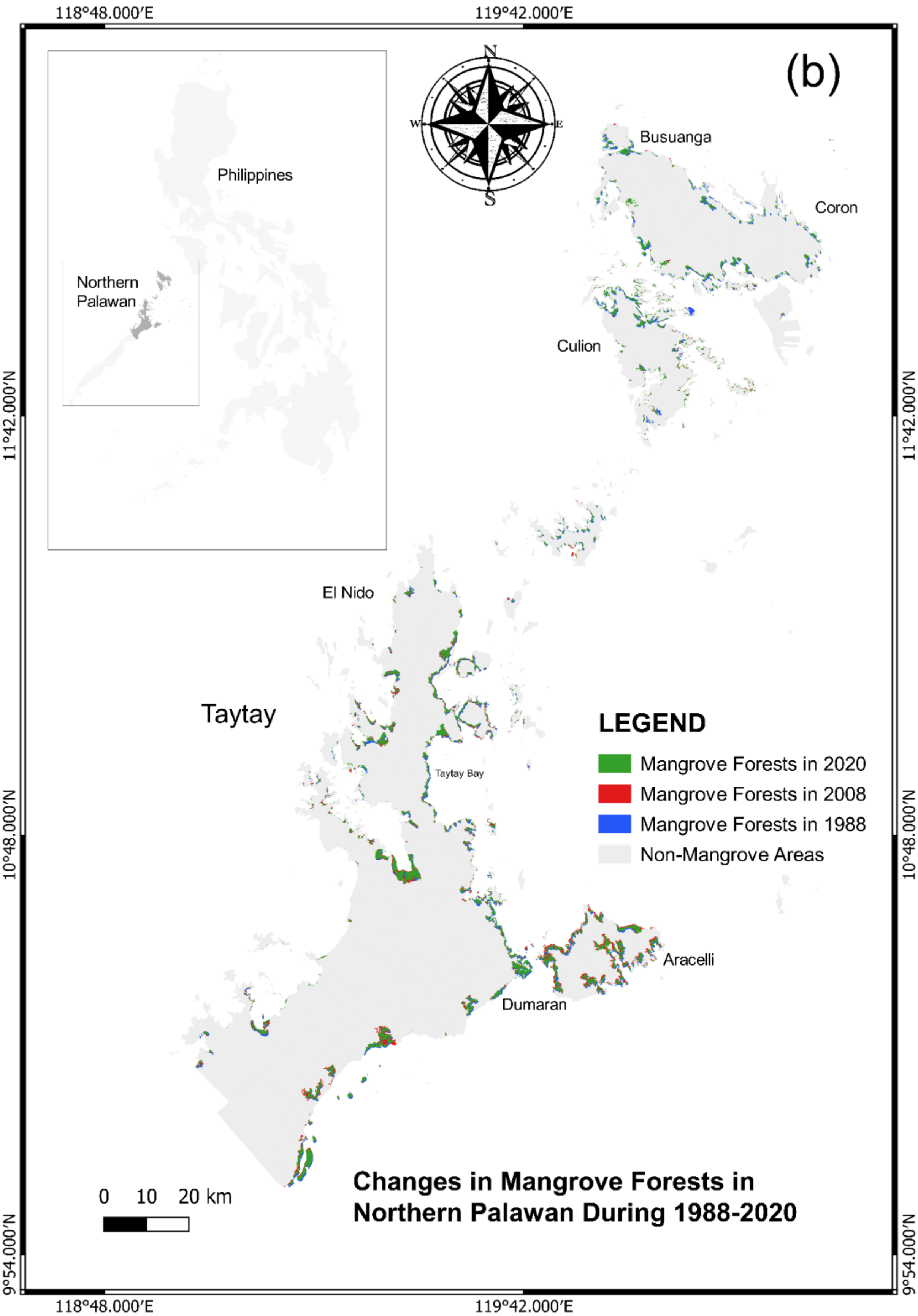


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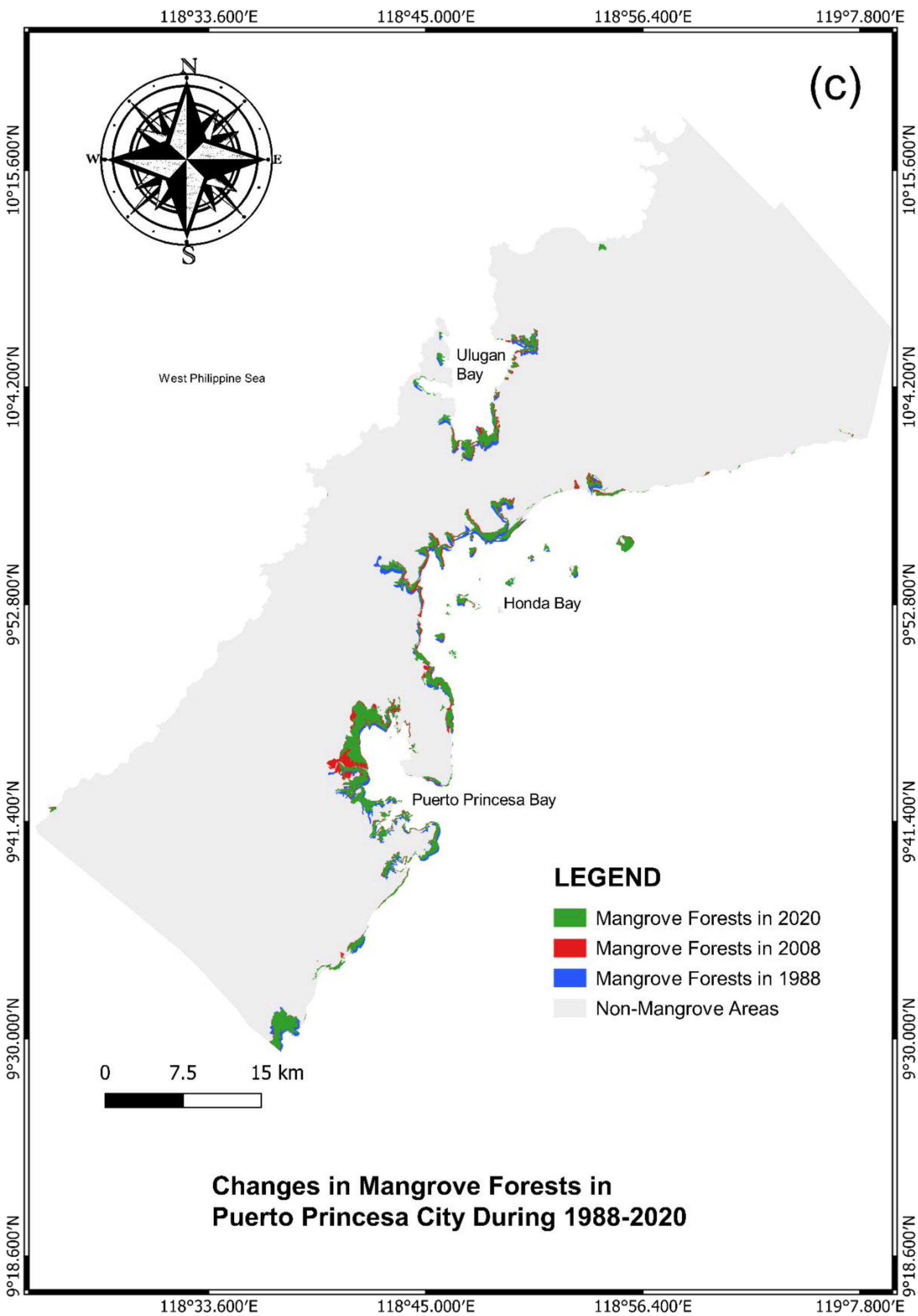
Figure 7. (Continued…)



