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Land Use Change and Future Prediction in Banggai Islands Regency, Central Sulawesi, Indonesia

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ABSTRACT

Land use and land cover (LULC) changes can influence policies in a region due to economic and social conditions caused by population growth. The objective of this study is to analyze and map LULC changes in 2002, 2012, and 2022 using the Random Forest approach on Google Earth Engine, and to predict land use in 2042 using Markov-CA, thereby supporting the provision of accurate and sustainable policy data related to LULC in Banggai Islands Regency. This method can provide accurate information about the spatial distribution of rational LULC, balancing development demands with sustainable environmental protection. The study's results indicate that LULC has undergone significant changes from 2002 to 2022. There has been an increase in plantation land, open land, and settlements originating from forest and scrubland. Predictions of LULC changes in 2042 show an increase in plantations, settlements, and open land, while other land uses are declining. Effective land use policies require spatial planning that considers the potential and limitations of land, as well as the space needs for residential, agricultural, and forest areas. This approach will facilitate the application of land conservation principles in sustainable, balanced agricultural and non-agricultural development in Banggai Islands Regency.

Introduction

Land is a vital natural resource that humans have utilized for various activities and sustenance. Over the years, land use and land cover change (LULC) has become a significant concern for many nations. Land use refers to the alterations made by humans to the Earth's surface, while land cover describes the physical and environmental characteristics of that surface [1]. Land is defined by distinct properties and essential elements that characterize its use and management. LULC is a prevalent issue in Indonesia, including the Banggai Islands Regency. Key drivers of LULC include rapid population growth, migration, and the transformation of rural areas into urban centers [2]. Given the region's limited land resources, the government must implement effective regulations for land management. Over the past two decades, numerous studies have explored various aspects of LULC; however, information remains incomplete in certain areas. Recent work by Anandhi et al. [3] has provided both narrow and broad definitions of land resources, encompassing ecological components such as climate, water, soil, landscape, flora, and fauna, as well as the socioeconomic systems that interact with agriculture, forestry, and other land uses within a defined system boundary.

Identifying land use change is critical to addressing the rapid and uncontrolled change that is occurring, and is critical to understanding land development, loss, and degradation [2]. Assessing LULC changes is essential for the sustainable planning of each region [4], as unmanaged land use can lead to degradation and loss of

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land capability, as well as overlapping regulations in land use in each sector. According to Alam et al. [5], evaluating land use and cover changes from various perspectives, such as land use planning and sustainable development, is critical to meeting the population's diverse needs [6].

Recent research on LULC has gained significant attention among researchers in Sulawesi [5–7]. According to Statistics Indonesia 2022, the area of forest cover in Central Sulawesi is over six million hectares [8]. This data is the basis for the importance of the research in Banggai Islands Regency. The area's rapidly increasing population is driving the need for land expansion to meet growing demands [9,10]. Furthermore, Dibaba et al. [11] note that population growth is a primary factor influencing LULC changes. Additionally, exploring LULC changes aims to enhance understanding through integrated research priorities [12], focusing on the causes and effects of these phenomena in the present and future contexts [13]. Furthermore, LULC studies are essential for updating data accurately [12] and providing policymakers with a comprehensive understanding of effective and sustainable land resource management [13,14]. There is a growing acknowledgment that policies significantly influence land use and management practices, extending beyond the traditional frameworks of land use and environmental planning systems. According to Munthali et al. [15], Kullo et al. [16], LULC information is crucial for environmental planners and observers due to its significant impact on both local and global environments. A wide variety of incentives and disincentives, including fiscal and tax incentives, industry subsidies, and the design of infrastructure or transport programmes, significantly influence decision-making and interventions across our region. However, these measures often result in negative consequences, such as loss of agricultural land, environmental degradation, and an increase in costly services [17].

Research on LULC is crucial for urban planners [18], policymakers in natural resource management [16,18], and agricultural and environmental experts [19,20]. Krawchenko and Tomaney [18] assert that the framework promotes an evaluation of incentives, disincentives, and complementarities across various policies and practices, highlighting the necessity for greater alignment to achieve land management objectives. Remote sensing serves as an effective tool for swiftly detecting changes in land cover. In the Banggai Islands, researching LULC change is essential for formulating timely policies, making remote sensing a necessary component of this study. Remote sensing involves processing satellite images through open-source platforms that utilize big data, such as Google Earth Engine (GEE), which is commonly used for mapping and monitoring land cover, vegetation, and urban expansion [21]. The GEE platform supports various sensors, including Landsat and Sentinel, allowing for the storage and processing of large datasets to aid decision-making [22]. Geospatial remote sensing data available on GEE has been extensively applied in research related to regional socio-economics [23], land cover mapping [24], land change detection [25], urban studies [26], rice mapping [27], rice crop detection [28], and oil palm plantations [29]. Furthermore, GEE features a programming language that enables rapid and accurate analysis of land cover changes [30].

