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Land Use Change and Prediction for Valuating Carbon Sequestration in Viti Levu Island, Fiji

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Abstract: This study examines land use changes and evaluates the past and projected forest carbon sequestration and its valuation in Viti Levu Island, Fiji, through a combination of remote sensing with a geospatial-based modeling approach. Land use classification was performed using Landsat 7 and Landsat 8 imageries of the years 2000 and 2020; then, cellular automata and artificial neural network (CA-ANN) modeling was conducted to predict the land use map of 2040. Carbon sequestration and the economic valuation were estimated using the land use maps of the past, present, and future (2000, 2020, and 2040) within the Integrated Valuation of Ecosystems Trade-off (InVEST) model. The results showed that deforestation occurred during the past two decades, and the forest area was predicted to keep decreasing in 2040, with the major contribution from the conversion to the agricultural area. Local communities' perceptions confirmed that the forest conversion to croplands would persist due to the demand for fertile lands. This study estimated a loss of −7.337 megatonnes of forest carbon (Mt C) with an economic loss of USD −1369.38 million during 2000–2020 due to deforestation. If the business-as-usual scenario does not change in the near future, a potential carbon loss of −7.959 Mt C is predicted in the upcoming 20 years. The predicted results can be used to assist as a reference in establishing a national baseline and reference level for implementing the REDD+ mechanism in Fiji and sustainably managing the limited pristine forest by implementing forest-related programs.

Keywords: carbon sequestration; land use change; land use prediction; carbon stock valuation; REDD+; Fiji

1. Introduction

The global surface temperature has risen as much as 1.09 (0.95 °C to 1.20 °C) °C in 2011–2020 compared to 1850–1900 and is predicted to continue increasing until the middle of the 21st century at a minimum of 1.5 °C and 2 °C unless significant carbon and other greenhouse gases (GHGs) emissions can be reduced in the coming decades [1]. An increase in anthropogenic activities coupled with developments including land-use change, deforestation, biomass burning, draining of wetlands, soil cultivation, and fossil fuel combustion have been reported to be the main causes of GHGs emissions. The terrestrial human activities in Agriculture, Forestry, and Other Land Use (AFOLU) immensely contributed to GHGs emissions accounting for 23% (12.0 +/− 3.0 Gt CO_2 e yr^{-1}) of total net anthropogenic emissions [2].

Land is a source of GHGs emissions, but on the other hand, is also the sink or sequester of carbon [2]. Carbon sequestration is the process of transfer and secure storage of atmospheric carbon dioxide (CO_2) into other long-lived carbon pools that would otherwise be emitted or remain in the atmosphere [3]. The total carbon quantities of biomass on Earth is ~550 Gt C across all kingdoms of life, dominated by plants (~80%; ~450 Gt C) [4]. The biomass of vegetation comprises those located above and below the ground, specified as above and belowground biomass, with the estimates of 287 Gt C and 122 Gt C, respectively [5]. Those estimates exclude the non-living biomass, such as soils that store three-fold the carbon of vegetation (1460.5 Gt C) [6].

Tropical forests store a large proportion of the global terrestrial carbon, with an estimated 59% and 29% of the carbon stored in global forest vegetation and soil pools, respectively, contained in the low-latitude tropical forest [7]. These values indicate the importance of tropical forests in the biomass storage context of their high carbon density, tropical forests in the Asia-Pacific region are increasingly viewed as an avenue for mitigating climate change [8,9]. To reduce deforestation and forest degradation by creating monetary value for the carbon in the forest, the United Nations has developed Reducing Emission from Deforestation and Forest Degradation (REDD) [10]. The program was continued by REDD+, which refers to enhancing forest carbon stocks through activities such as forest conservation, forest restoration, and sustainable forest management [11]. Under the requirements of REDD+, participating countries are required to periodically assess their forest resources at a national scale for the results-based payment [12]. This process is particularly challenging in the tropics because of technical difficulties related to estimating aboveground forest biomass stocks, restricted availability of affordable remote sensing images, and a lack of forest inventory data [13].

The aboveground biomass (AGB) of Fiji's forests in 2011 was estimated to be around 52.43 Mt C, yet the accuracy is still lacking due to the dataset anomalies [14]. The latest forest carbon estimates conducted by Mundhenk et al. [15] under the Forest Reference Level document of the Fiji REDD+ reported the emission of 241,424 t CO_2 e yr^{-1} (65,837 t C yr^{-1}). The loss of carbon in the country is mainly due to the deforestation that occurred during the observation time. With the requirement of emission that should not exceed the RFL in the REDD+ initiatives, forest conversion needs to be restricted at a certain level. Fiji has committed to the REDD+ program commenced in 2009 with the support of the Secretariat of the Pacific Community (SPC) and Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) project "Coping with Climate Change in the Pacific Island Region" [16]. Some outcomes have been successfully developed after one year of establishment, followed by the completion of the Readiness phase. As a result, the Fijian Ministry of Forestry signed the emission reduction payment agreement, marking Fiji's entry into carbon trading in 2021.

Remote sensing technology provides spatial observation methods to monitor changes in land use/land cover at a high level of accuracy. Remote sensing data and geospatial techniques are widely used to identify land use changes and estimate forest cover conversion affecting forest carbon pools, especially for aboveground biomass [17–19]. The availability of long-term observation by Landsat series enables decadal monitoring at 30 m spatial resolution, which is suitable for regional analysis [20–23].

Considering the dynamics of land use by human activities, a prediction can preliminarily see the estimated carbon stock and economic valuation based on it. Prediction is possible by using geographical information system (GIS)-based simulation using the observed land use data in the previous periods. Several models have been widely used to run land use/land cover prediction tasks, such as logistic regression [24], cellular automata Markov-chain (CA-Markov) [25], multi-layer perceptron–Markov chain analysis (MLP-MCA) [26], and cellular automata and artificial neural network (CA-ANN) [27]. With the availability of predicted land use data, some studies incorporated the use of land use prediction models with the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model to project the assessment of carbon sequestration [28–30]. InVEST model has been utilized for quantifying the economic valuation of carbon stock based on land use change [31–33]. In addition, the InVEST model can provide broader estimates of what the ecosystem services can provide directly or indirectly to the people [29,34].

This study aims to monitor the valuation of carbon sequestration based on land use change and prediction in Viti Levu Island, Fiji. The CA-ANN model was used to predict land use in 2040 based on the years 2000 and 2020. The land use datasets for 2000 and 2020 were obtained from image classification on Landsat images. Carbon sequestration and economic valuation were then quantified using the InVEST model. Questionnaire surveys were also conducted to understand the perception of local people on land use changes. This research may assist the Ministry of Forest, Fiji, and the REDD+ project to explore the potential of Fiji's forest regarding its social, economic, and environmental benefits to communities, especially forest owners. There are only a few studies that have been conducted in the country related to carbon sequestration or examining the direct or indirect benefits of forest and ecosystem services to the landowners and forest owners.

