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Factors affecting land use and land cover change and fragmentation in selected protected areas in the Philippines

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ABSTRACT

The establishment of protected areas (PA) is one of the most prominent biodiversity conservation policies in the Philippines. Functions of the country's PA policy include the reduction of deforestation, forest conservation, and decreasing human pressure on natural resources. This study aimed to assess the drivers of forest intactness and fragmentation in selected terrestrial PAs. Management Effectiveness Tracking Tool (METT) scores were used to consider the impact of drivers of land use and land cover (LULC) change, including economic development, population, road networks, cultivation, and PA management, on the percentage of forest cover and different fragmentation metrics in the PAs. The study conducted a Canonical Correlation Analysis (CCA) and Multiple Regression Analysis to identify the significant drivers of LULC change for each response variable. CCA and Multiple Regression Analysis results showed the most important predictors of LULC based on their canonical weights: cultivation within the PA, the human development index, and the regional gross domestic product. Aside from

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Email Address: avbuhay@up.edu.ph
Date received: 28 February 2022
Date revised: 30 May 2023
Date accepted: 8 June 2023

KEYWORDS

Protected Area Management Effectiveness, Protected Area Policy, Land Use and Cover Change, Fragmentation

being the most important driving factor based on the CCA, cultivation inside the PA was also found to be a common significant variable for most dependent variables. Other significant factors were poverty index, population, and road density, which could all provide a basis for the observed PA fragmentation. The study also found that higher METT scores had a negative influence on the open forest and a positive effect on patch richness. This indicates that open forests tend to decrease as PA management improves while patch richness tends to increase. Furthermore, there is no data to support that METT scores have a significant influence on other response variables.

INTRODUCTION

Protected areas (PAs) are designated areas of land or water that are legally protected and managed to conserve natural and cultural resources, including plants, animals, and their habitats, as well as cultural heritage sites. PAs promote biodiversity conservation, constrain the impacts of land conversion and deforestation, and sustain ecosystem services (Lu et al., 2017). The PA system preserves the natural state of forest cover within the boundaries, limiting destructive human activities and halting land cover change (Mansourian et al., 2009, Ohnesorge et al., 2013; Erdelen, 2020; Almond et al., 2020). These areas can take many forms, including national parks, wildlife sanctuaries, nature reserves, and marine protected areas (Bertzky et al., 2019). In the Philippines, PAs have been established since the early 1900s, with the creation of the Mount Banahaw-San Cristobal National Park in 1909 (Durán and Vargas, 2017). Currently, the country has 244 PAs, including national parks, wildlife sanctuaries, and marine protected areas (DENR-BMB, 2020). These PAs cover over 15.4% of the country's total land area and 7.3% of its territorial waters (de la Torre-Castro and Lindström, 2019; Enright and Newton, 2019).

The benefits of PAs are numerous and well-documented, both in the Philippines and worldwide. PAs generally provide a range of ecological, social, and economic benefits. Ecologically, protected areas help conserve biodiversity and maintain natural ecosystems, providing valuable ecosystem services such as clean water, air, and soil (Janzen and Hallwachs, 2019). PAs can also act as refuges for endangered species, helping to prevent their extinction. In addition, protected areas can provide opportunities for scientific research and education, which can help to improve our understanding of the natural world. Socially, PAs can provide opportunities for recreation, tourism, and cultural experiences, which can contribute to local and national economies (Sánchez-Rodríguez et al., 2018). It can also help preserve traditional cultural practices and knowledge and provide a sense of place and identity for local communities (Loh and Harmon, 2005). Economically, PAs can provide various economic benefits, including employment opportunities, revenue from tourism, and increased property values in nearby areas (Khan and Williams, 2018). In addition, PAs can help regulate ecosystem services essential for human well-being, such as water purification and climate regulation.

However, PAs in developing countries have elevated human pressure and other underlying factors that negatively affect natural resources (Schulze et al., 2018). Land use and land cover (LULC) change refers to the alteration of natural or semi-natural land cover types by anthropogenic activities such as agriculture, urbanization, and infrastructure development, among others (Lambin and Meyfroidt, 2011). It involves the transformation of the natural landscape into a different LULC type, with potential impacts on ecological processes, biological communities, and ecosystem services. It is driven by a combination of factors, including population growth, economic development, urbanization, agricultural expansion, and infrastructure development (Lambin and Meyfroidt, 2011). These factors vary across regions and countries, leading to different patterns and trajectories of LULC change. In many cases, LULC change has led to the loss and degradation of natural habitats, fragmentation of ecosystems, and decline in biodiversity (Butchart et al., 2010; Foley et al., 2005).

Land use change caused by human activities affects conditions in the protected area and negatively influences ecosystem functions and their sustainability to provide goods and services (Huang et al., 2019; Qian et al., 2019; Hasan et al., 2020). Continuous pressure from human interventions causes further fragmentation and eventually diminishes habitat of biologically important species (Soriano et al., 2019). Sims (2013) also stated that conservation policies influence the amount of forest cover loss and patterns of forest fragmentation. Assessment of the effectiveness of a protected area system and related policies plays a crucial role in pursuing biodiversity and ecosystem conservation, which are essential for providing wildlife habitat, food, shelter and other goods and services.

In the Philippines, it is expected that the National Integrated Protected Areas System (NIPAS) law will facilitate the protection of forests within terrestrial PAs against degradation due to human activities. While there has been an isolated assessment of the changes in forest cover within PAs (Soriano et al., 2019; Buitre et al., 2019; Singh, 2020), in-depth analysis has not yet been done in the country to determine the drivers of forest cover change in PAs. This study focused on the tool used in achieving PA management objectives, the Protected Area Management Effectiveness (Ervin, 2003). However, determination of the effects of a policy is challenging since observations take time and evaluators need to identify evidence of the policy's direct effects (Morestin, 2012). This approach may still support policymakers in identifying discrepancies in factors, such as the intactness of forest cover, and help in constructing informed policy decisions.