The platform is both efficient and computationally advantageous, providing various algorithms, including the Random Forest (RF) algorithm, which facilitates access and classification [31–33]. Developed by Breiman in 2001, the RF method is a non-parametric classification technique that employs multiple decision trees for effective decision-making [34,32]. Landsat imagery with a spatial resolution of 15–60 m and sentinel-2 with a spatial resolution of 10–60 m can be used in LULC classification [35,36] with a classification process using the Random Forest (RF) algorithm through the Google Earth Engine (GEE) mapping platform to monitor land use in the Banggai Islands Regency. The medium resolution of these images allows for adequate detail in area identification. Additionally, land use predictions in this study are conducted using Markov Chain and Cellular Automata (Markov-CA). Both Markov-CA models have been widely applied in spatial and geographic analyses, yielding accurate results in land use change assessments [37–39]. The Markov-CA model provides a more robust and comprehensive framework for predicting land use changes compared to single-method models. Its application in the Banggai Islands serves as a valuable tool for forecasting future land use dynamics. The Cellular Automata (CA) component utilizes neighbourhood interactions to model systems that evolve based on simple, predefined rules over time. Meanwhile, Markov chains, a fundamental aspect of probability theory, have increasingly been integrated into spatial sciences. This study employs the Markov-CA approach to project land use changes, aiming to offer a spatial perspective that can inform regional planning aligned with anticipated land use patterns in the Banggai Islands Regency.

The Banggai Islands are home to a variety of endemic species, including primates, reptiles, and birds. However, the biodiversity of the Banggai Islands is threatened by human activities such as illegal logging and unsustainable practices, including land use change from forest to agricultural land, which results in the loss of habitat for these endemic species. Current regulations governing the management of natural resources and biodiversity in the Banggai Islands may be ineffective, partly due to limited human and financial resources that hinder conservation efforts. In addition, the involvement of local communities in managing these resources is still suboptimal, potentially leading to conflicts over resource use. The case study conducted in the Banggai Islands can provide valuable lessons on how to overcome complex land management challenges so that natural resources can be utilized appropriately and effectively, monitoring changes in land use provides valuable recommendations for policymakers in formulating appropriate and effective strategies. Furthermore, the findings of this study can be used as a reference for land management and for future research on more effective integration of various land uses to protect biodiversity in the Banggai Islands.

Over the past three decades, the Banggai Islands Regency has undergone significant changes in LULC, primarily driven by population growth, agricultural expansion, and various development initiatives. However, systematic monitoring of these changes remains insufficient, and assessments are infrequently conducted. This study aims to evaluate and simulate the spatial and temporal dynamics of LULC changes in the Banggai Islands Regency. Specifically, it seeks to map and quantify LULC changes from 2002 to 2022 using Landsat 5, 7, and Sentinel-2 satellite imagery. Additionally, the research projects on land use conditions in 2042 provide insights into land use conditions and the relevance of policies aimed at promoting appropriate and sustainable land use in the region.

Materials and Methods

Research Location

The research was conducted in the Banggai Islands district of Central Sulawesi province, located geographically between 1°06‘30”–1°35’58” N and 122°37‘6.3”–123°40’1.9” E, in the northeastern part of Sulawesi Island, covering an area of 2,376.71 km². To the north, it borders Banggai Regency, while the Maluku Sea lies to the east (Banggai Islands Central Statistics Agency 2022). The study area comprises 12 districts, as illustrated in Figure 1.