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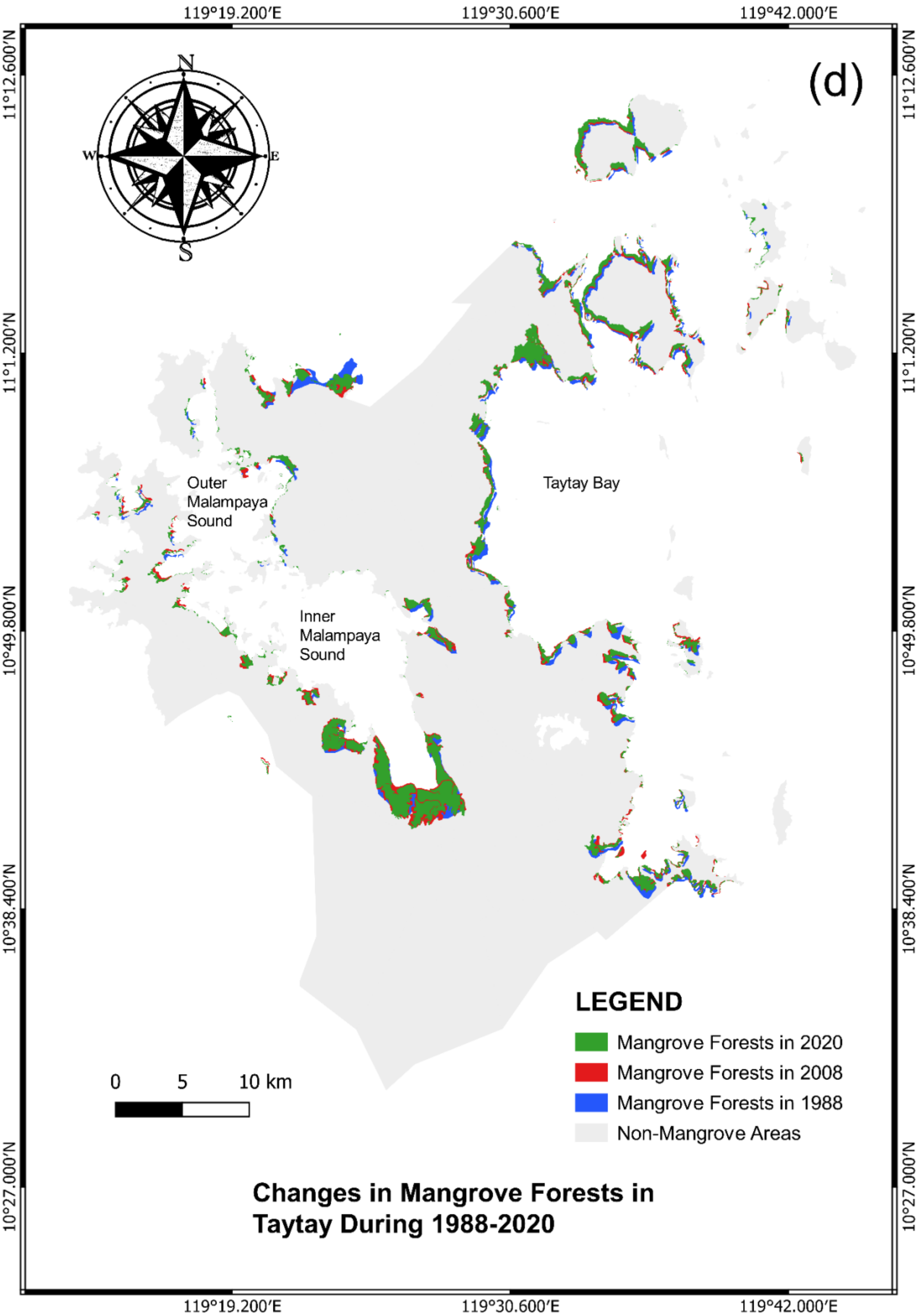
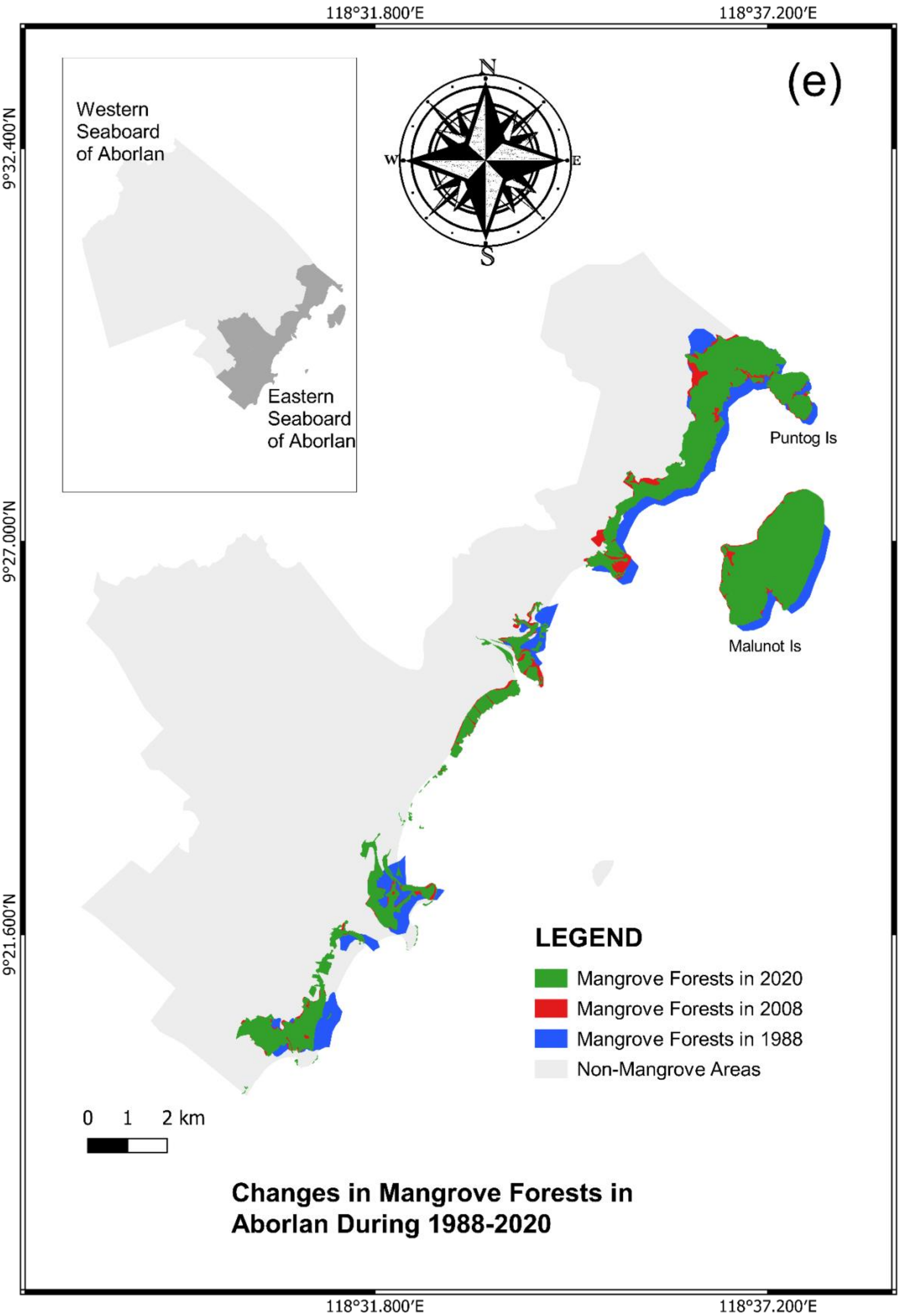