2. Materials and Methods

2.1. Study Area

Fiji is located within the coordinates of 15°30′28.59′′ S–21°13′43.76′′ S and 176°40′11.17′′ E–180°159′48.35′′ E, covering a total land area of about 18,270 km^2. It is located 2000 km northeast of New Zealand's North Island. The closest neighbors are Vanuatu to the west, Tonga to the east, and Tuvalu to the north. The last census in 2017 reported the country′s total population is 884,887, of which 55.9% live in urban areas [35]. Our study area is located in the island of Viti Levu, the largest island is inhabited by 81% of the population (Figure 1).

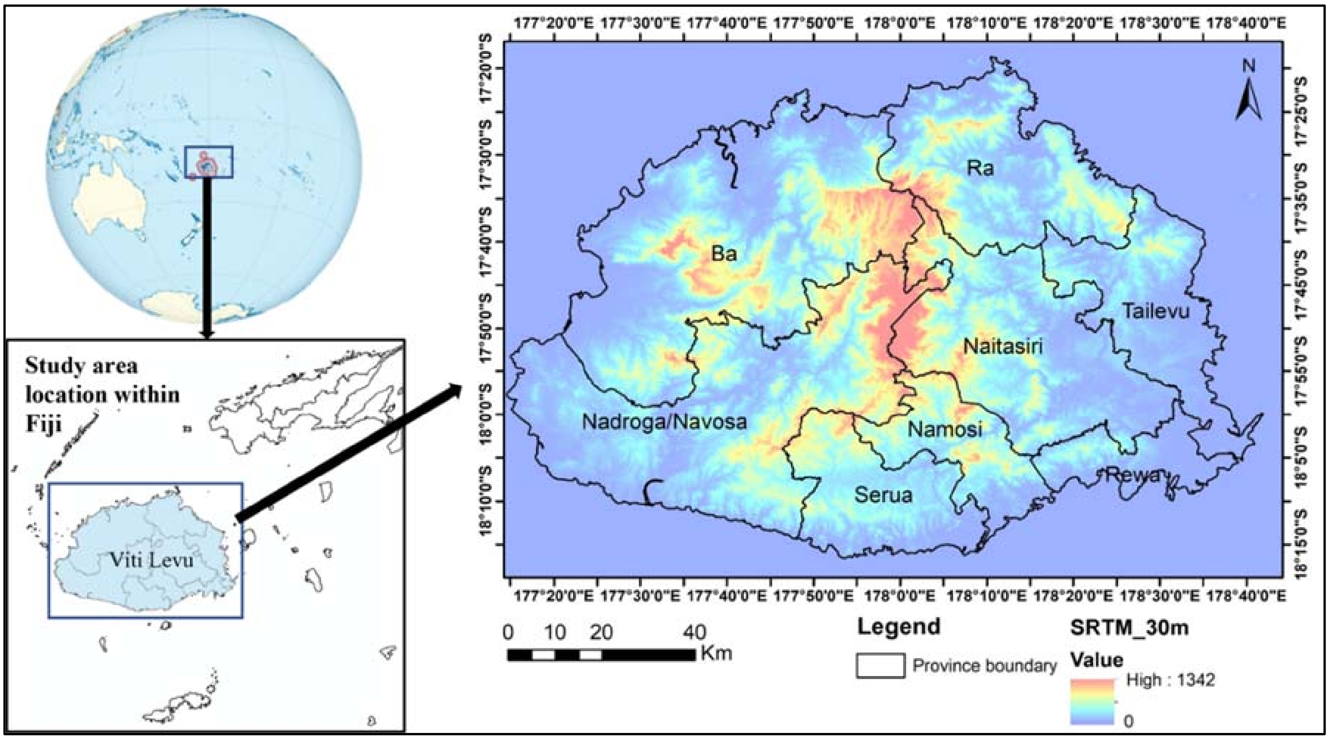


Figure 1. Map of study area located in Viti Levu Island.

Closed and open forest (natural forest) accounts for 53.46% of the total land area, whereas plantations (pine, hardwood, and coconut) account for 8.72% [36]. Agriculture is an important sector in Viti Levu Island, where about 13.5% of the land area is covered by agriculture area that employs 60% of the people. On the other hand, the development of agriculture becomes a major threat to forests, together with logging, urban development, and tourism expansion.

2.2. Methods

In general, the methodology consists of land use classification, land use prediction, accuracy assessment, and carbon sequestration valuation, as illustrated in Figure 2. Before estimating the carbon storage, multi-temporal land use changes were developed consisting of the land use in 2000, 2020, and 2040. The CA-ANN approach was used to predict 2040 land use and land cover (LULC). The valuation was calculated using land-use-based carbon storage for each year. Field checking and questionnaire surveys were also conducted to validate the land use classification and observe people's perceptions on the land use change. The details of the methods are elaborated in the following Sections 2.2.1–2.2.4.