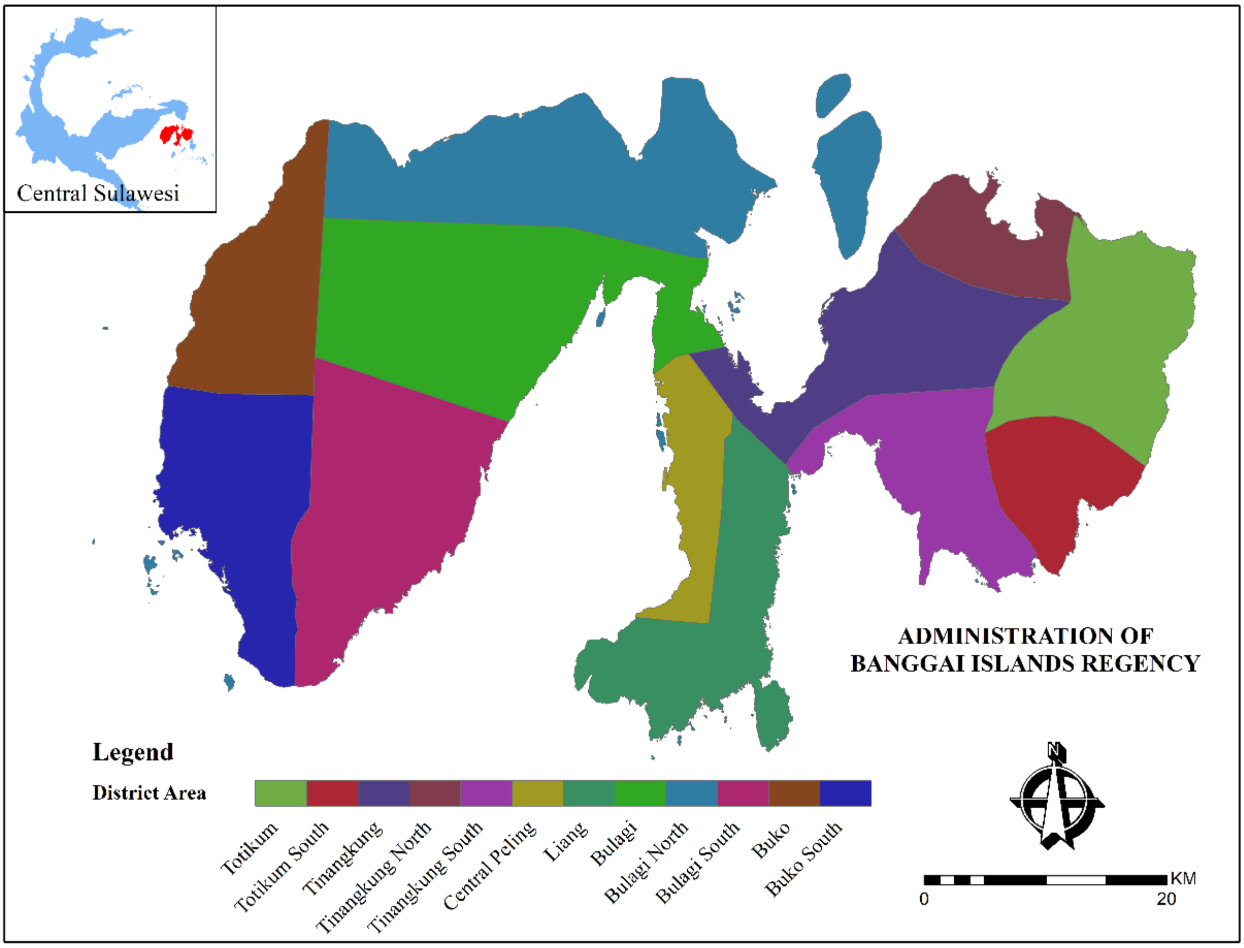

Figure 1. Research location.

Data Collection and Processing

The processing and analysis of remote sensing imagery begins with data pre-processing. According to Andries et al. [40], Wei et al. [41], land use and cover can be visually classified from images as needed. Agricultural patterns in the Banggai Islands Regency apply mixed agricultural patterns, such as agroforestry systems, so agricultural land use and plantations are classified into plantations. In this study, LULC types will be digitally classified, such as forests, plantations, Built-up, open land, mangroves, rice fields, shrubs, and water bodies, using the Random Forest (RF) algorithm (ntree=500) on the Google Earth Engine (GEE) [42]. The GEE platform offers corrected Landsat image data, streamlining the pre-processing phase. The RF algorithm, an ensemble model based on decision trees, was selected for its effectiveness in classifying remote sensing data [42,43]. Landsat and Sentinel image processing is done directly in GEE, with the output image set at a spatial resolution of 30 metres [44]. It employs a bootstrap method on 70% (1,600 sampling total) of the training dataset to create a new dataset, followed by a majority decision process that determines the mode from each decision tree's output. The dataset was obtained using LULC class polygons and distributed across all geographical characteristics of the study location, covering the entire administrative area.

This case study utilizes Landsat-5 Thematic Mapper (TM) and Landsat-7 Enhanced Thematic Mapper Plus (ETM+) imagery from 2002 and 2012, along with Sentinel-2 MultiSpectral Instrument (MSI) imagery from 2022. The approach refers to Simonetti et al. [45], combining various bands to assess land use in the study area. The bands from all satellites include Green Band, Blue, Red, Near Infrared (NIR), and Short-wave infrared (SWIR). In addition, there are derivative indices used, namely NDVI, NDWI, NDMI, EVI, SAVI, ARVI, IBI, SLAVI, NDBI, GNDVI, MNDWI, MMRI, DVI, RVI, PSSRA, and LWSI, to improve processing performance. Validation involves assessing 30% of all samples for accuracy using the RF algorithm result data, with classification results compared against field checks or available reference data [46,47]. Field checks were conducted to gather information on land use, and the validation results were used to evaluate the accuracy of the 2022 image interpretation using the kappa value.