637 **Figure 7.** (Continued…)



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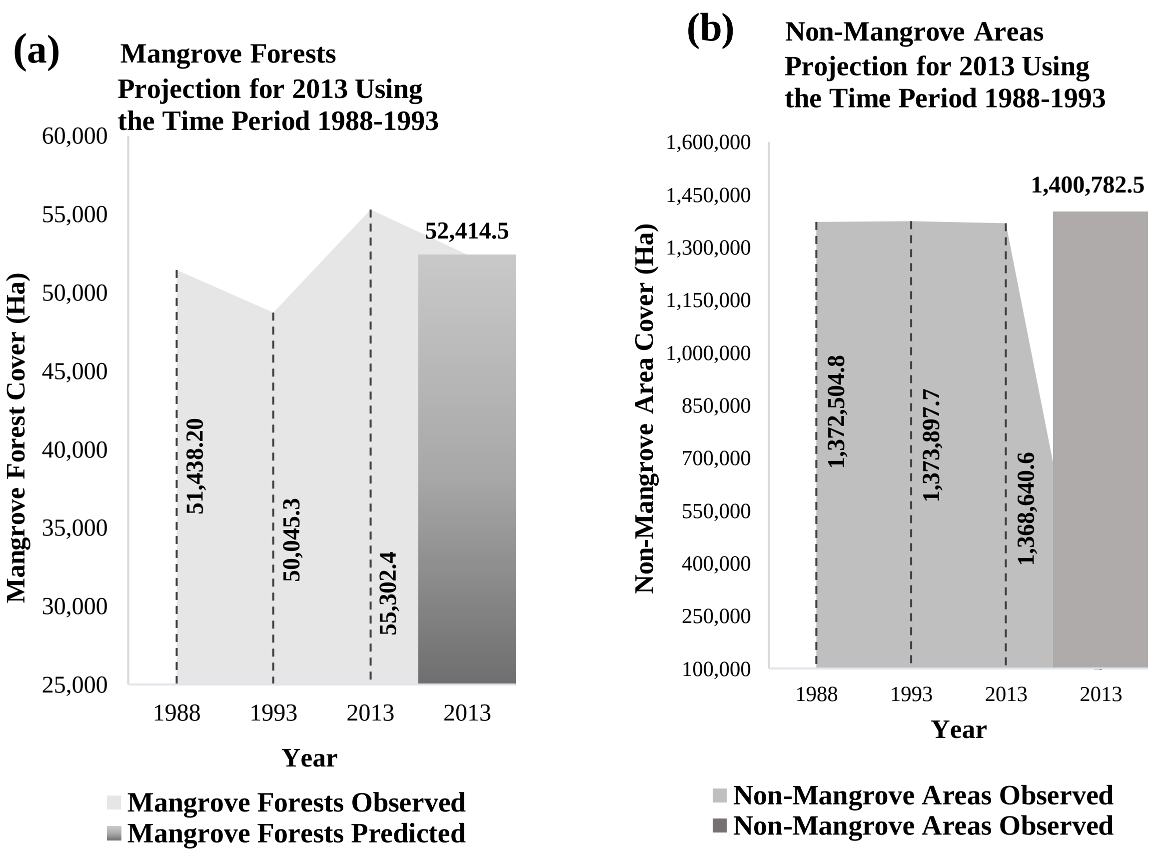
3.4. Mangrove Forests Projection and Model's Accuracy