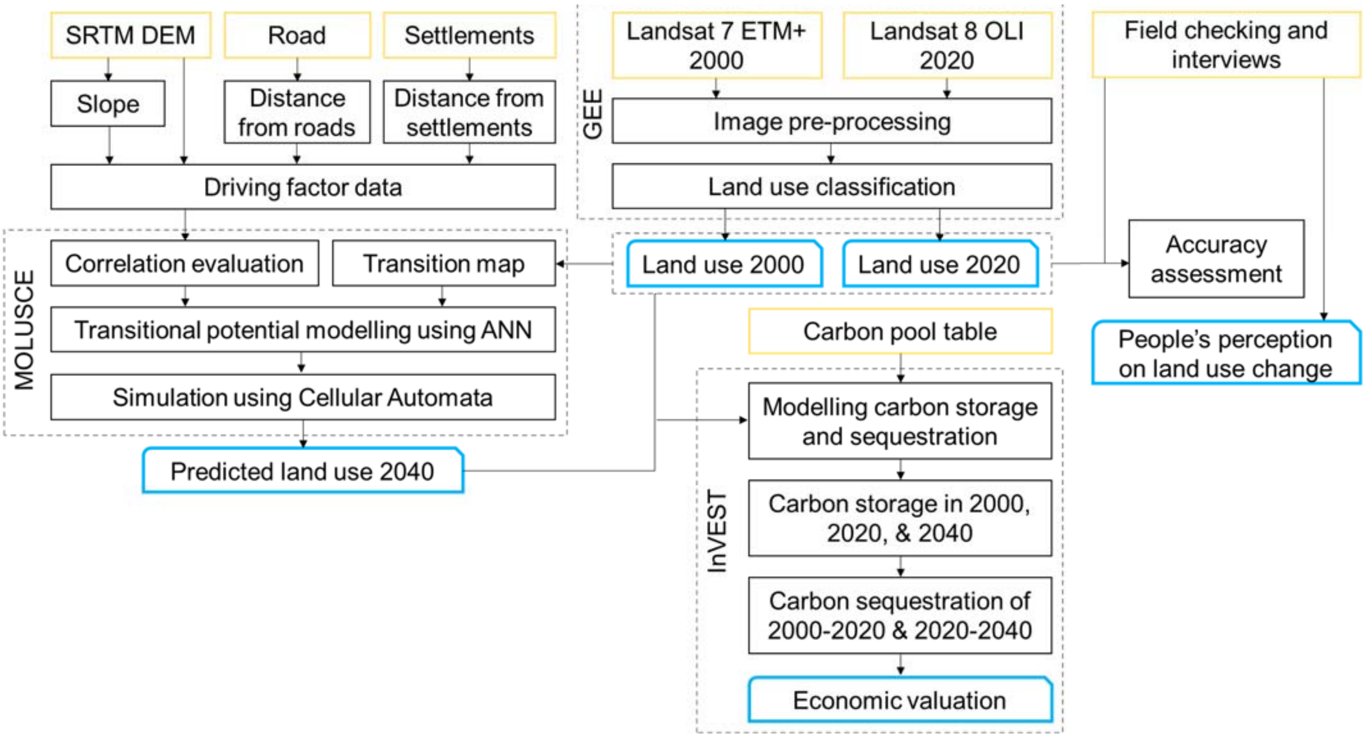


Figure 2. Flow chart of the study.

2.2.1. Land Use Classification

This study specifically concentrates on developing the land use maps for two different years, i.e., 2000 and 2020. Google Earth Engine (GEE), a geospatial cloud computing platform, was used in this step to obtain and pre-process the images, as well as to classify the land use types. Firstly, Landsat data acquired in 2000 and 2020 were selected as the primary inputs of this study. Landsat data used are in the level of surface reflectance that has been corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) [37] and Land Surface Reflectance Code (LaSRC) [38] for Landsat 7 and Landsat 8, respectively. Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) and several image transformations, including Mangrove Vegetation Index (MVI) [39] and Modified Normalized Difference Wetness Index (MNDWI) [40] were incorporated as the predictors along with reflectance bands. Four different land use land cover classes were defined, including agricultural area, forest, built-up, and shrubs to denote the varying amount of carbon availability. Training samples were taken by visually interpreting high-resolution imageries, as well as the local knowledge in the study area. A machine learning method, random forest (RF) with a parameter of 10 decision trees, was implemented to run the classification [41].

2.2.2. Land Use Prediction

A prediction of land use was conducted using MOLUSCE (Modules of Land Use Change Evaluation) plugin in QGIS [42]. Land use maps derived from image classification of two images are the main inputs, which, in this study, comprise the land use of 2000 and 2020, to predict land use in the year 2040. Variables that drive land use change were also entailed in the processing, including elevation, slope, distance from roads, and distance from settlements (Figure 3). These factors are widely known as the major drivers of regional development [43,44]. Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) with 1 arc-second resolution was used to provide elevation data. The DEM was then also converted into slope data with the resolution and extent referring to the land use data. Proximity tools were utilized to generate distance from roads and settlements from road networks and existing settlements, respectively. All driving factors were then evaluated the correlation (Pearson's correlation) among them to see whether there are inter-relationships or not.

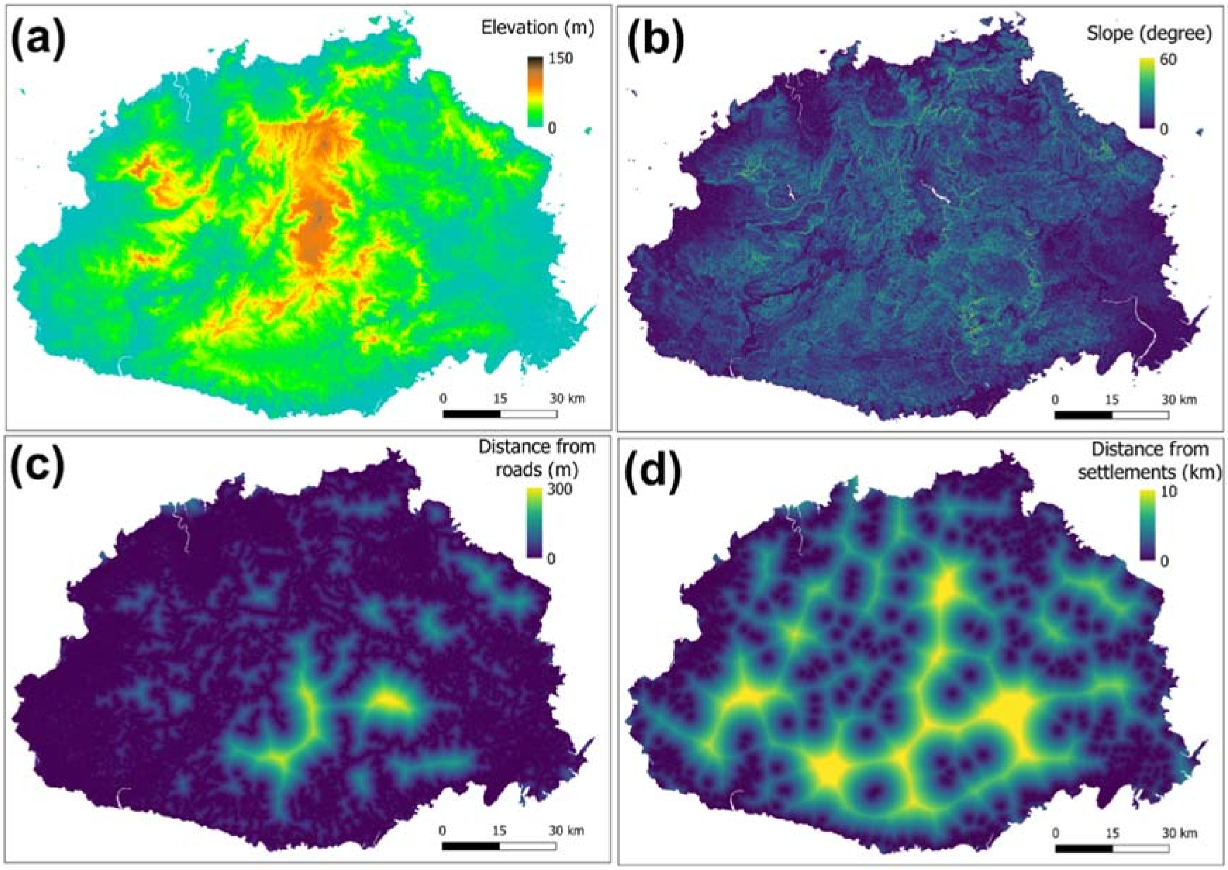


Figure 3. Spatial variables used for land use prediction.