Accuracy testing is conducted to evaluate classification errors and determine the percentage of accuracy. This is achieved by creating a contingency matrix, also known as an error or confusion matrix, calculated using the error matrix function in the GEE platform (Table 1). From this matrix, various accuracy metrics can be derived, including overall accuracy, user accuracy, producer accuracy, and kappa accuracy. According to Sivanpillai et al. [48], Hidayah et al. [49], the minimum accuracy value of more than 80% is required for land use interpretation to be classified as excellent. Overall accuracy is calculated using the formula where X represents the number of correctly interpreted land cover points aligned with ground truth results, and N is the total number of ground truth points [50]. Kappa value equal to 1 indicates the classification results get perfect agreement, while a kappa value equal to 0 indicates the classification results cannot be approved, Furthermore, Foody [51] defines kappa accuracy with equations (1 to 4). The kappa coefficient (κ) assesses how classification results compare to chance, calculated from the error matrix by combining diagonal and off-diagonal elements [48]. The range of kappa values and their classifications is presented in Table 2.

Table 1. Error matrix.

Classification result of land use	Reference land use					
	Pi+	Pi+	…	…	Pi+	Total
Pi+	Xii					X+i
Pi+		Xii				X+i
…			Xii			X+i
…				Xii		X+i
Pi+					Xii	X+i
Total	Xi+	Xi+	Xi+	Xi+	Xi+	N

Where, P+i: The i-th land use type of the classification result; Pi+: The i-th land use type from field check; X+i: Number of classification result points on the i-th land use type; Xi+: Number of points from field check on the i-th land use type; Xii: Number of land use types that correspond to the classification result and the field check results; i: Row or column; r: Number of land use types; N: Number of land use points validated; k: Kappa value. The overall accuracy between the remote sensing classification data and the reference data can be calculated using the following Equations 1–4.

User accuracy (UA) = $\frac{X_{ij}}{X_{i+}} x\ 100\%$ (1)

Producer accuracy (PA) = $\frac{X_{ij}}{X_{i+}} x\ 100\%$ (2)

Overall accuracy (OA) = $\frac{1}{N}\sum_{i=1}^{r} X_{ii}\ x\ 100\%$ (3)

Kappa accuracy (K) = $\frac{N\sum_{i=1}^{r} xii - \sum_{n=1}^{r}(X_{i+} + X_{+i})}{N^2 - \sum_{n=1}^{r}(X_{i+} + X_{+i})}$ (4)

Where X_{ii} is the diagonal value of the confusion (error) matrix, and X_{ij} is used for the land use class. The matrix size r = 2, X_{i+} is the number of pixels in the row *i* obtained from remote sensing analysis, X_{+j} is the number of columns of *j* obtained from referenced land use data, and *N* is the number of pixels in the data.

Table 2. Categorization based on a range of kappa values.

Kappa range	Interpretation
<0.00	Very poor
0.00–0.20	Poor
0.21–0.40	Fair
0.40–0.60	Moderate
0.61–0.80	Good
>0.81	Very good

Source: [52,48].

LULC change prediction can be analyzed through multitemporal spatial changes [53,54]. This approach is recommended for its ability to model land use based on temporal trends. Cellular Automata (CA) is a crucial geospatial element that highlights the dynamics of change events and can simulate the characteristics of complex systems both spatially and temporally. In this study, spatial data from the initial year (T0), specifically 2022, is utilized alongside 20 years of change data from 2002 to 2022, employing Markov Chain and Cellular Automata methods. Research by Bondansari et al. [55], Sejati et al. [56], Bindajam et al. [57] indicates that the Markov Chain and Cellular Automata (Markov-CA) method yields optimal predictions based on kappa values, particularly when the predicted year distance matches that of previous periods [58–60]. This method helps identify potential land use changes over specific time frames [61,62]. The integration of these two maps serves as input data for training the Markov-CA model, facilitating an evaluation of the 2022 land use simulation. The Markov-CA model can generate predictions for various LULC and development scenarios, as well as illustrating interactions between regions.

The modelling process begins with land use data from 2012 and a transition area matrix covering 2002–2012 to predict land use for 2022, which is then validated against actual land use data from that year. The Markov-CA modelling and prediction for LULC is facilitated by the MOLUSCE (Modules for Land Use Change Simulations) plugin within the software QGIS 2.16 series. The prediction process involves several steps: first, input raster data from land use maps for 2002, 2012, and 2022, along with factors influencing LULC change, is prepared. Next, a correlation assessment is performed using the MOLUSCE plugin to evaluate relationships between rasters, where a value of 0 indicates no relationship, while values of 1 and -1 indicate strong relationships. This information is then automatically input into the transition probability matrix (TPM), which reflects the proportion of pixels expected to change from one land use type to another. The multilayer perceptron method is applied to optimize iterations and minimize the loss function, enhancing accuracy. Subsequently, Cellular Automata processes the land cover images to generate a probability transition matrix, transition area matrix, and iteration results for the desired land use prediction. Accuracy validation can also be conducted through ground checks, which are recorded in an error matrix. The error matrix serves as a tool for measuring the accuracy of the LULC change map. According to Jensen and Lulla [63], Jensen [64], Artikanur et al. [65], established guidelines, a validation value of 85% allows for predictions of LULC changes in 2042, using 2022 as the base input. Evaluation of the 2042 prediction model using the accuracy listed in the MOLUSCE plugin data processing. The overall process of transforming land use change data into predictive models is illustrated in Figure 2.