The Markov's transition probability matrix was generated for the two time periods, 1988–1993 and 2013–2020 (see Supplementary Information). These numbers suggested the probabilities of change in mangrove forest and non-mangrove area classes in Palawan. The projected areal extent of mangroves for 2013 (52,414.5 ha) slightly corresponds with the observed 2013 extent at 51,438.2 ha (Figure 8a), which indicated fewer variations between the two datasets. For this instance, we confirmed that the transition matrices between 1988 and 1993 could be effective for predicting the dynamics of change in the mangrove forests and non-mangrove areas in Palawan.

We found that the mangrove forests in the region will likely increase by 8.18% (64,946.3 ha) and 11.56% (66,972.1 ha) in the years 2030 and 2050 (Figure 8c). Conversely, it was projected that the non-mangrove areas in Palawan were likely to reduce by 4.53% (1,302,149.6 ha) and 7.21% (1,265,498 ha) in 2030 and 2050, respectively (Figure 8d). There was a slight increase in mangrove forests in Palawan for the simulated time period 2030 (64,946.3 ha) compared with 2013 (52,414.5 ha) and 2050 (66,972.1 ha; Figure 8a, Figure 8c).



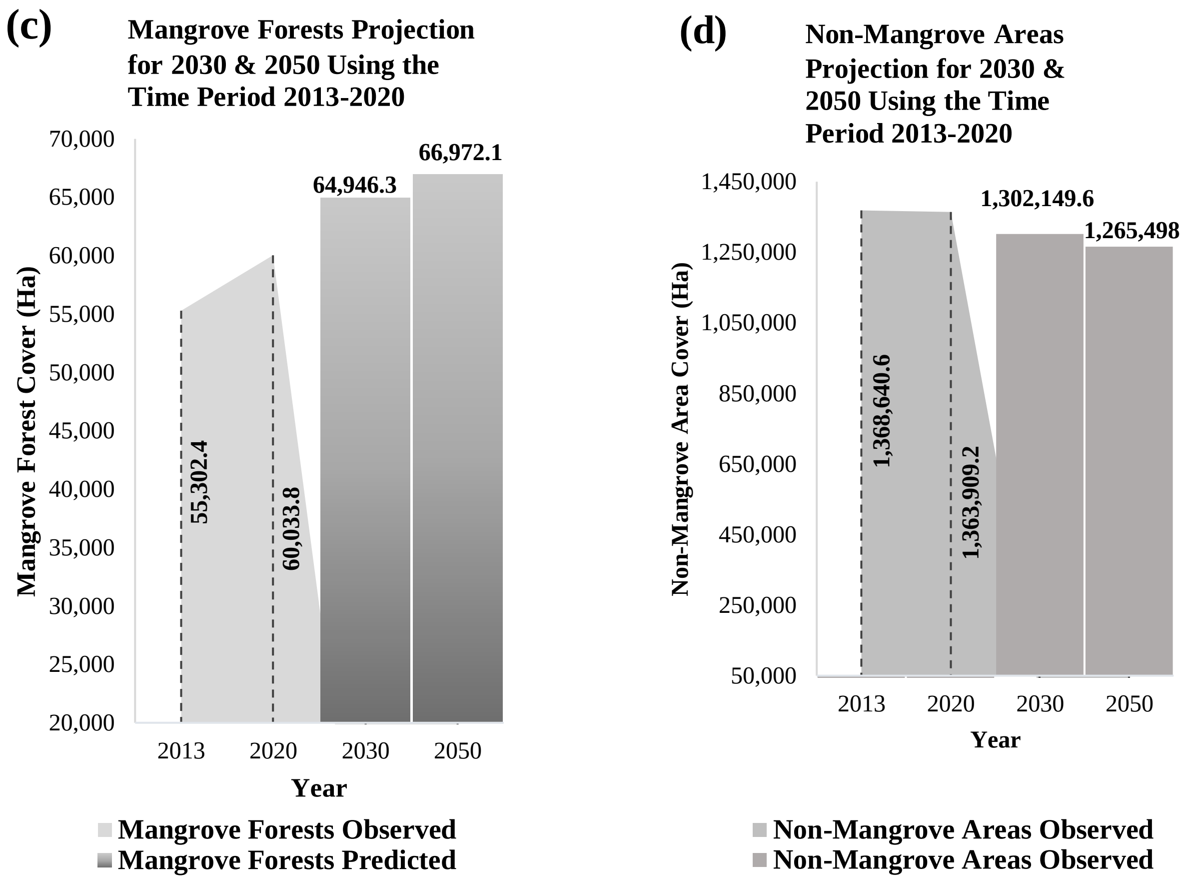


Figure 8. Projected probability of changes in mangrove forests and non-mangrove areas in Palawan.

The result of the accuracy assessment using the time period 1988–1993 and the projected 2013 output was evaluated using a χ^2 test, indicating a value of 150.8 which was larger than 3.841 for the critical level of p=0.05 with $(2–1)^2$ degrees of freedom. This suggests that the hypothesis of statistical independence for the data was rejected. Therefore, predictive modelling using the Markov Chain can be used for forecasting mangroves in Palawan.