The Measurement of Effectiveness Tracking Tool (METT) evaluates protected area management effectiveness by measuring factors like legal status, staffing levels, planning, budgeting, and enforcement (Hocking et al.,2006; Geldmann et al., 2018). The tool is used via interviews with the staff to identify strengths and weaknesses in managing the area (Geldmann et al., 2019). The METT tool is essential for three primary reasons. Firstly, it provides a structured and uniform evaluation of the effectiveness of protected area management that aids in monitoring performance over time and identifying areas requiring improvement. Secondly, it identifies key success factors that inform future planning and execution of protected area management. Finally, the tool promotes communication and coordination among all stakeholders managing protected areas (Stolton et al., 2016). The METT tool provides an advantage for its simplicity, usability, and efficiency in completing the PA assessment (Belle et al., 2012). It also offers flexibility to meet the unique needs of various protected areas. Compared to other tools such as the World Heritage Site Management Effectiveness (WHSM) tool or the Rapid Assessment and Prioritization of Protected Area Management (RAPPAM) tool, the METT tool is less intricate (Hockings et al., 2006). The tool was first applied in the Philippines in 2003 and 2005, simultaneously with other PAs across the globe (Stolton et al., 2007).

The fragmentation analysis is a technique to measure landscape fragmentation caused by land use and cover changes (Nagendra et al., 2004; Jin et al., 2019; Ramirez et al., 20-19). It entails computing spatial metrics that characterize the distribution of land covers in an area. This approach aims to supply details regarding habitat dispersal and interconnectivity among distinct patches within a landscape, which is useful for conservation and management initiatives (Beita et al., 2021). It studies the spatial patterns and ecological processes of landscapes. Fragmentation happens from human actions such as urbanization, agriculture, and logging that transform intact natural habitats into disconnected ones. It negatively impacts biodiversity by causing habitat loss, reduced gene flow, and increased edge effects (Oxbrough and Pinzón, 2019; Hooper and Ashton, 2020). Fragmentation analysis has been utilized in several studies to investigate the effects of land use and land cover changes on landscapes. In one study, Radeloff et al. (2005) examined forest fragmentation in the Upper Midwest region of the United States using this approach. The findings revealed that converting forests into agricultural or urban areas increased fragmentation and diminished connectivity between forest patches. Liu et al. (2019) utilized fragmentation analysis to evaluate land use change effects on forest fragmentation in China, indicating that converting forests to agriculture and urban uses resulted in heightened fragmentation and diminished patch connectivity, negatively affecting forest biodiversity. A study conducted in the Philippines (Lasco et al., 2006) used fragmentation analysis to evaluate how land use change affected forest cover in Laguna Province. The results revealed that converting forests into agricultural and urban areas increased fragmentation, diminished the connectivity of forest patches, and negatively impacted biodiversity.

The objective of this study is to evaluate the underlying factors of changes in land cover with a particular focus on forest coverage within specifically chosen PAs in the Philippines. The degree and extent of fragmentation present in these PAs are determined through fragmentation analysis using various metrics. The assessment analyzed the relationship of multiple factors identified against fragmentation and changes in the landscape and provide valuable insight for the improvement of PA management.

MATERIALS AND METHOD

Study site

The 33 terrestrial PAs included in this study were selected based on the Biodiversity Management Bureau's evaluation using the Management Effectiveness Tracking Tool (METT) conducted in 2013 and 2017. These PAs fall under the International Union for Conservation of Nature (IUCN) Category II (National Parks) and V (Protected Landscape /Seascape). IUCN Category II or the National Parks category is preserved for ecological processes, species, and ecosystems preservation while supporting compatible spiritual, scientific, educational, recreational, and tourism activities. While IUCN category V, also known as the Protected Landscape or Seascape, is where people-nature interaction is present resulting in distinct ecological, biological, cultural, and scenic features. Table 1 shows the list of the selected 33 PAs and their corresponding regional location and IUCN category, while Figure 1 shows each PA's location on the map.

Table 1: List of 33 Protected Areas, Region and IUCN Category

NO.	PROTECTED AREA	REGION	IUCN Category
1	Mt. Pulag National Park	CAR	II
2	Kalbario-Patapat Natural Park	1	II
3	Baua-Wangag Watershed Forest	2	V
4	Casecnan Protected Landscape	2	V
5	Amro River Protected Landscape	3	V
6	Aurora Memorial National Park	3	V
7	Bataan National Park	3	II
8	Dinadiawan River Protected Landscape	3	V
9	Simbahan-Talagas Protected Landscape	3	V
10	Talaytay Protected Landscape	3	V
12	Quezon Protected Landscape	4a	V
13	CALSANAG Watershed Forest Reserve	4b	V
14	Mt. Guiting-guiting Natural Park	4b	II
15	Abasig-Matogdon-Mananap Natural Biotic Area	5	V
16	Bicol Natural Park	5	II
17	Bulusan Volcano Natural Park	5	II
18	Catanduanes Watershed Forest Reserve	5	II
19	Mt. Isarog Natural Park	5	II
20	Northwest Panay Peninsula Natural Park	6	II
21	Central Cebu Protected Landscape	7	V
22	Rajah Sikatuna Protected Landscape	7	V
23	Samar Island Natural Park	8	II
24	Mt. Timolan Protected Landscape	9	V
25	Pasonanca Natural Park	9	II
26	Mt. Balatukan Range Natural Park	10	II
27	Mt. Inayawan Range Natural Park	10	II
28	Mt. Malindang Range Natural Park	10	II
29	Aliwagwag Protected Landscape	11	V
30	Allah Valley Protected Landscape	12	V
31	Mt. Matutum Protected Lanscape	12	V
32	Alamio, Buyaan, Carac-an, Panikian Rivers and Sipangpang Falls Watershed Forest Reserve	13	V
33	Basilan Natural Biotic Area	BARMM	V