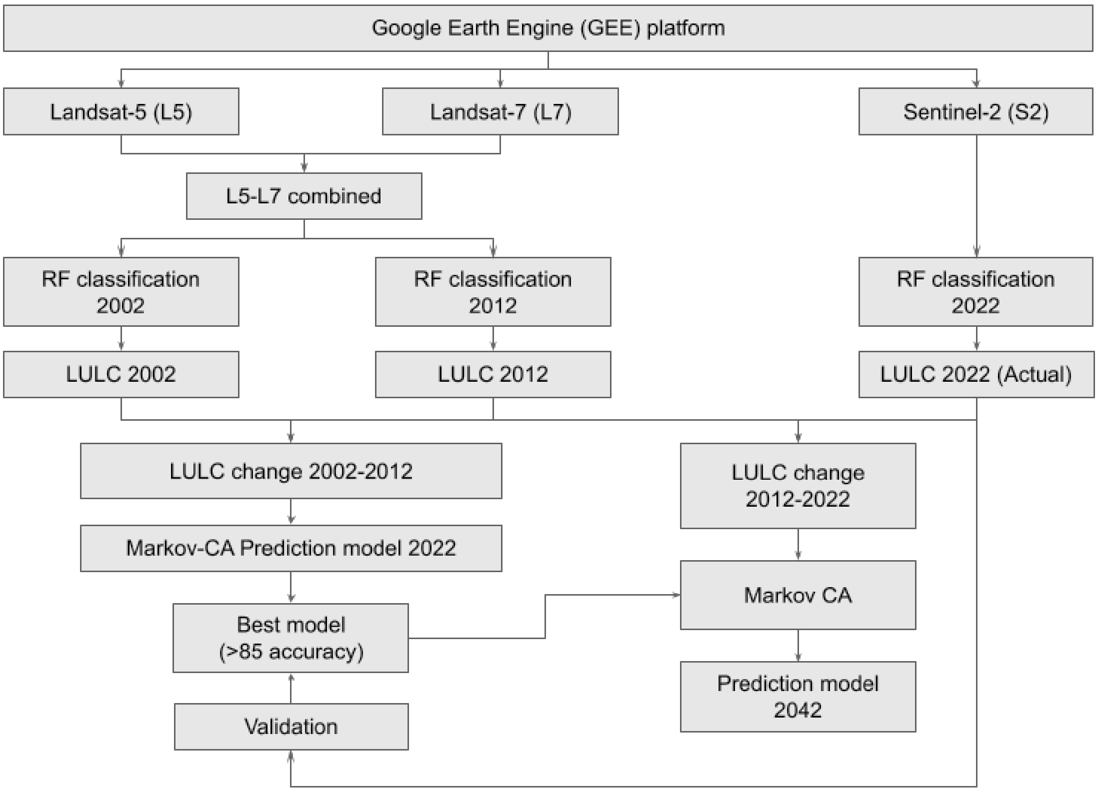

Figure 2. Data processing of land use and land cover change in 2002, 2012, 2022, and land use prediction in 2024.

Results and Discussion

Results

Land Use and Land Cover (LULC) Identification in 2002, 2012, and 2022

LULC identification was conducted through image classification from Google Earth Engine (GEE) for 2002 and 2012, utilizing a combination of Landsat 5 and 7 imagery and Sentinel-2 imagery for 2022. The classification included eight land use types: forests, gardens, settlements, open land, shrubs, rice fields, mangroves, and water bodies. The overall accuracy of the RF classification for 2002, 2012, and 2022 was found to be 84%, 90%, and 89%, respectively. According to Sivanpillai et al. [48], Hidayah et al. [49], these accuracy values fall within the excellent category, exceeding the 80% threshold. This indicates that the land use data for the Banggai Islands Regency meets the validation requirements, making the resulting land use map suitable for this study. The area proportions and LULC maps for the Banggai Islands Regency for 2002, 2012, and 2022 are presented in Table 3 and Figures 3 and 4, while the patterns of land use/cover change from 2002 to 2022 are detailed in Table 4.

Table 3. Land use and land cover area in 2002, 2012, and 2022, in Banggai Islands Regency.