4. DISCUSSION

The course of major development in Palawan was started in 1981 with the implementation of the Palawan Integrated Area Development Project (Baylon et al. 1993). Following the acquisition of Landsat data for 1988 in this study, this major project has been almost completed. Therefore, we deemed that this condition serves as a good baseline of information to envisage the changes in land use patterns in Palawan. But perhaps, the major framework for all development undertakings in Palawan was the passage of the Republic Act 7611 known as the SEP for Palawan Act in 1992. Within this law, the spatial basis for the implementation of its main goal is the ECAN Zonation Project (PCSDS 2005).

The strategic approach of ECAN is composed of three main components: terrestrial, coastal/marine zones, and tribal ancestral lands. The multiple utilizations of every resource within these components are defined according to different zones, particularly within the multiple/manipulative zone and buffer zone. The buffer zone is further divided into three distinct zones where the level of restriction in resources extraction differs. The buffer zone is comprised of restricted use area (*i.e.*, where limited non-consumptive activities may be allowed as long as they will not impair the ecological balance), controlled use area (*i.e.*, activities such as mining, logging, tourism development, research, and other minor resources extraction may be allowed to operate but must be strictly in compliance with the law), and traditional use area (*i.e.*, located along the edges of intact terrestrial forests where traditional use has already been established). The intensive utilization of land use in Palawan is clearly defined under the multiple/manipulative use zone areas (PCSDS 2015b; Aguilla et al. 2020). Due to the ECAN zoning strategy, multiple land-use areas in Palawan have been assessed, marked, and delineated based on their biophysical or natural and anthropogenic attributes to regulate activities, sustain the ecological integrity, and properly manage the carrying capacity (PCSD 2010).

Polidoro et al. (2010) and Gilman et al. (2008) asserted that the economic growth and the augmentation of the human population are two major factors that influence the changes in the extent of mangrove forests and other land use areas. In Puerto Princesa City specifically, where the greatest housing development projects in Palawan are generally concentrated, the conception of the city's housing project in 1992 had managed to transform different land use across its boundaries. For example, the multiple housing projects in Barangay Sicsican, Mangingisda, San Jose, San Manuel, Bahile, Tagburos, Sta. Cruz, and Bahile, converted hundreds of hectares of collective land use areas into residential space. Although this number seems fairly alarming, the local government of Puerto Princesa City asserted that these initiatives could promote the smooth spatial expansion of the migration of mangroves in the future because most of the relocated local residents were previously inhabiting within the adjacent areas where mangroves are located (Puerto Princesa City Government 2012).

Prior to the declaration of the protected area networks in Palawan, in 1981 and 1991, the mangrove areas in the province including the adjacent parcels of mangrove forests in the county were estimated at 74,267 ha (Melana et al. 2000). Following the time after the integration of SEP law in Palawan in 1992, the mangrove areas changed significantly (PCSDS 2015a) with at least 50,045 ha remaining areas in 1993 (Figure 4). In contrast, a significant decrease of non-mangrove areas, which was notably recorded from this study from 1998 to 2018 (Figure 5), coincides with the time periods where massive deforestation in the southern part of Palawan led to the reduction in the areal size of the forested areas during 2003–2010 (WAVES 2016). Explicitly, we have found a significant increase in non-mangrove areas between 2013 and 2020 which was approximately three years after the implementation of the National Log Ban and the institutionalization of an Anti-Illegal Logging Task Force in 2011. Interestingly, according to the most recent report of DENR (2020), among all the provinces in the Philippines, Palawan had the largest areal extent of forestland in 2020, totalling about 1,035,926 ha. We had identified that this study poses limitations against the generated results about the non-mangrove area class because we only referred to the generalization of spectral separability. For this instance, we recommend that future similar studies should also focus on the spatial dynamics of multiple LU/LC areas.

Based on a joint venture initiative by NAMRIA and JAFTA in 1992, an aerial survey was conducted in Palawan. Among the notably remotely sensed information they obtained were the evidence of small-scale logging activities, particularly in Taytay, and the slash and burn cultivation "Kaingin" in the central boundary of Puerto Princesa City (*e.g.*, Honday Bay, Ulugan Bay; Figure 8b) and across the municipalities of San Vicente and Taytay (DENR-JAFTA 1992-2000). The PCSDS (2005) further reported that a massive extraction of mangrove raw products for fuelwood consumption was rampant in Taytay. These anthropogenic stresses were assumed to caused changes in the land use/land cover areas in the northern part of the island during the pre- and post-establishment of a marine reserve within a small portion of the north-western tip of mainland Palawan (*e.g.*, Bacuit Bay in El Nido municipality) in 1991.

However, following the expansion of the protected areas in northern Palawan (e.i., extension for 1991-declared Bacuit Bay marine reserve) under the establishment of the El Nido-Taytay Managed Resources Protected Area in 1998 (NIPAP 2001), the results obtained from this study (*i.e.*, Figure 7c), suggests as the reason for an increasing trend in mangrove forests cover in Taytay. Correspondingly, about an 8.7% increase in old-growth forest coverage in the protected area of Bacuit Bay has been reported a year after it become fully protected under the law in 1991 (JICA 1997). Moreover, the PCSDS (2005) reported that two endemic mangrove species in the Philippines namely, *Rhizophora stylosa* and *Compostenum philippinnensis*, were abundant in the Northern Part of Palawan including Taytay. For this reason, we supposed that the abundance of their presence in this region contributes to the successful protection and recovery of mangrove forests.

Richter et al. (2022) recently reported that communities interviewed generally perceived mangrove condition in Palawan had improved over the last 10 years. Richter et al. (2022) reported that the perception of the local communities in Taytay, in reference with the mangrove forest ecosystem quality in their area, suggested no change in condition compared with the findings from this study that showed a decrease in extent over the past 10 years, although it is apparent that the extent has increased significantly over the interviewees lifetime. Similarly, Richter et al. (2022) reported that the communities in Aborlan and Puerto Princesa City perceived an improvement in mangroves over the last 10 years This study indicates while there was a gain in mangrove extent between 2008-2013, since 2013 there has been slight decline in mangrove cover or cover has remained stable in these areas (Figure 6, Table 3).