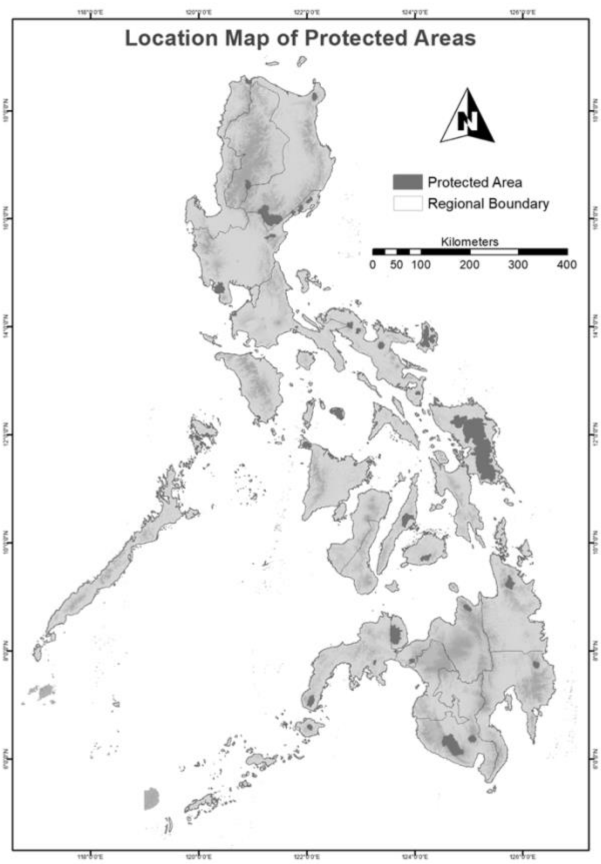

Figure 1: Location map of the protected areas

Land use and land cover dataset
Available land cover maps from 2003, 2010 and 2015 were obtained from National Mapping and Resource Information Authority (NAMRIA) in the Philippines. These were used for mapping the land cover of the thirty-three terrestrial PAs. Vector files of each PA boundary were collected from the World Database on Protected Areas of the International Union for Conservation of Nature.

The following equations were used to determine the relative change of each land cover type in hectares, relative change in percent, and the annual rate of change of each land cover type.

A1 – A2 = Relative change in hectares
*A1 – A2 / (A1 * (100/1)) = Relative change in percent*
(A1 – A2)/ (T1 – T2) = Annual rate of change

Where:
A1 = area in year 1
A2 = area in year 2
T1= year 1
T2= year 2

The quantified land cover types in hectares were extracted using the tabulated intersection tool under the data analysis options of ArcGIS software. This automatically computed the intersection between two feature classes and cross-tabulates the intersecting features' area, length, or count. By using this tool, changes per land cover type were determined. The two input features are the consecutive land cover data: first, 2003 and 2010, and second, 2010 and 2015. This helped determine the changes in the land cover over time.

Fragmentation analysis
Fragmentation analysis involves the quantification of forest fragments or patches and other land use patches in the studied areas. This study assessed fragmentation in the land cover maps using FRAGSTATS software. The researchers considered the following landscape-level metrics to identify landscape patterns, fragmentation, and relationships among patches within a PA landscape mosaic: patch density (PD), number of patches (NP), and large patch index (LPI). Other metrics, such as contagion (CONTAG) and aggregation index (AI) were analyzed to identify clumping of patches. The isolation of one patch type from another was analyzed using diversity metrics: Shannon's diversity index (SHDI) and Simpson's diversity index (SIDI), while the Euclidean nearest neighbor (ENN) metric was used to quantify distances between patches. These metrics also analyzed patterns and interaction changes through time (McGarigal et al., 2012).

Drivers of change
Socioeconomic drivers of change, such as poverty, human development, gross domestic product, population, and road density, were utilized in the study to measure human disturbances on the natural resources of PAs. Furthermore, the study also examined the application of METT responsible for determining the success of overall management of PAs and the important habitats.

Barnes et al. (2016) found that changes in HDI within the protected areas had a positive relationship with improved conservation measures. Another study by Jha and Bawa (2006) included HDIs of the provinces of selected protected areas as a variable to assess their relationship with changes in forest cover (open and closed canopy forest), cultivated areas, and other land uses. The researchers therefore obtained data for poverty and human development indices for multiple years, including 2003, 2006, 2009, 2012, and 2015 from the Philippine Statistics Authority. The poverty index was used in this study to determine the influence of poverty on the protected areas. Some initiatives have successfully linked protected areas to local socio-economic development. Yet, there is still a need to improve the capacity of conservation initiatives in the Philippines to alleviate poverty (Naughton-Treves, 2005).

A global study shows that high-income nations experience low deforestation rates while low-income nations encounter high deforestation rates (Ewers, 2006; Cuaresma, 2017). A recent study on identifying the relationship between economic activity to forest trends and biodiversity of arthropods using the Kuznets curve approach also implied that the quality and quantity of the new forest in a middle-income nation has increased to the least extent (Benedek and Ferto, 2020). However, this contradicts a globally and tropically sampled study by Morales-Hidalgo et al. (2015), where per capita income was positively associated with improved forest areas, protected forest, and conservation areas. For this study, the researchers explored the gross domestic product per region as a possible driver of change. Data for this was obtained from the official dataset of the World Bank.

Road data was obtained from NAMRIA. To determine the trend of encroachment and infrastructure development based on accessibility to forestlands, the researchers included the percentage of forested areas in relation to road density in the analysis.

One documented reason for forest clearing is to use the land for cultivation. Expansion of cultivated lands continues, but land availability is decreasing, which induces farmers to intensify crop productivity, often resulting in soil degradation. These further pushes farmers to expand their farms to other lands, including forest areas, for subsistence farming. The migration of farmers from rural communities to tropical forests is the dominant driver of deforestation in a study by López-Carr and Burgdorfer (2013). Therefore, the percent cover of cultivated area inside and outside PA boundaries were assessed in this study to identify how forest areas are affected by the expansion of cultivated areas.