No	Land use and land cover	Land area					
		2002		2012		2022	
		ha	%	ha	%	ha	%
1	Forest	132,786.9	55.9	94,780.2	39.9	97,148.4	40.9
2	Plantation	70,809.5	29.8	130,911.5	55.1	104,194.0	43.8
3	Built-up	529.7	0.2	1,014.2	0.4	1,795.3	0.8
4	Open land	3,908.3	1.6	2,121.3	0.9	10,451.4	4.4
5	Rice fields	142.7	0.1	313.2	0.1	315.2	0.1
6	Shrubs	26,230.1	11.0	6,158.2	2.6	19,430.9	8.2
7	Mangroves	1,588.9	0.7	1,446.4	0.6	1,636.8	0.7
8	Waterbody	1,674.9	0.7	926.0	0.4	2,671.1	1.1
Total		237,671	100	237,671	100	237,671	100

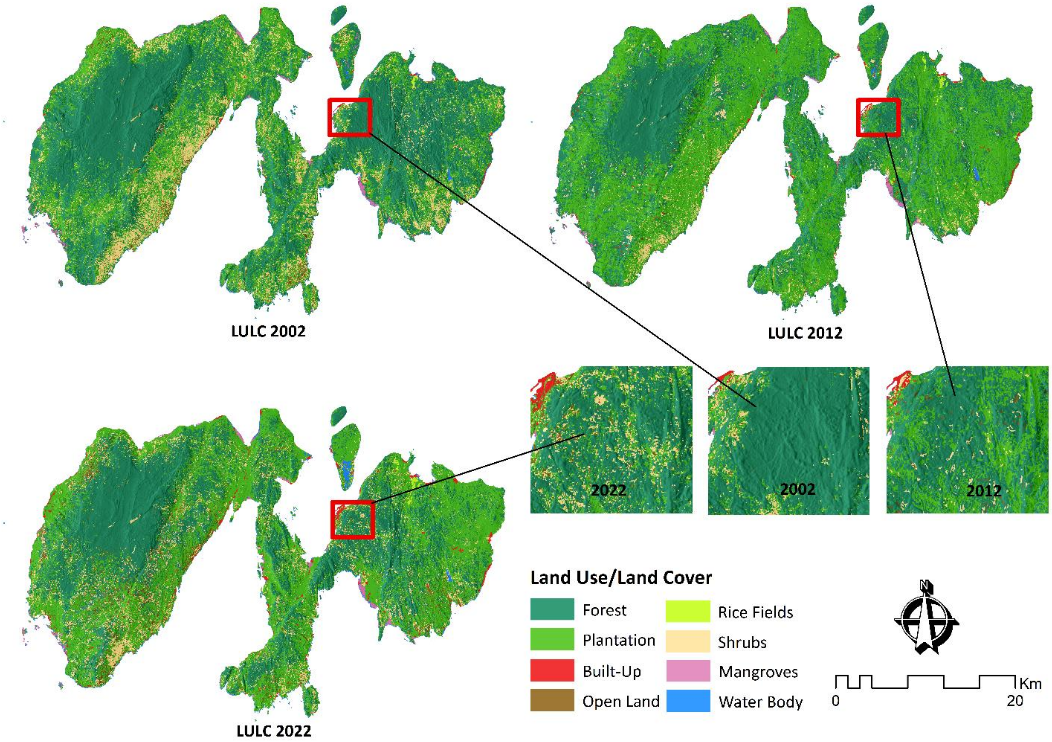

Figure 3. LULC map of 2002, 2012, and 2022 in the Banggai Islands Regency.

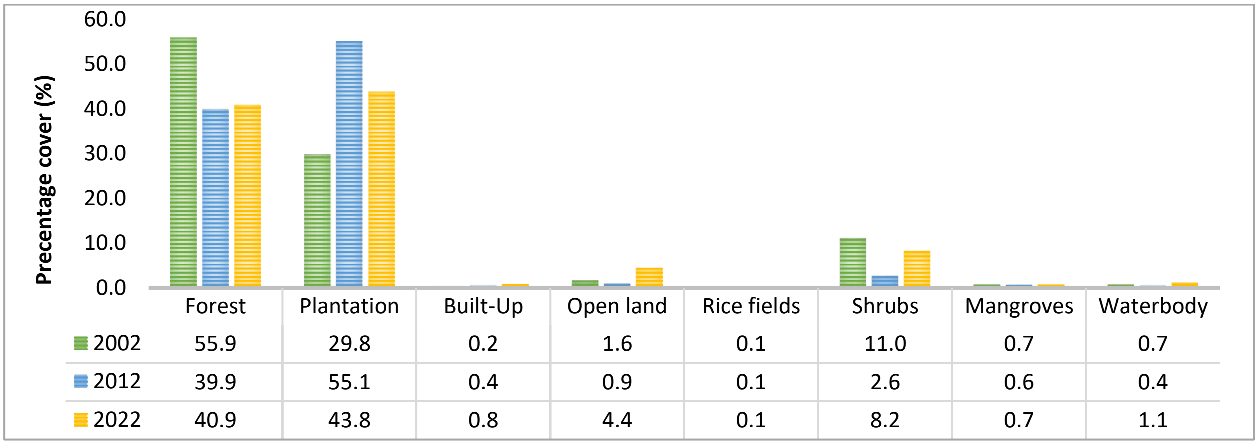

Figure 4. Distribution of LULC patterns 2002–2022, the Banggai Islands Regency.