The discrepancy in these results could be attributed to the reputation of Palawan for having still relatively high mangrove forest cover in comparison with the other provinces in the Philippines. The positive outlook of the local communities may had influenced by the environmental regulatory conceptions where they think that the province has strict regulated forest activities since the entire mangrove forests in the study area are located within the existing protected area networks (*i.e.*, IUCN, SEP Law, ECAN Zoning Project). Also, because local communities were actively involved in yearly "mangrove tree planting" activities across Palawan, for example, the local government of Puerto Princesa City has already planted around 800,000 mangroves since 2003 (https://puertoprincesa.ph/?q=tourism/february-14-love-affair-nature), they may presumed that this type of activity is a good indicator of a successful mangrove management. However, there is still no local studies that investigate whether the different mangrove rehabilitation programmes in Palawan are successful or not. It is also likely that, since this study used lower-to-moderate resolution satellite data, the ability to detect young mangroves that are small and sparce (*i.e.,* sapling) is low so these areas may not be included in the extent figures. The perceptions of interviewees may also indicate improvements in mangrove condition and health, rather than simply on extent of mangrove coverage, which is information harder to attain by remote sensing.

On the other hand, we presumed that a large percentage of change in non-mangrove areas in Palawan could be attributed to the progressive changes of other ground features in the region (*e.g.*, deforestation, forest regeneration, and infrastructure, industrial, and residential developments). For example, in Puerto Princesa City alone, a large portion of non-mangrove area in the outskirt region of Barangay Sta. Lourdes, which was previously a part of higher elevated grassland/bushland region, has been converted into a sanitary landfill. Also, we have noted that the projected changes in the non-mangrove area class might be attributed to the mining activities in the southern portion of Palawan, particularly in the municipalities of Bataraza, Brooke's Point, Aborlan, and Narra. Another contributing element, which we assumed could have a large contribution to the changes in non-mangrove areas in Palawan, was the inception of the Philippine government's infrastructure-growth-targeting program known as 'Build! Build! Build', which was started in the last quarter of 2016. Major highways, roads, and bridges have been expanded or re-constructed across the country, including Palawan, which led to the conversion of other land use areas. We expected that this type of development will continue to transform landscape patterns in Palawan until the end-term of the current government administration. Lastly, an increase in non-mangrove areas for the years 2030 and 2050 was also expected due to the influence of tourism demand in Palawan. As the global COVID-19 pandemic become slightly shifting to an endemic approach, the tourism industry in the province is now gradually gaining momentum. For example, such type of situation spurred global interest to visit/revisit the region's historical and applauded tourism sites which were restricted for almost two years due to the global outbreak of COVID-19.

The largest projection increment in mangrove aerial extents was recorded in the next 30 years in 2050. We expected this evaluation following the assumption where the current 'Build! Build! Build!' program of the Philippine government could catch up with rapid urbanization and population growth, which could potentially facilitate the optimization of mangrove forests protection in the province. This is because we assumed that relocating the local residents living within the coastal areas could lessen the threat to the mangrove ecosystem and foster community growth.

5. CONCLUSIONS

Our study demonstrates the capability of Markov chain model in predicting the future expanse of mangrove forests in Palawan using the multi-date Landsat satellite images from 1988 to 2020. This study found that in all study areas mangrove extent has increased from 1988 levels, although the trajectories since 2008 are more variable. Our analysis has shown the high likelihood of increase in areal extent of mangroves in Palawan, from our most recent estimate in 2020 (60,033.8) ha) up to the years 2030 (64,946.3 ha) and 2050 (66,972.1 ha). However, these projections should be considered a baseline and must be interpreted with caution, as this work did not integrate environmental factors that may or had influenced the changes in mangrove forests. For this instance, it would still be good to view that mangrove forests remain in constant threats especially in the context of the global climate change. The impact mechanism of sea level rise on mangroves presses on with as the greenhouse gas emissions continues. Furthermore, other threats such as coastal conversion, water pollution, and raw products extraction are not slowing down and remain potentially impacting the mangrove ecosystems worldwide. Integrating mangrove forest projection at regional scales is viably important to determine specific resiliency response to climate change impacts.

The potential of the Markov chain model to project the potential changes of mangrove forests and other land use areas conveys its importance in the future, especially in the contexts of landscape management, ecological sustainability, and policy intervention. However, since we did not create this type of model to directly assess our current policies, we recommend that future research should integrate the Cellular Automata in Markov Chain modelling. This way, research bodies can evaluate the impacts of different policies (*e.g.*, 1992 SEP Law, 1981 Mangrove Swamp Forest Reserve) in the future state of mangroves in Palawan. Further, it would be good to conduct a similar study but should also focus on the assessment of different LU/LC patterns to determine whether the demand of development that spurs the decrease or increase of certain features of non-mangrove areas is beneficial to the environment or not. This approach might alleviate uncertainties about the state of other multiple land-use areas in Palawan, other than mangrove forest, and the potential changes can be dissected and utilized for more effective management applications.

Also, it would also be necessary to investigate the pressures of different socio-economic activities of village communities on the extent of mangrove forests within the different multiple zones (*i.e.*, based on ECAN Zoning Project) as changes in the distribution and intensity of these activities in response to social and economic drivers have the potential to contribute to changes in LU/LC areas. Given all the other driving factors that could influence the changes of mangrove forest cover in Palawan, we further encourage the implementation of spatio-statistical modelling techniques in the future, where the changes in land-use areas are to be fitted with environmental covariates. We think that this type of approach is timely, relevant, cost-effective and could enable the evaluation of different management interventions and policies not only in Palawan but also in the Philippines and neighbouring Southeast Asian countries.

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7. CONFLICT OF INTEREST

The authors declare no competing financial and/or non-financial interests in any materials discussed in this article, either partially or entirely, directly or indirectly, and outside the 3-year time frame.