The METT scores were included in the analysis to indicate the effectiveness or success of the NIPAS Law in protecting forest cover in PAs. This is because METT scores are primarily assessed based on the quality of various facets of PA management.

Statistical Analysis
To obtain the interrelationships between two multivariate sets of variables, the study utilized a canonical correlation analysis (CCA). This was also used to determine and quantify the associations between two sets of variables. This derives the structure of each variate or set of variables to maximize their correlation (Wilks, 2011). This established the application of linear multiple regression.

Regression analysis is a statistical method that allows analysis of the relationship between two or more variables of interest (Draper and Smith, 1998; Millington et al., 2007). It involves using regression models to predict the value of a dependent variable based on the values of one or more independent variables. It can also be used to predict a dependent variable's value for an independent variable's given value (Southworth, 2004; Nurwanda et al., 2020). The independent variables in the analysis include the management effectiveness (METT score), poverty index (PI), human development index (HDI), regional gross domestic product (RGDP), population, road density, and presence of cultivated area as parameters in the process of change in land cover.

The most recent data available were used for both dependent and independent variables. Before proceeding with the regression analysis, similar variables of the same data that only differed in the year were initially removed. All independent variables were initially included for all protected areas, and various tests were run to identify the significant variables. The best-fit regression model was determined at 95% confidence level.

RESULTS AND DISCUSSION

Forest cover change in selected PAs

The forest cover change analysis, open and closed forest, data from 2003 to 2010 indicated that 11 out of the 33 PAs selected still had 50-95% closed forest cover. However, according to data from 2010, only seven PAs had a closed forest cover above 50% of their total area. Within this 7-year interval, it was observed that 12 PAs had increases ranging from 2% to 53% in their respective closed forest cover (Figure 2). Most of the study sites had up to 80% forest loss in their closed forest cover within this period.

From 2010 to 2015, 11 PAs recorded a loss of up to 23% of closed forest cover. Only 6 PAs in 2015 had a closed forest cover of 50% and above. These findings show that higher density forest cover becomes less dominant in most of the selected PAs.

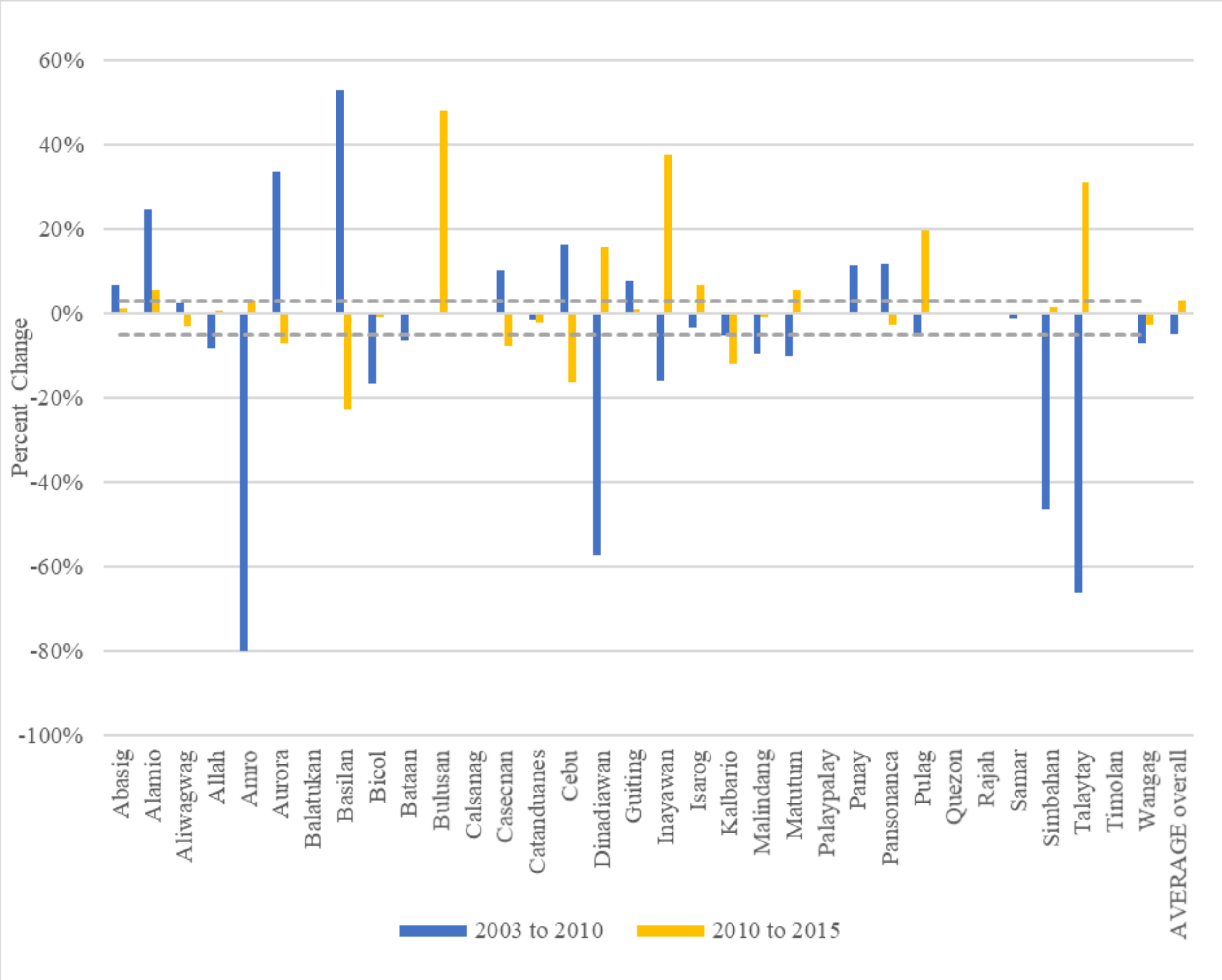

Figure 2: Forest cover gain and loss of selected protected areas in the two periods

Fragmentation metrics and the relationship between the driving factors

The correlation matrix in Table 2 shows a very weak to moderate relationship between fragmentation and the identified driving factors. The highest correlation (0.57) observed for the number of patches in the PAs and population indicates a moderate positive relationship between the two variables. Associated with more anthropogenic activities, population increases often result in changes in land cover and land use patterns. These changes then influence fragmentation and increase forest and habitat degradation.