Multi-layer perceptron (MLP), one of the artificial neural network (ANN) methods, was used to learn the transitional potential. MLP is a class of feedforward ANNs that propagates signals from node to node, modified by the weights linked to each connection through the hidden layer and the output layer [45]. Before reaching the output layer, multiple summations were performed on the data moving forward from node to node. With a non-linear activation function, this algorithm can model non-linear functions and predict unseen data from its learning process [46]. Several parameters need to be defined, including neighborhood = 1; iterations = 2000; hidden layer = 10; momentum value = 0.05; and learning rate = 0.1. The algorithm iterated the learning procedure until the best prediction was reached. To simulate the trained algorithm, Cellular Automata (CA) was applied to build the predicted land use in the year 2040. The Monte Carlo approach was used to decide the states of cells by comparing the transition probability (in this case, generated by ANN) with a random number [47,48]. This model is renowned for its capability to integrate spatial and temporal aspects for simulating urban development [47].

2.2.3. Carbon Storage and Economic Valuation

The land use and land cover (LULC) analysis results for these different years were used to assess carbon stocks, carbon sequestration, and carbon value at different intervals together with a carbon sequestration map using the InVEST model [28,33]. The InVEST model was used in this study as the best fit model to estimate the carbon stock, sequestration, and carbon value for the forest [49,50]. The model requires inputs from the four-carbon pools (i.e., aboveground, belowground, soil organic carbon, and litter layer) to estimate the total carbon stock [51,52]. Once the carbon stocks are estimated, the model will allow the process and production of the estimated carbon stock map for each grid cell across the study area. It also allows the calculation of the net changes in the carbon stock over time, taking into consideration the historical and current land use maps. Any changes in the carbon stocks assumed that it was due to changes from one land use to another. Therefore, any grid cells that did not change their land cover will have a sequestration and loss value of 0 over time. Due to the limited data and our focus on forest areas, only carbon pools of forest were included in the model. The estimated carbon pool data for aboveground (C above = 95.31 t C/ha) and belowground (C below = 20.48 t C/ha) biomass were obtained from the Global Forest Assessment 2020 [53], while the soil organic carbon (C soil = 86.00 t C/ha) and carbon in the dead matter (C dead = 17.50 t C/ha) were derived from the overall assessment in the Oceania [54].

In addition, the economic value of carbon sequestration was also quantified. The changes in carbon sequestration were measured and the difference in carbon storage was calculated based on the current and projected future landscape. This processing involves the economic data, including the value of the sequestered carbon, the market discount rate, and the annual rate of change in the price of carbon. A social cost of carbon valued at USD 187.17/t C (converted from USD 51/t CO_2) was used with a discount rate of 3% [55]. This cost includes all the social aspects related to the detrimental impacts of climate change. The annual rate of carbon price was assumed to be zero.

2.2.4. Accuracy Assessment and Interviews

Ideally, ground-truthing is conducted together with the use of aerial photographs at or near the time of the satellite overpass [56,57]. However, due to limitations of the data, high-resolution Google Earth images interpreted from Google Earth Pro software and local knowledge were used to assess the accuracy of the classified land cover maps of 2000 and 2020. The Google Earth images acquired on 1 January 2020 were used to validate LULC 2020; meanwhile, the validation for LULC 2000 used the images in a period between 20 March 2000 and 30 May 2004 due to the partial coverage in the year 2000. Moreover, ground checking was conducted at some points that are accessible in the field. A stratified random sampling method was used to prepare the 395 reference points for accuracy assessment using ACaTaMa plugin in QGIS software. The accuracy of each land use was quantified by a confusion matrix. Questionnaire surveys were also carried out during the site visit by circulating questionnaires to 200 people in targeted communities across the island, i.e., half in the central division and another half in the western division. The questionnaires were intended to understand the perception of the people about land cover and the change in the last two decades.

3. Results

3.1. Land Use Maps and the Changes in 2000 and 2020

Landsat images were classified to generate LULC maps of the study area for the year 2000 and 2020, as shown in Figure 4. Forest is the main class in the study area, covering 7190 km^2 (68.2% of the total area) and 6855 km^2 (65.0%) in 2000 and 2020, respectively. A decrease of 334.6 km2 (3.2%) in forest area was observed from 2000 to 2020. In contrast, the built-up area has increased more than double during the last two decades, from 142.2 km^2 (1.3%) to 328.1 km^2 (3.1%). It is followed by the significant rise in agricultural areas with an increase of 696.7 km^2 (6.6%) to reach 2362.0 km^2 in 2020. This is mainly because population increases may lead to a rise in demand for expansion in agricultural land.