8. ETHICS STATEMENT

This research did not contain any studies involving animal or human participants, nor did it take place on any private or protected areas where physical interventions are subjected for ethical approval. No specific permissions were required for corresponding areas.

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10. AUTHOR'S CONTRIBUTIONS

CBC conceptualized the study, collected and analyzed the data, interpreted the results, and wrote the manuscript; ES edited the manuscript and contributed to the results, and discussion sections; PIM revised the manuscript, analyzed the data, and suggested to the improvement of data visualization and in depth interpretation of the results; DC edited the manuscript; LAC edited the manuscript, supervised the acquisition of reference data, helped during the conceptualization of the study, and supervised the funding acquisition. All authors have read and approved the final manuscript.

11. DATA AVAILABILITY

The data supporting the conclusions of this articles are included within the article. Any queries regarding these data may be directed to the corresponding author on reasonable request.

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SUPPLEMENTARY INFORMATION

Supplementary Information / "Multi-Spatiotemporal Analysis of Changes in Mangrove Forests in Palawan, Philippines: Predicting Future Trends Using Support Vector Machine Algorithm and Markov Chain Model"

Landsat Sensors Used

The multi-temporal resolution and multi-spectral Landsat 4-5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) sensors were utilized for this study. The different ranges of frequencies along with the electromagnetic (EM) spectrum for TM, ETM+, and OLI are summarized in Table 1.

Table 1. Summary of band designations and spatial resolution for TM, ETM+, and OLI (USGS 2015). The empty cells correspond to the unavailability of the sensor for a particular feature. 'B' represents the band number and the corresponding wavelength range, enclosed in a parenthesis, and in a micrometer unit.

Sensor	Landsat 4-5 TM	Landsat 7 ETM+	Landsat 8 OLI	Spatial Resolution
Coastal aerosol	-	-	B1 (0.43-0.45)	30 m
Blue	B1 (0.45-0.52)	B1 (0.45-0.52)	B2 (0.45-0.51)	30 m
Green	B2 (0.52-0.60)	B2 (0.52-0.60)	B3 (0.53-0.59)	30 m
Red	B3 (0.63-0.69)	B3 (0.63-0.69)	B4 (0.64-0.67)	30 m
NIR	B4 (0.76-0.90)	B4 (0.77-0.90)	B5 (0.85-0.88)	30 m
SWIR 1	B5 (1.55-1.75)	B5 (1.55-1.75)	B6 (1.57-1.65)	30 m
SWIR 2	B7 (2.08-2.35)	B7 (2.09-2.35)	B7 (2.11-2.29)	30 m
Thermal	B6 (10.40-12.50)	B6 (10.40-12.50)	B10 (10.60-11.19)	30 m
	-	-	B11 (11.50-12.51)	-
Pan-Chromatic	-	B8 (0.52-0.90)	B8 (0.50-0.68)	15 m
Cirrus	-	-	B9 (1.36-1.38)	30 m

Sourced Dataset

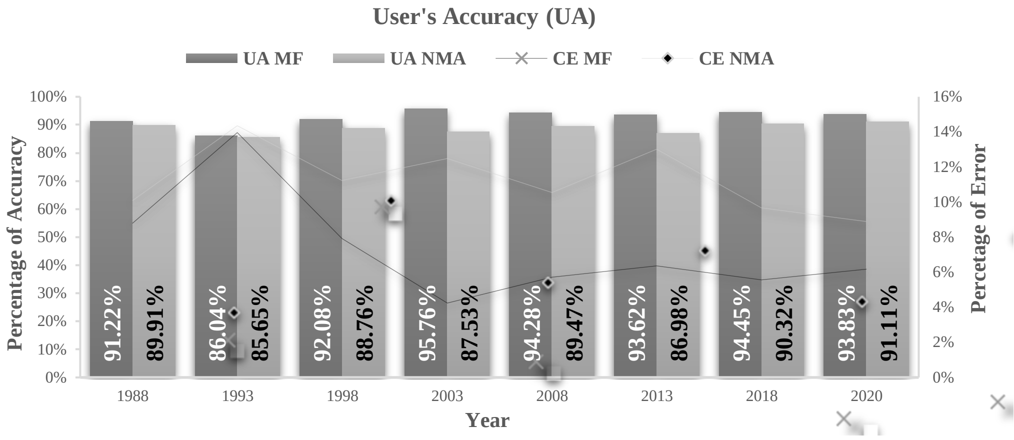
The TM, ETM+ and OLI datasets in multiple years 1988, 1993, 1998, 2003, 2008, 2013, 2018, and 2020 were sourced using the Semi-Automatic Classification Plugin (SCP) version 7.9.0 Matera in Quantum Geographical Information System (QGIS) version 3.22.1 Białowieża (Table 2).

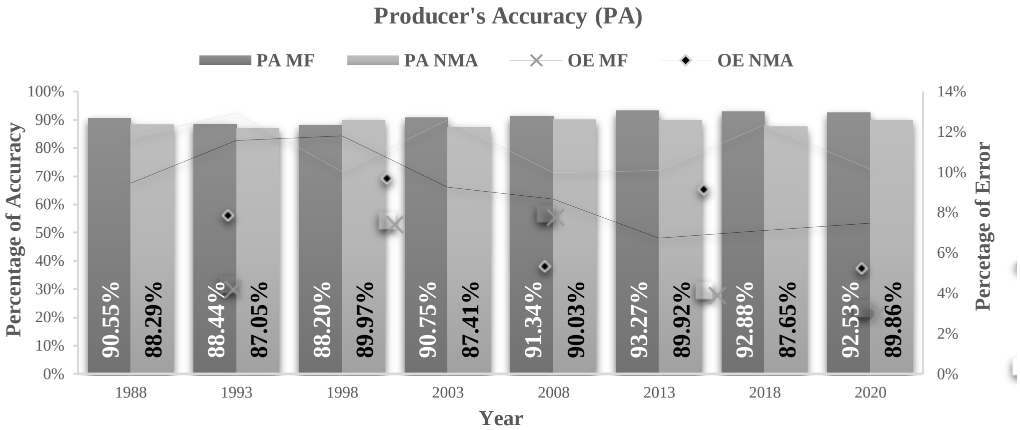
Table 2. Details of acquired Landsat satellite data were selected for this study. For satellite sensors, the multispectral Landsat 4–5 is denoted by ‘TM’, the Landsat 7 Enhanced Thematic Mapper Plus is denoted by ‘ETM+’, and the ‘OLI’ stands for Landsat 8 Operational Land Imager. The spatial resolution for each satellite image is denoted by ‘SRes’ and the ‘WRS’ means worldwide reference system, indicated in path ‘P’ and row ‘R’.