The next notable coefficients are -0.438 and -0.427, implying a weak relationship between Cultiv_Buff and Cultiv_PA to Closed Forest. The increase of cultivated areas inside and outside the PAs caused a decline in the closed canopy cover. Therefore, cultivation could be identified as another prominent driver of land cover change within and outside of PAs. Other contributing factors to cultivation could be increasing population, which results in increasing demand for food and supplies, as well as forest clearing resulting from subsistence farming in the rural communities within and adjacent to the PA boundaries.

Table 2: Correlation matrix of the two variates

Variables	CF	OF	NP	PD	LPI	PAFRAC	ENN_MN	ENN_SD	CONTAG	SHDI	SIDI	AI	METT	PI	HDI	GRDP	POP	RoadDen	Cultiv_PA	Cultiv_Buff
CF	1	-0.594	-0.174	-0.340	-0.049	-0.110	-0.224	-0.235	0.245	-0.095	-0.093	0.319	0.216	-0.057	0.132	-0.421	-0.222	0.103	-0.427	-0.438
OF	-0.594	1	-0.127	0.032	0.309	-0.269	0.261	0.139	0.241	-0.451	-0.381	-0.193	-0.403	-0.066	-0.181	0.351	-0.259	-0.072	-0.285	0.052
NP	-0.174	-0.127	1	-0.093	-0.292	0.839	0.511	0.551	-0.450	0.497	0.372	-0.625	0.409	0.294	-0.091	-0.157	0.572	-0.381	0.365	0.137
PD	-0.340	0.032	-0.093	1	-0.305	0.097	-0.402	-0.384	-0.278	0.211	0.195	0.065	0.083	-0.236	0.130	0.195	-0.137	0.067	0.134	0.557
LPI	-0.049	0.309	-0.292	-0.305	1	-0.340	-0.024	-0.108	0.681	-0.727	-0.791	0.173	-0.288	-0.299	-0.089	0.092	-0.206	0.003	-0.257	-0.244
PAFRAC	-0.110	-0.269	0.839	0.097	-0.340	1	0.203	0.353	-0.436	0.558	0.408	-0.451	0.371	0.128	0.086	-0.274	0.503	-0.392	0.350	0.085
ENN_MN	-0.224	0.261	0.511	-0.402	-0.024	0.203	1	0.911	-0.178	0.037	0.054	-0.833	0.060	0.384	-0.254	0.054	0.300	-0.253	0.119	0.066
ENN_SD	-0.235	0.139	0.551	-0.384	-0.108	0.353	0.911	1	-0.207	0.169	0.175	-0.752	0.121	0.400	-0.162	-0.023	0.485	-0.353	0.161	-0.008
CONTAG	0.245	0.241	-0.450	-0.278	0.681	-0.436	-0.178	-0.207	1	-0.913	-0.908	0.468	-0.301	-0.240	0.026	-0.080	-0.339	-0.009	-0.548	-0.527
SHDI	-0.095	-0.451	0.497	0.211	-0.727	0.558	0.037	0.169	-0.913	1	0.960	-0.292	0.443	0.262	0.123	-0.076	0.416	-0.111	0.493	0.370
SIDI	-0.093	-0.381	0.372	0.195	-0.791	0.408	0.054	0.175	-0.908	0.960	1	-0.261	0.358	0.284	0.030	0.026	0.338	-0.041	0.414	0.309
AI	0.319	-0.193	-0.625	0.065	0.173	-0.451	-0.833	-0.752	0.468	-0.292	-0.261	1	-0.116	-0.224	0.245	-0.056	-0.310	0.234	-0.217	-0.268
METT	0.216	-0.403	0.409	0.083	-0.288	0.371	0.060	0.121	-0.301	0.443	0.358	-0.116	1	-0.010	-0.060	-0.114	0.378	-0.300	0.194	0.130
PI	-0.057	-0.066	0.294	-0.236	-0.299	0.128	0.384	0.400	-0.240	0.262	0.284	-0.224	-0.010	1	-0.042	-0.445	0.352	-0.269	0.052	0.193
HDI	0.132	-0.181	-0.091	0.130	-0.089	0.086	-0.254	-0.162	0.026	0.123	0.030	0.245	-0.060	-0.042	1	0.093	-0.186	-0.015	-0.126	-0.065
GRDP	-0.421	0.351	-0.157	0.195	0.092	-0.274	0.054	-0.023	-0.080	-0.076	0.026	-0.056	-0.114	-0.445	0.093	1	-0.213	0.162	0.140	0.015
POP	-0.222	-0.259	0.572	-0.137	-0.206	0.503	0.300	0.485	-0.339	0.416	0.338	-0.310	0.378	0.352	-0.186	-0.213	1	-0.221	0.536	0.214
RoadDen	0.103	-0.072	-0.381	0.067	0.003	-0.392	-0.253	-0.353	-0.009	-0.111	-0.041	0.234	-0.300	-0.269	-0.015	0.162	-0.221	1	0.106	-0.159
Cultiv_PA	-0.427	-0.285	0.365	0.134	-0.257	0.350	0.119	0.161	-0.548	0.493	0.414	-0.217	0.194	0.052	-0.126	0.140	0.536	0.106	1	0.447
Cultiv_Buff	-0.438	0.052	0.137	0.557	-0.244	0.085	0.066	-0.008	-0.527	0.370	0.309	-0.268	0.130	0.193	-0.065	0.015	0.214	-0.159	0.447	1

Abbreviations: CF= closed forest; OF= open forest; NP= number of patches; P= patch density; LPI= largest patch index; PAFRAC= perimeter-area fractal dimension; ENN_MN= mean Euclidean nearest neighbor; ENN_SD= standard deviation Euclidean nearest neighbor; CONTAG= contagion; SHDI= shannon's diversity index; SIDI= simpson's diversity index; AI= aggregation index; METT= management effectiveness tracking tool score; PI= poverty index; HDI= human development index; GRDP= regional gross domestic product; POP= population; RoadDen= road density; Cultiv_PA= cultivated inside PA; Cultiv_Buff= cultivated outside PA. Significant correlation at 5%.