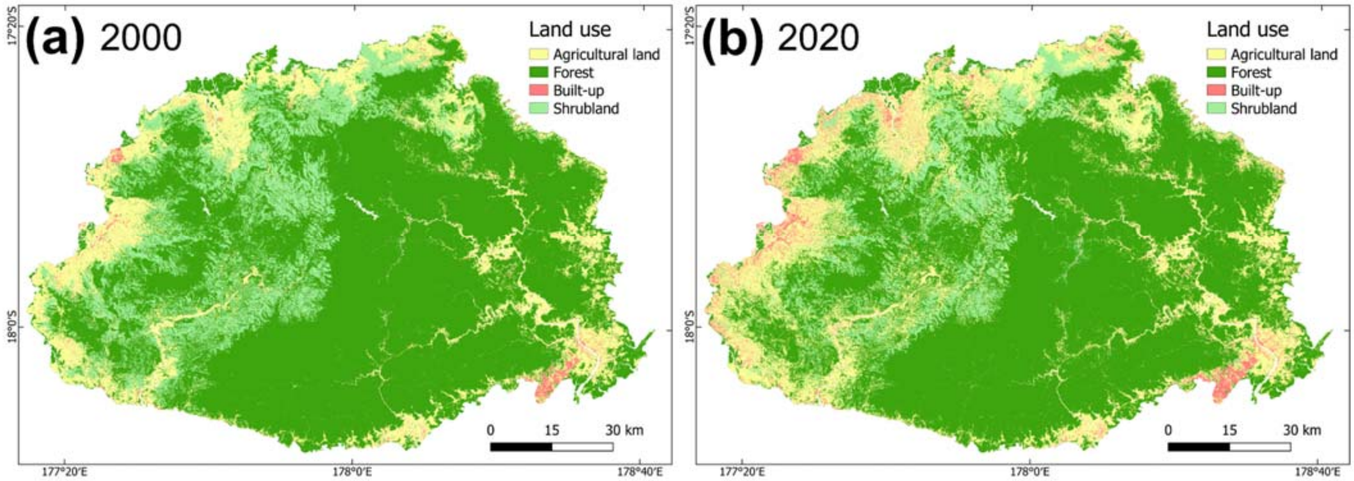


Figure 4. Land use land cover maps of 2000 and 2020.

The transition matrix in Table 1 shows that the conversions to the agricultural area (340.13 km^2) and shrubs (186.01 km^2) contributed to the loss of forest during 2000–2020. However, a trade-off was also observed that some areas of shrubland were also changed to forests with a total of 202.27 km^2. Other than forests, the increase in the agricultural area in 2020 also originated from 33% of the existing shrubs in 2000. Meanwhile, the development of built-up areas took place in the agricultural lands comprising 152.32 km^2.

Table 1. Transition matrix (in km^2) of land use change between 2000 and 2020.

Land Use 2000	Land Use 2020				Total
	Agriculture	Forest	Built-Up	Shrub	
Agriculture	1511.21	0.04	152.32	1.74	1665.31
Forest	340.13	6653.11	10.84	186.01	7190.09
Built-up	3.46	0.10	138.48	0.16	142.2
Shrub	507.19	202.27	26.50	812.25	1548.21
Total	2361.99	6855.52	328.14	1000.16	10,545.81

3.2. Land Use Prediction of 2040

Before predicting the future land use, driving factors were firstly evaluated in their relationship using Pearson's Correlation, as shown in Table 2. As observed, there is no strong relationship between the variables ($r < 0.7$), showing that only DEM versus slope possesses a correlation of higher than 0.6 ($r = 0.619$). The lowest relationship is between slope and distance from settlements ($r = 0.259$), and the others ranged between 0.413 and 0.525. The low correlations indicate that there is no multi-collinearity detected among the variables [58]; thus, all parameters can be further used in the processing.

Table 2. Pearson's correlation (r) values among spatial variables.

Spatial Variables	DEM	Distance from Roads	Slope	Distance from Settlements
DEM	-	0.524	0.619	0.505
Distance from roads		-	0.413	0.525
Slope			-	0.259
Distance from settlements				-

The transitional potential was performed using ANN to learn the land use change based on given driving factors. Several parameters were defined to train the ANN. The training is finished when the best accuracy is reached. The curve of ANN process is illustrated in Figure 5. The CA method was used to simulate the prediction, taking the learning results of transitional potential.

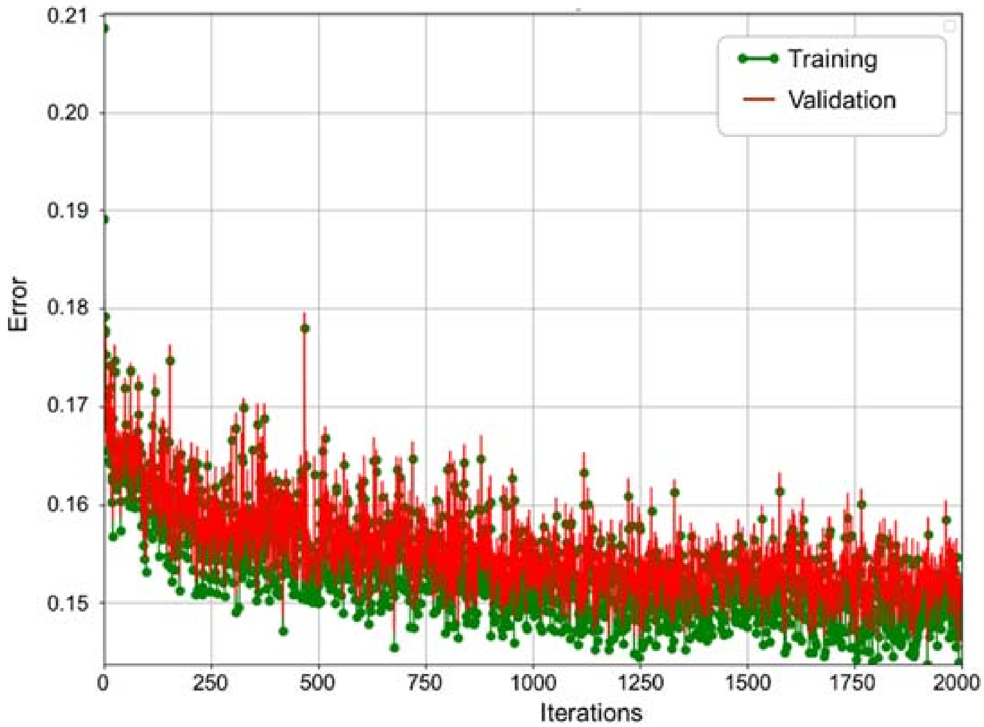


Figure 5. Neural network learning curve.

Figure 6 shows the predicted LULC in 2040, 20 years after the current land use data of 2020 by taking the temporal gap with the past land use (2000). The area changes between two periods, i.e., 2000–2020 and 2020–2040, are presented in Figure 7. Similar to previous classified LULC maps, forests dominated the island with a total area of 6492.8 km^2 (61.6%), although a decline was estimated with a forest loss of 362.8 km^2. The development of agricultural area slowed to only an increase of 282.3 km^2 as compared to a 696.7 km^2 increase during 2000–2020, yet it comprises a quarter of the land area (25.1%). A similar rate to the past land use change was detected in built-up areas that are projected to increase by 186.1 km^2 in 2040.