Satellite sensor	Acquisition date (mm/dd/yy)	SRes (m)	WRS P/R	Satellite sensor	Acquisition date (mm/dd/yy)	SRes (m)	WRS P/R
TM	03/12/1988	30	115/053	ETM+	01/14/2003	30, 15	118/054
TM	01/31/1988	30	116/052	ETM+	01/23/2008	30, 15	115/053
TM	04/20/1988	30	116/053	ETM+	04/19/2008	30, 15	116/052
TM	06/30/1988	30	117/053	ETM+	10/12/2008	30, 15	116/053
TM	09/18/1988	30	117/054	ETM+	04/10/2008	30, 15	117/053
TM	01/29/1988	30	118/054	ETM+	10/03/2008	30, 15	117/054
TM	11/05/1993	30	115/053	ETM+	04/01/2008	30, 15	118/054
TM	12/14/1993	30	116/052	ETM+	10/19/2013	30, 15	115/053
TM	05/20/1993	30	116/053	ETM+	02/28/2013	30, 15	116/052
TM	10/27/1993	30	116/053	ETM+	05/19/2013	30, 15	116/053
TM	07/14/1993	30	117/053	ETM+	03/07/2013	30, 15	117/053
TM	06/12/1993	30	117/054	ETM+	06/27/2013	30, 15	117/054
TM	03/15/1993	30	118/054	ETM+	05/01/2013	30, 15	118/054
TM	11/10/1993	30	118/054	OLI	12/12/2013	30, 15	115/053
TM	01/03/1998	30	115/053	OLI	08/29/2018	30, 15	116/052
TM	03/31/1998	30	116/052	OLI	02/18/2018	30, 15	116/053
TM	03/31/1998	30	116/053	OLI	04/30/2018	30, 15	117/053
TM	01/17/1998	30	117/053	OLI	12/10/2018	30, 15	117/054
TM	01/17/1998	30	117/054	OLI	04/05/2018	30, 15	118/054
TM	02/09/1998	30	118/054	OLI	04/05/2020	30, 15	115/053
ETM+	04/15/2003	30, 15	115/053	OLI	09/19/2020	30, 15	116/052
ETM+	02/17/2003	30, 15	116/052	OLI	09/19/2020	30, 15	116/053
ETM+	02/01/2003	30, 15	116/053	OLI	08/25/2020	30, 15	117/053
ETM+	03/12/2003	30, 15	117/053	OLI	08/25/2020	30, 15	117/054
ETM+	04/13/2003	30, 15	117/054	OLI	05/12/2020	30, 15	118/054

Accuracy Assessment

Using the 2010 LU/LC NAMRIA map as our ground reference data, the mangrove classification accuracies for years 1988, 1993, 1998, 2003, 2008, 2013, 2018, and 2020 were generated (Figure 1). The training mangrove forest polygons were validated through the established testing samples and the accuracy was assessed using the producer’s accuracy, the user’s accuracy, the overall accuracy, and the kappa coefficient values (Congalton 1991).





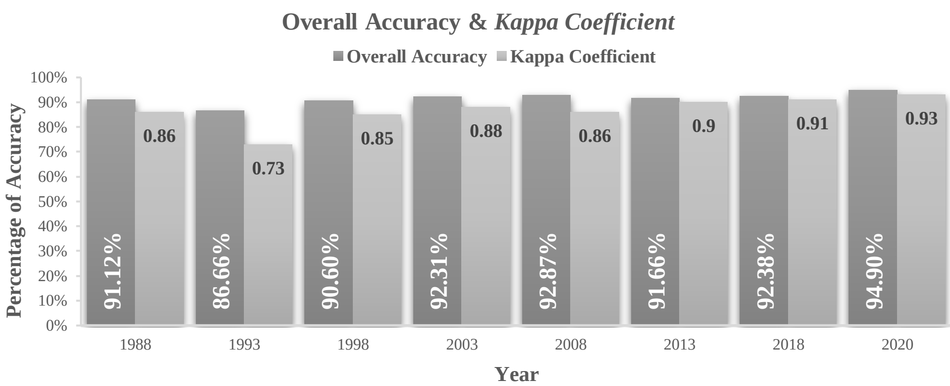


Figure 1. Classification error matrix of the Landsat TM, ETM+, and OLI data for multiple years, 1988, 1993, 1998, 2003, 2008, 2013, 2018, and 2020. The ground reference data used was the 2010 map derived from NAMRIA. The mangrove forests class is donated by 'MF' while the class of non-mangrove areas is denoted by 'NMA'. Additionally, the measure of commission error (type 1 error) is denoted by 'CE' while the omission error (type 2 error) is denoted by 'OE', respectively.

Mangrove Forests Projection and Model's Accuracy

Based on the calculation of the transition probabilities of one system at time t_2 with the state of the system at time t_1 according to the specific year (Houet and Hubert-Moy 2006; Kanjirappuzha et al. 2010; Murugesan et al. 2012; Kumar et al. 2014), the Markov's transition probability matrix was generated for the two time periods, 1988–1993 and 2013–2020 (Table 3).

Table 3. Calculated transitional probabilities during 1988–2020.

Time Period	Probability Matrix	Mangrove Forests	Non-Mangrove Areas
1988-1993	Mangrove Forests	0.531	0.469
	Non-Mangrove Areas	0.401	0.599
2013-2020	Mangrove Forests	0.548	0.452
	Non-Mangrove Areas	0.633	0.367

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