Table 4. LULC from 2002 to 2022 period.

No	Land use	Extent					
		2002–2012		2012–2022		2002–2022	
		ha	%	ha	%	ha	%
1	Forest	-38,006.7	-16.0	2,368.2	1.0	-35,638.5	-15.0
2	Plantation	60,102.0	25.3	-26,717.5	-11.2	33,384.5	14.0
3	Built-up	484.6	0.2	781.1	0.3	1,265.6	0.5
4	Open land	-1,787.0	-0.8	8,330.1	3.5	6,543.1	2.8
5	Rice fields	170.5	0.1	30.0	0.0	200.5	0.1
6	Shrubs	-20,071.9	-8.4	13,272.7	5.6	-6,799.2	-2.9
7	Mangroves	-142.5	-0.1	190.4	0.1	47.9	0.0
8	Waterbody	-749.0	-0.3	1,745.1	0.7	996.1	0.4

LULC in the Banggai Islands Regency was assessed based on classifications from 2002, 2012, and 2022, highlighting the extent of changes in LULC. Table 4 illustrates these changes, revealing that the decline in land use was inconsistent. This is because farmers clear agricultural land in a mobile manner, and after harvesting, they will leave the land for eight years before reopening it. Naturally, the abandoned land will become overgrown with wild plants and will be detected as forest, as well as other land uses. For instance, the forest area decreased by 16% from 2002 to 2012, followed by a slight increase of 1% from 2012 to 2022. Similarly, the plantation area increased by 25.3% during 2002–2012 but decreased by 11.2% in the subsequent period. The reduction in plantation area can be attributed to population growth, which frequently leads to the conversion of plantation land to non-plantation uses. Furthermore, local government policies have not sufficiently supported the plantation sector in Banggai Islands Regency. Juniyanti et al. [66] notes that a significant factor contributing to the decline in plantation land is the government's lack of emphasis on plantations and agriculture, as policies prioritize other sectors. This shift can diminish farmers' motivation to sustain their plantations or agricultural land.

The transitions in open land and shrubs also exhibited variability, attributed to shifting agricultural practices, with changes of 0.8% and 8.4% for open land and shrubs in 2002–2012, and 3.5% and 5.6% in 2012–2022, respectively. In contrast, residential land steadily increased over the 20 years, growing from 529.7 ha (0.2%) in 2002 to 1,795.3 ha (0.8%) by 2022. Paddy fields experienced significant growth as well, with an increase of 170.5 ha from 2002 to 2012 and an additional 30 ha from 2012 to 2022. Mangrove areas, however, displayed unstable changes, decreasing by 142.5 ha between 2002 and 2012 due to unsustainable harvesting for firewood, but rebounding with an increase of 190.4 ha from 2012 to 2022. Water bodies in the study area experienced a decrease of 0.3% from 2002 to 2012, followed by an increase of 0.7% between 2012 and 2022. This fluctuation is attributed to seasonal droughts lasting from ten months to a year, during which the lake's water levels drop significantly. However, the lake replenishes during the rainy season, leading to an increase in water levels.

Land Use and Land Cover (LULC) Change in Banggai Islands Regency from 2002 to 2022

This study analyzed LULC changes over two years, using 2002 as the baseline and 2022 as the endpoint. The initial analysis of land use changes from 2002 to 2022 produced a matrix detailing the increases and decreases in the area of each land use type, illustrating the transitions between different land uses. The land use change matrix is presented in Table 5.

Table 5. LULC transition matrix 2002 to 2022.

LULC	2022							
2002	1	2	3	4	5	6	7	8
1	75,174.8 (31.6%)	47,411.81 (19.9%)	167.35 (0.07%)	2,586.79 (1.09%)	84.06 (0.04%)	6,193.16 (2.6%)	403.86 (0.17%)	850.78 (0.35%)
2	17,817.8 (7.49%)	40,008.36 (16.8%)	469.96 (0.2%)	4,274.16 (1.8%)	119.32 (0.05%)	7,856.97 (3.3%)	45.58 (0.02%)	261.22 (0.1%)
3			519.66 (0.22%)					
4	443.3 (0.19%)	1,620.93 (0.68%)	330.28 (0.14%)	644.56 (0.27%)	8.42 (0.00%)	694.36 (0.29%)	13.16 (0.01%)	155.53 (0.07%)
5	0.36 (0.00%)	12.31 (0.01%)	0.69 (0.00%)	3.61 (0.00%)	84.3 (0.04%)	28.64 (0.01%)	0.65 (0.00%)	1.46 (0.00%)
6	3,677.81 (1.55%)	14,636.22 (6.16%)	330.6 (0.14%)	2,891.11 (1.22%)	19.1 (0.01%)	4,623.9 (1.95%)	1.31 (0.00%)	60.21 (0.03%)
7	11.45 (0.00%)	289.15 (0.12%)	7.72 (0.00%)	1.54 (0.00%)	0.09 (0.00%)	5.43 (0.00%)	1,095.78 (0.46%)	177.79 (0.07%)
8	17.21 (0.01%)	214.12 (0.09%)	173.45 (0.07%)	5.71 (0.00%)		28.42 (0.01%)	76.5 (0.03%)	1,159.83 (0.49%)