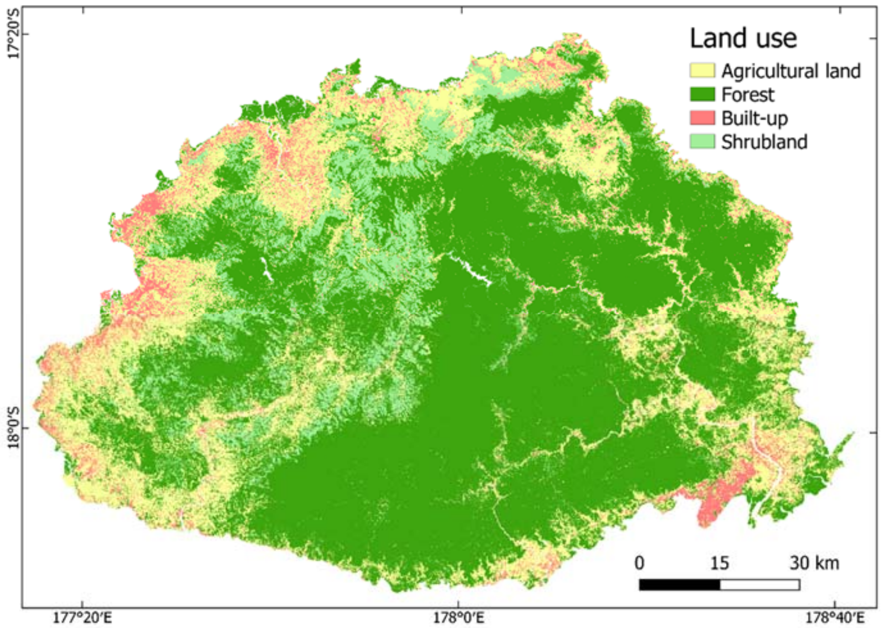


Figure 6. Predicted LULC map of 2040.

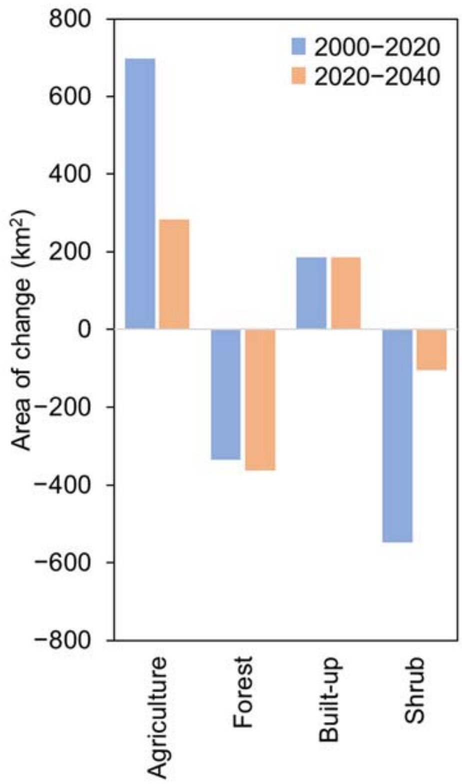
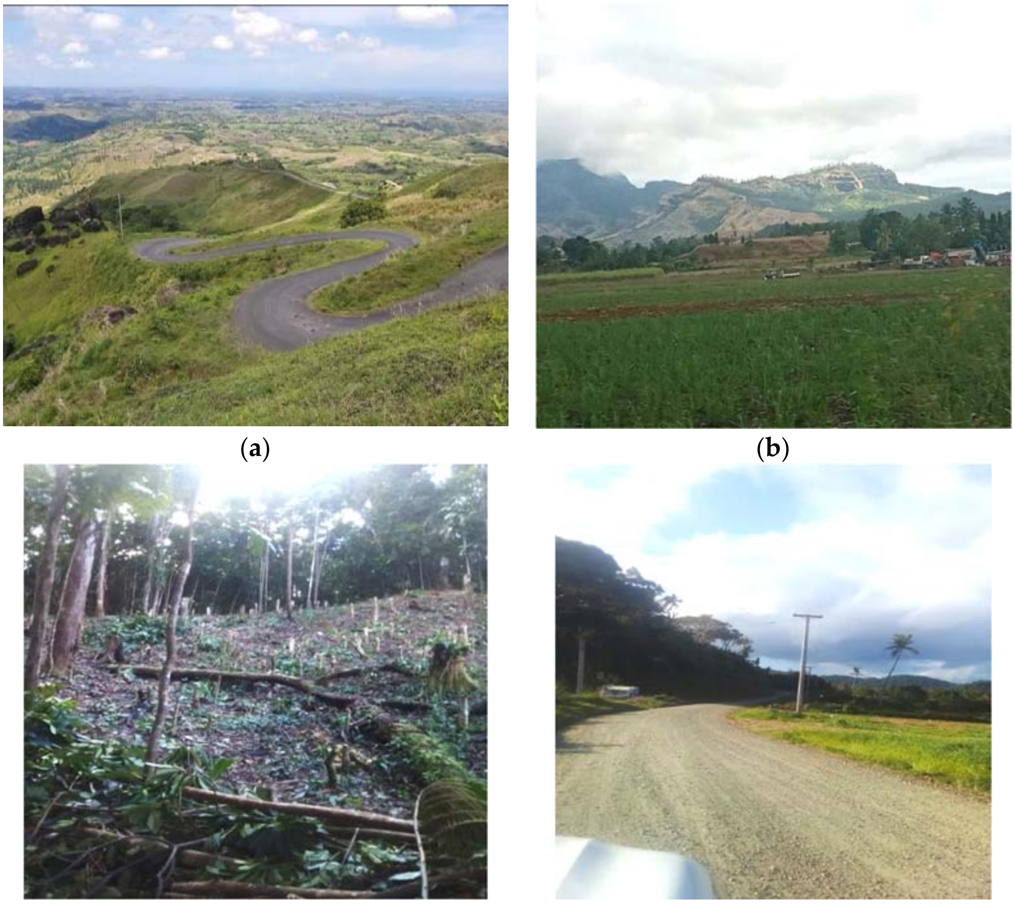


Figure 7. Area changes between 2000–2020 and 2020–2040 in km^2.

3.3. Accuracy Assessment

An accuracy assessment was conducted to ensure that the land use classification results are accurate enough to be presented. A total of 395 land use classification samples, generated from ACaTaMa plugin with a stratified random approach, were assigned with the information on land uses in 2000 and 2020. Stratified random sampling means that the number of samples of each class corresponds to its area with a random distribution. All samples were then compared with the actual condition of the land use type. In addition, the visual interpretation of high-resolution images and field visit was also conducted to recheck the validation samples. Figure 8 shows some selected samples representing different conditions of land use types in the study area. Some land conversions were also identified, such as a conversion to agricultural area (Figure 8b) and a deforested area (Figure 8c). The validation samples with the land use information derived from interpretation of high-resolution images and field visits were used to generate confusion matrices, as shown in Tables 3 and 4.