The correlations between the canonical coefficients and the variables or loadings in each set of the individual variables are different per canonical function and contribute to the variables' representation to the relationship being investigated. Selecting among the variates (Table 3) to be interpreted is critical. But in most cases, the generally legitimate is the first function. A study applying CCA by Kabir et al. (2014) used three criteria in selecting functions: first is the level of significance as determined by p-value; second is the magnitude of the canonical correlation; and third is the measure of redundancy for the variance percentage accounted for from the two data sets like multiple regression's r-square.

Based on Table 3, only the first function is noteworthy and the only significant with a p-value less than 0.05. This indicates that the null hypothesis (there is no relationship between the two sets of variables, forest cover plus fragmentation and the driving factors) should be rejected, which implies that the two sets of variables are dependent on one another. The canonical correlation of 0.96 indicates a strong positive relationship between the two. However, despite the high canonical correlation, the redundancy index, which measures the magnitude of the relationship, implies that only 12.7% of forest cover and fragmentation change was explained by the driving factors.

Table 3: Canonical Correlation, Wilks' Lambda and Redundancy of 8 variates

Canonical Variates	Canonical Correlation	Wilks' Lambda test:			Redundancy
		Lambda	F-Statistics	P-value	
Variate 1	**0.9651**	0.0002	1.8980	0.0030	0.1273
Variate 2	0.9496	0.0028	1.4650	0.0550	0.0979
Variate 3	0.9223	0.0280	1.0220	0.4650	0.0794
Variate 4	0.7272	0.1875	0.5730	0.9730	0.0625
Variate 5	0.6355	0.3980	0.4390	0.9920	0.0409
Variate 6	0.4399	0.6675	0.2930	0.9980	0.0097
Variate 7	0.3468	0.8277	0.2480	0.9930	0.0051
Variate 8	0.2433	0.9408	0.2010	0.9570	0.0069

Canonical weights (standardized coefficients) were investigated to identify the most important predictor among the driving factors of forest cover and fragmentation. According to the study of Lambert and Durand (1975), the rule of thumb is that any weight greater than the absolute value of 0.30 can be taken as an important contributor to the function. The results in Table 4 show that Cultiv_PA (-0.78) is the most important predictor for forest cover change and PA fragmentation, and these variables are negatively correlated. Two other variables, HDI and RGDP, were also found above the absolute value of 0.30. HDI could be seen as negatively correlated with forest cover and fragmentation, while RGDP is positively correlated.

Table 4: The canonical weight of independent variables in variate 1

Independent Variables	Weight (Variate 1)
METT	-0.13
PI	0.12
HDI	**-0.54**
RGDP	**0.54**
POP	-0.08
RoadDen	0.14
Cultiv_PA	**-0.78**
Cultiv_Buff	0.06

Regression analysis

Table 5 shows the results and the corresponding R-squared of each dependent variable. No significant variables were found for LPI, AI, and SIDI, possibly due to data and sample size limitations. RGDP and the presence of cultivated areas inside the PAs were found to negatively impact closed forest cover. As RGDP and cultivated areas increase, closed forest cover tends to decrease. This can be explained by the reliance of the Philippines on natural resources for economic growth. Furthermore, agriculture expansion significantly contributes to deforestation.

Farmers, especially those who are poorer, tend to expand their farmlands into forest areas to increase yield and reach the rich fertile soils in the forest.

A significant driver for change in open forest is the performance of the PA management. As management of the PA improves, open forest decreases. This could point to the transformation of the open canopy forest to closed canopy forests as the management of PAs progresses. Improved management may have also reduced threats that previously caused declines in increasing canopy cover. Another implication could be that other indicators under METT (e.g., budget, manpower, etc.) may have improved, while some of the indicators may not directly benefit the protection and conservation of the forest.

The population was found to be a significant factor affecting number of patches in PAs. This implies that the establishment of PAs (and subsequent isolation of forest areas) cannot confine the encroachment on PAs. In addition, the geographical closeness of PAs to active anthropological activities can lead to relatively higher human pressure on the area. Similarly, the increase in population tends to increase the isolation of patches, as reflected by the ENN_SD.

Increased patch density resulting from heightened poverty and increased cultivated areas outside the PAs may be due to yield decline caused by unproductive agricultural lands. Small-scale farmers will more likely clear forests to expand their farms into more productive land. This would increase their agricultural yield to compensate for the loss from farming their unproductive land. Consequently, the aggregation of cultivated areas and diminishing forest cover would contribute to the reduction in the patchiness of the PA landscape.

The study also found that the perimeter-area fractal dimension (PAFRAC) tends to increase as cultivation increases. This may be observed in PAs with the presence of high cultivation. It is observed that as cultivated areas expand, this causes other land cover types to be more irregular in shape. The negative impact of increasing cultivation to the patch forms of land covers implies the need for judicious regulation of road construction inside the PA. Since accessibility to forestlands through road networks is a main contributing factor for increased encroachment and settlement.