(**a**) (**b**)

(**c**) (**d**)

Figure 8. Land use pictures taken in the study area: (**a**) shrubs in the western highlands part of Viti Levu, (**b**) agriculture conversion for sugar cane plantation in the Ba Province, (**c**) the forest clearance for small-scale farming in the central division, and (**d**) vicinity of the typical Fijian village set up with subsistence farming for food security outside the village boundary (Source of photographs: personal documentation).

Table 3. Confusion matrix of land use classification in 2000.

	LULC Classes	Reference Data					User's Accuracy (%)
		Agriculture	Forest	Built-Up	Shrub	Total	
Classified data	Agriculture	49	4	4	5	62	79.0
	Forest	9	238	5	18	270	88.2
	Built-up			5		5	100.0
	Shrub	1	5	1	51	58	87.9
	Total	59	247	15	74	395	
Producer's accuracy (%)		83.1	96.4	33.3	51.0		
Overall accuracy (%)		86.8					
Kappa Coefficient (T)		0.747					

Table 4. Confusion matrix of land use classification in 2020.

	LULC Classes	Reference Data					User's Accuracy (%)
		Agriculture	Forest	Built-Up	Shrub	Total	
Classified data	Agriculture	71	7		9	87	81.6
	Forest	15	237		5	257	92.2
	Built-up	7		3	2	12	25.0
	Shrub	2	4		33	39	84.6
	Total	95	248	3	49	395	
Producer's accuracy (%)		74.7	95.5	100	67.4		
Overall accuracy (%)				87.1			
Kappa Coefficient (T)				75.5			

Both classified land use maps of 2000 and 2020 achieved overall accuracies of 86.8% and 87.1%, with Kappa coefficients of 0.747 and 0.755, respectively. As observed, forests relatively possessed the highest accuracy among other land use types in both observation periods, followed by the agricultural area. Shrubs area had high user's accuracies, yet the producer's accuracies are low, i.e., 51.0% and 67.4% in 2000 and 2020, respectively. The user's accuracies of built-up area are 100% and 25% for the LULC classification of 2000 and 2020; meanwhile, the producer's accuracies are 33.3% and 100%, respectively.

3.4. Valuation of Carbon Sequestration

LULC information of the past (2000), present (2020), and future (2040) were used in the InVEST model to monitor carbon. The total carbon estimated in the forest area of Viti Levu Island is 157.673 Mt C in 2000 and 150.336 Mt C in 2020, resulting in a negative carbon sequestration at −7.337 Mt (Table 5). As predicted, the forest area kept decreasing in 2040 with a total carbon of 142.376 Mt C and the calculated carbon sequestration of −7.959 Mt C. This signified a further decrease in carbon compared to the 2000–2020 period. This has shown a reduction in carbon stock or carbon loss to the environment. As a result, economic loss was also projected showing a negative trend in the net present value, decreasing from USD −1369.382 Million to USD −1485.490 Million in 2040.

Table 5. Total carbon stored, carbon sequestration, and net present value derived from InVEST model.

Year	Total Carbon (Mt C)	Carbon Sequestration (Mt C)	Net Present Value (Million USD)
2000	157.673	n/a	n/a
2020	150.336	−7.337	−1369.382
2040	142.376	−7.959	−1485.490

3.5. Questionnaire Survey Results

A questionnaire survey was conducted to determine the main factors affecting the changes, for example, anthropogenic, natural, and/or climate changes. According to the questionnaires filled by the 200 people in targeted areas/communities across Viti Levu Island, the majority of the people agreed that the forest area was reduced significantly. The response from communities during the interview shows that most people used to depend on firewood for energy sources explained that firewood is tougher to be collected compared to 20 years ago. This is in accordance with the decrease in forests in the last two decades revealed by land use change analysis.

The results of the survey signified the perception of the people regarding the population, whether it is increasing or decreasing in the future: what they think about the agricultural activities and their accessibility to infrastructure and quality services. Figure 9 shows that 40% of the people interviewed agreed that the forest might be changed for agricultural development in the future; hence, agricultural area, on the other hand, increases with people seeking and expanding fertile land thus impacting forest areas.

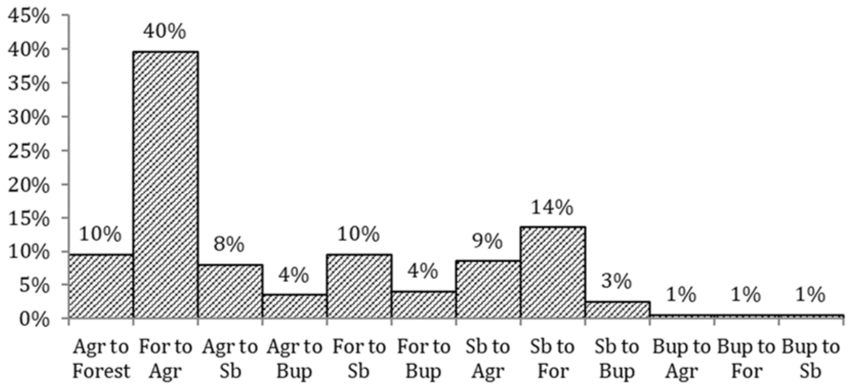


Figure 9. Perception of people for the future change in land use.

People who are living in urban and semi-urban areas have good access to infrastructure and quality services, while those who reside in the rural areas and outer islands have difficulty finding better services and infrastructure. Our survey shows that most of the respondents (57%) believe that the population is increasing and will increase in the future. On the other hand, about a quarter (23%) of the people think that the decline in population is happening, while 21% of them have no idea about the population trend.

4. Discussion

4.1. Land Use Changes and Prediction of Future Maps

Agriculture and forestry were assumed to be the main factors shaping the land use of Viti Levu Island, Fiji. Agriculture areas increased from 2000 to 2020 and are also predicted to expand in the future year, 2040. Concurrently, the island is the heart of Fiji, considered the biggest island and center for everything, where the capital city is situated, and it is also the political, economic, and cultural center of Fiji. In addition, the bulk of the population of Fiji lives in Viti Levu, comprising more than 60% of the total population. Therefore, the changes in land use mostly occurred due to human activities.