Cultivation inside and outside the PA was found to negatively affect the contiguity of land cover types – contiguous land cover areas tend to break down into smaller and more dispersed patches due to cultivation. This then results in further destruction of habitats across the PA landscape and increased threats to biodiversity.

The diversity of land use and land cover types or patch richness tends to increase as the METT score and cultivated area increase. Other than intensified human activity in the PAs, another possible explanation for the increase in land cover patch diversity is the presence of tenurial instruments such as special use agreement for protected areas (SAPA). SAPAs are issued by the government to allow use of land in a PA for production purposes, while maintaining their protected state. Therefore, this reveals a problem with the scoring process of the METT. Aside from the noted subjectivity in the METT questionnaire and results solely depending on people's perceptions, the scoring process also creates a bias in overall results which leans towards higher METT scores.

Table 5: Significant variables and the best fit model for each dependent variable

Dependent Variables	Significant Factors at 95% Confidence Level	Best-fit Model	R^2
CF	RGDP, Cultivated area inside PA	CF = 0.485 - (0.008) RGDP - (0.995) Cultiv_PA	0.31
OF	METT	OF = 1.503 - (0.009) METT	0.16
NP	Population	NP = 127.16 + (0.002) POP	0.33
PD	Poverty Index, Cultivated area outside PA	PD = 1.12 - (0.024) PI + (1.608) Cultiv_Buff	0.43
PAFRAC	Road Density, Cultivated Area inside PA	PAFRAC = 1.34 - (0.049) RoadDen + (0.363) Cultiv_PA	0.31
ENN_MN	Poverty Index	ENN_MN = 145.70 + (12.341) PI	0.15
ENN_SD	Population	ENN_SD = 662.64 + (0.004) POP	0.24
CONTAG	Cultivated Area inside and outside PA	CONTAG = 75.53 - (29.953) Cultiv_PA - (11.352) Cultiv_Buff	0.40
SHDI	METT score, Cultivated area inside PA	SHDI = 0.502 + (0.0099) METT + (1.249) Cultiv_PA	0.37

DISCUSSION

The factors affecting land use/cover change and the presence of fragmentation in PAs determine the effectiveness of PA management. The results of the regression analysis support the outcome of the canonical correlation analysis. The r-square ranging from 15% to 43% is sufficient to identify the underlying factors affecting land use/cover change and fragmentation within the PA and to understand their relationships. Despite the low range of the values, these values are still sufficient to evaluate the factors of forest cover change and other land cover types in PAs. This also implies that these factors are complex, as stated by the case study of Minjiang River Basin in China by Li et al. (2022). Hence, it supports that there is a broad range of drivers of LULC change, and this further strengthens the need to obtain a more comprehensive understanding of the factors driving these changes. Similarly, regression models proved that further investigation and a deeper understanding of the intricate connections among variations in LULC and the underlying factors are necessary for future research (Ren et al., 2020).

One of the major findings shows that cultivated area inside the PA significantly affects most of the dependent variables and is determined to be the most important driving factor in land use and land cover change. These outcomes agree with observations by Acheampong et al. (2019). Other than negatively affecting closed forest cover, it further increases fragmentation in terms of patch isolation (CONTAG), complexity (PAFRAC), and heterogeneity of patch types (SHDI). These fragmentation processes demonstrate existing disruptions amidst the establishment of the PA and indicate threats to natural habitat and biodiversity. Therefore, forest protection needs to be strengthened, and laws need to be strictly enforced. These actions may reduce the encroachment and agricultural expansion into the forests.

The effect of PA management was considered by including METT scores in the analysis. It was assumed that higher METT scores implied that more PA policy provisions have been implemented. At a 95% confidence level, this study found that the performance of the PA management affects open forest cover and the number of land cover types in the PAs as follows. Higher scores in PA management performance led to a lower percentage of open forest cover. This could be explained by reduced threats or hindrances towards forest canopy growth in effectively managed PAs. However, increased PA management effectiveness could also mean development of other indicators (e.g., facilities, staff training, etc.) that indirectly affect the forest canopy increase, leading to its decline despite the higher score. In addition, higher assessment scores for management contributed to higher SHDI or diversity of the land cover types in the PA. This implies that more variations of land cover types, other than the dominant ecosystem, can be present other than the major ecosystem identified in the PA. Therefore, PA management plans to be developed and implemented need to consider the maintenance of the different land cover types present.

The effect of the population factor is evident in the changes found in patch density and distances of similar land cover types in the PAs, as reflected by the ENN_SD. These changes, which intensify disturbances to the ecosystems, show that habitat fragmentations are related to the presence of humans. According to Sodhi et al. (2010), forest habitats eventually collapse as human modification of land use is intensified. These findings are common among the developing countries in Asia (Elias, 2014). The effects of an increasing number of patches are further explained by Lewis (2005), in that tropical rainforest fragmentation causes severe impacts on the intactness of old-growth forests, particularly its forest structure and ecosystem dynamics, and also affects biodiversity to some degree.

In addition, Geldmann et al. (2019) found that PA designation still needs to prevent encroachment, as the increasing population growth surrounding the PAs may eventually lead to migration of people experiencing poverty to the uplands and forested areas. These findings are similar to Garg (2017), who found that population growth has a global effect on land use patterns for agriculture, forest cover, and other types, further putting pressure on natural resources. This can be manifested through the change in distances among land cover types. Therefore, better management of PAs and provision of livelihood to the people are needed to preserve the PAs. This could be done by providing them with better access to viable livelihood opportunities and suitable housing locations or residential areas outside the PAs to control further encroachment and settlements. One factor that was identified to influence fragmentation in terms of patchiness and patch distances is poverty, as reflected by the PD and ENN_MN. Low-income families in the lowlands would migrate to the uplands where forest resources are available for their livelihoods, similar to the findings of Carandang et al. (2013). In contrast, a study by Brockington et al. (2015) found that poverty increased due to the restrictions imposed by PAs. This is, however negated by the results of a previous study that, on the average, PAs lowered deforestation and enhanced reforestation, but land cover changes in PAs neither diminished nor heightened poverty (Ferraro and Hanauer, 2014).