Our findings showed that major forest changes included infrastructure development, increase in population, agriculture and shifting cultivation, logging by respective landowners, encroachment for wild boar hunting, fishing, and the demand for firewood cutting in the forest. This elaborates on the emission reduction paper document by the REDD+ division of the Ministry of Forest that reported the main causes of deforestation are agriculture expansion, settlement, and infrastructure [16]. On the other hand, the impact of natural causes such as tropical cyclones, flooding, fire, and natural changes should not be overlooked. In Fiji, the impact of natural disasters such as tropical cyclones, flooding, and fire should not be underestimated as they impose major threats to people's lives and land use. For instance, 65,243 ha of mangroves were lost due to cyclones during 2001–2018 [59].

Although shrublands decreased in 2020 and are projected to decline slightly in 2040, the areas are still considered vast, i.e., 9.48% and 8.48% in 2020 and 2040, respectively. In this study, shrubland is defined as those lands that are not included as a forest, it can be grassland, bare land, and woody plants that are smaller than a tree arising at or near the ground. Increase in shrubs can result from poor agriculture practices, and the search for fertile land by the farmers. In Fiji, slash-and-burn and shifting cultivation are commonly practiced, whereby farmers plant root crops such as taro, cassava, yam, and kava on a semi-commercial basis. This is revealed by the trade-off area between forest and shrubland in the transition matrix. In the beginning of 2015, the government implemented a reforestation program by the Ministry of Forestry and supported by the REDD+ program to facilitate the reforestation and afforestation in shrublands and degraded areas [16].

The highest transition potential, as observed in this study, is witnessed from shrubland to agriculture. In Fiji, the degraded forests and shrublands are left alone for natural regeneration but with the support of some projects on reforestation, afforestation, and rehabilitation landowners are encouraged to plant and rehabilitate their degraded land either converted to forest plantations or for sustainable agriculture. Since most of the land and forest are communally owned in Fiji (>80%), the government is working closely with communities through its rural integrative and collaborative approach to assist in developing land-use plans from the community level, district level right up to the national level.

Development in Fiji and the movement of people from rural areas to urban areas has increased in the past 20 years. This has resulted in a slight increase in the built-up areas in this study from the year 2000 to 2020 and including the predicted year 2040. As the Viti Levu's population increased, coupled with the large economic zone for Fiji, economic growth was witnessed since 2015, mainly driven by tourism development and construction industries with the increase in manufacturing, finance, and transportation sectors [60].

4.2. Monitoring and Prediction of Carbon Sequestration and Its Economic Valuation

The estimation of carbon sequestration in this study was specifically concentrated on forest class for the years 2000–2020 and 2020–2040 because there is no sufficient information on carbon pool data issued by the Fijian government and the previous studies conducted. The forest carbon pools available for Fiji only include the above-ground carbon and the below-ground, while the forest soil organic carbon was derived from the Global Soil Organic carbon. The results indicated that the total carbon for the three different years for forest class alone considered the availability of data for the three-carbon pools.

A previous study estimated the total carbon stock for the national forest is 52.43 Mt C for only the above-ground biomass [14]. The Forest Reference Level (FRL) under the REDD+ program stated a total carbon stock of 129.6 Mt C [15]. The FRL incorporated all open and closed forests, including mangroves, that have distinct carbon pools; however, the assessment did not involve the amount of carbon in the soil, litter, and dead woods. Meanwhile, we estimated a carbon stock in 2020 at 150.336 Mt C by including all carbon pools; thus, a slight overestimate was observed compared to the FRL.

Estimating the economic value of carbon sequestration requires extensive calculation incorporating the discount rate, the carbon current market price, and the social value of sequestered carbon to quantify the net present value (NPV) of sequestered carbon for the periods of 2000–2020 and 2020–2040. Babbar et al. [28] suggested that the discount rate requires the value of time for carbon sequestered, which enables the calculation of the NPV. Otherwise, it is difficult to interpret the results of the studies without using the carbon discount method.

Our analysis showed that the NPV is negative showing the loss of economic value in both periods, i.e., USD −1369.382 million (2000–2020) and USD −1485.490 million (2020–2040). In contrast to a study by Babbar et al. [28] that reported the identified economic loss of USD 214.57 million (2000–2018) can potentially be reduced to USD −17.19 million (2018–2035). It is mainly due to the location being designated as a reserved area of Sariska Tiger Reserve. In contrast, the land ownership tenure is unique in the sense that the majority of the land (>80%) is communally owned by the Itaukei people (indigenous Fijian). Such ownership is recognized by the constitution of the Republic of Fiji. Customary right of access to land and forest for communal use is recognized under the Forest Decree [61]. Therefore, it is important to inform them of the expression of the ecosystem services in monetary value and to convey the significance of ecosystem services and biodiversity among policymakers [28,29,62].

Improvements in technologies and the introduction of spatial information have assisted policymakers and government officials in making wise decisions with regard to reforestation, afforestation, and conservation. Under the REDD+ project in Fiji, the Monitoring, Reporting, and Verification (MRV) component has been strengthened to ensure efficient and reliable information is disseminated at all levels. In addition, it is also cost-effective and ensures that the limited funding available is utilized optimistically. In addition, we encouraged future studies to calculate carbon pools in the field with various types of forests in the study area. Therefore, an accurate estimate of carbon stocks and their valuation could be achieved.

Within the Asia-Pacific region, there has been a concerted effort to study carbon sequestration in all carbon pools due to a concern of excessive disturbance of the environment. The study directly measures carbon sequestration spatially by aggregating stored carbon in different carbon pools using land use maps. This method is quite straightforward compared to the traditional method used for surveying, which is time-consuming and costly. The use of remote sensing data and GIS, especially on multi-temporal satellite images has offered easy access to monitor whether the carbon has been sequestered or lost. This study is relevant and useful in the REDD+ program as the results will assist by providing baseline information for the implementation of the key components of the project. As forest class is found to be dominated in the study area, it is prominent that the chance of increasing or maintaining the carbon sequestration level is paramount.

5. Conclusions

Our results showed that forest area decreased during the period of 2000–2020 (-334.6 km^2) and was predicted to decline in 2040 (-362.8 km^2). This corresponds to the simultaneous decrease in carbon stocks by the forests, i.e., -7.337 Mt C and -7.959 Mt C, subsequently. An economic loss was estimated at USD -1369.382 million (2000–2020) and was predicted to further increase to USD -1485.490 million in 2020–2040. Therefore, to avoid carbon losses to the atmosphere in the future, the business-as-usual scenario must be changed, and existing plans for sequestration must be implemented accordingly. In conclusion, this study is important to understand the spatial distribution of land use types and the carbon stock of Viti Levu Island, as it can contribute to establishing baseline information that can be useful for policymakers in decision making. However, we applied general carbon pools assessed from previous reports, which may lead to biases. Therefore, future studies are encouraged to assess the carbon pools in the field and consider various types of forest.

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