The negative relationship between PD and poverty in this study shows that the decrease in patchiness of the PA landscape is an effect of aggregating cultivated areas and diminishing forest cover in the PA. In addition, the increase in poverty pushes people to relocate to open-access forest areas, exploit resources for their survival, and engage in extensive agricultural expansion. This further reduces the density of the forest areas and contributes to the increase in other land uses, such as agricultural areas and settlements. Therefore, there is a need for enhancing mechanisms for poverty eradication, such as providing alternative livelihoods and sources of income to the people.

Global studies show that the effects of GDP on forest cover vary according to a given country's general income level. Positive impacts on forests are observed in high-income countries, while adverse effects on forest cover are seen in low-income countries (Ewers, 2006; Cuaresma et al., 2017). A probable cause of forest depletion is the economic goal of increasing GDP. According to Wolverson (2013), countries would rather choose logging for production, which would contribute to the value increase of GDP, over sustaining forests for ecosystem benefits. One of the results of this study included the negative effect of increasing RGDP on the condition of closed forest cover. The Philippines is a developing country that relies on natural resources to increase its GDP, increasing pressure on forestlands. Since GDP cannot be restricted, this would imply the need for strict protection and implementation of rules and regulations in the PAs. In addition, there must be strict regulation of forest resource use, particularly the banning illegal extraction of trees for timber, logs, and other forest products. Agroforestry practices and other tree-based types of farming systems should also be encouraged and developed to increase sustainable practices.

The positive effect of increasing road density on the patch complexity, as reflected in the decline in PAFRAC, demonstrates roads' regulatory effect on PAs. Road networks in the PAs become a tool for regulation, whereby park managers can access remote areas and enforce regulations for confining intense human activities to specific areas in the PA. Park regulations are also better implemented in the communities already established inside the PA.

This is similar to the finding of Newman et al. (2014), wherein increased road density simplified the shapes of patches in the forest reserves of Jamaica. A study by Kummer (1990) further argues that regulation of activities in the PAs is not achieved when roads are constructed farther from the PA. These studies, however, contradict others which show that high road density accelerates deforestation (Ewers, 2006; Nagendra et al., 2003), since accessibility to forestlands through road networks is a main driver of increased encroachment and settlement. However, this study's findings reveal road networks benefit PA managers by increasing ease of transport for monitoring purposes. Therefore, restricting access to roads to those without permission from the PA management board is necessary. These findings further emphasize the proper and legal construction of roads in PAs, mainly for improving park regulation and forest protection.

CONCLUSIONS

Forest cover within the PA had notable changes amidst it being mandated by law to restrain the extraction of forest resources. The results from the CCA show that there is a relationship between the land use and driving factors. Furthermore, the three strongest predictors are the cultivated area inside PA, which seems to imply that more agricultural activities within the PA negatively impact its land cover. This is followed by HDI, which also appears to indicate a negative effect towards changes in PAs' land cover as the level of social and economic development surrounding the PA increases. Following HDI is the regional GDP positively impacting land cover change and fragmentation in PAs. Therefore, the regulation of human activities, particularly the expansion of cultivated areas that deteriorate forests, must be given attention by PA managers.

These findings are parallel with the Multiple Linear Regression Analysis. The results from each dependent variable showed that cultivated area is the most common variable that significantly affects land use particularly CF, PAFRAC, CONTAG, SHDI.

This paper provides evidence that PA policy and management effectiveness is observed to be weak in protecting forest habitats from deterioration and fragmentation. METT scores are weakly correlated to the land cover condition of the Pas, and the analysis does not prove that METT scores are positively correlated with the improved conditions of the forest cover. Therefore, the researchers recommend re-evaluating the METT scoring procedure to better measure the positive impacts of proper PA management.

The following may be considered to improve the scoring process: (i) provide higher weights to both the regulation of drivers of forest cover change external to the PA, such as cultivation within the periphery of PAs, and the management and regulation of road systems in the PAs; (ii) identify programs or policies being implemented to protect the site and rate their respective effectiveness; (iii) complement the subjective performance evaluation with use of more objective quantitative evaluation, such as the use of GIS-aided land fragmentation analysis for assessing the overall condition of the forest cover.

While this study had limitations, it has provided a better understanding of the effects of socioeconomic factors on land use/cover change and fragmentation in natural parks and protected landscapes. This paper recommends testing the effects of other variables, such as local government activities, and livelihood of stakeholders, and including demographic variables, such as quality of life among stakeholders and sources of income. Integrating more fragmentation metrics, such as edge effects, shape index, edge contrast index, and run analyses down to patch level is also recommended. Furthermore, the researchers suggest a more holistic, ridge-to-reef approach in analyzing PA management effectiveness. Studies could look at the PAs in a broader context, considering the connections of PA conditions to the physical and anthropogenic activities that are taking place in other parts of the landscape units where the PA is located.

ACKNOWLEDGEMENT

The authors would like to thank the Philippine Council for Agriculture, Aquatic and Natural Resources Research and Development (DOST-PCAARRD) and Science Education Institute (DOST-SEI) of the Department of Science and Technology for providing financial assistance in conducting this study through the Graduate Research Education Assistantship for Technology (GREAT) Program. The authors also extend their gratitude to Dr. Canesio Predo and Ms. Odessa Dacmay for their support on the statistical analysis of this study, and to Ms. Amy Cruz for editing and proofreading.

CONFLICTS OF INTEREST

The authors affirm that the study has no conflict of interest.

CONTRIBUTIONS OF INDIVIDUAL AUTHORS

AFV Buhay conducted the land use and land cover change and analysis of its results with the supervision of RVO Cruz. AFV Buhay wrote the manuscript with substantial comments, suggestions, and reviews of RVO Cruz, CL Tiburan Jr., and JM Pulhin.

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