Notes: LULC = land use and land cover; 1 = forest; 2 = plantation; 3 = Built-up; 4 = open land; 5 = paddy field; 6 = shrubs; 7 = mangrove; 8 = water body.

Overall, the Banggai Islands Regency experienced a decline in forest and shrub areas from 2002 to 2022, with reductions of 15% and 2.9%, respectively. This loss of forest land was converted into various land uses, including water bodies, open land, mangroves, Built-up areas, plantations, rice fields, and shrubs. Forests that have been detected to have changed into built-up land are located in the capital development expansion area, while open land and shrubs are found in shifting plantations. In addition, the opening of new rice fields has been linked to the conversion of forests into rice fields. Meanwhile, forest conversion to water bodies is observed in coastal lake areas, where land transitions from forested to waterlogged regions—a phenomenon more prevalent in island environments. In the study area, this conversion from forest to aquatic zones, such as lakes, occurs naturally.

In line with the results of research by Juniyanti et al. [66], changes in mixed gardens, open land, and forests can occur, and experience changes to water bodies. These areas will be detected on the coastal part of the island around the mangrove area. As detailed in Table 4, forest land was transformed into plantations covering 47,411.8 ha, Built-up totaling 167.4 ha, mangroves at 403.9 ha, and rice fields at 84.1 ha. Additionally, 6,193.2 ha of forest were converted to shrubs, and 2,586.8 ha to open land. Consequently, LULC changes in the Banggai Islands Regency varied, with areas classified as open land and shrubs in 2002 reverting to forest by 2012, while forested areas transitioned to open land by 2022. An example of land use change in the study area can be seen in Figure 5.

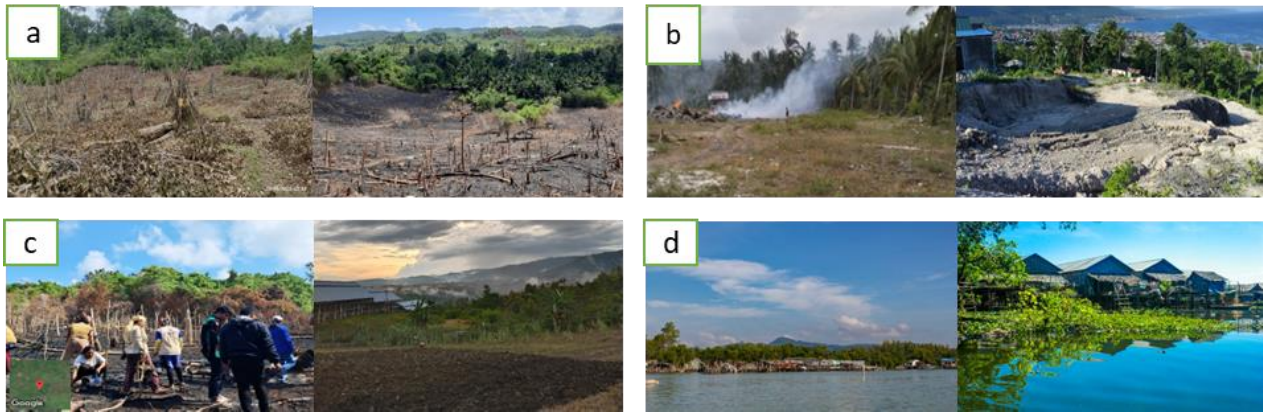

Figure 5. (a) LULC change from forest to open land; (b) LULC change from forest and plantation to developed land; (c) LULC change from forest and open land to plantation; and (d) LULC change from mangrove and water body to developed land.

Predicted LULC in Banggai Islands Regency in 2042

The modeling process will initially assess the model's capability to predict LULC for the target year. The prediction for land use in 2022 was derived from the trends observed in 2002 and 2012 using the CA-Markov simulation model. The accuracy of this prediction for the Banggai Islands Regency in 2022 was determined to be 93%, allowing for further predictions of land use in 2042. The proportions of land use and cover areas are presented in Figure 6 and Table 6. In contrast, the distribution map illustrating predicted land use changes for 2042 in the Banggai Islands Regency is shown in Figure 7.

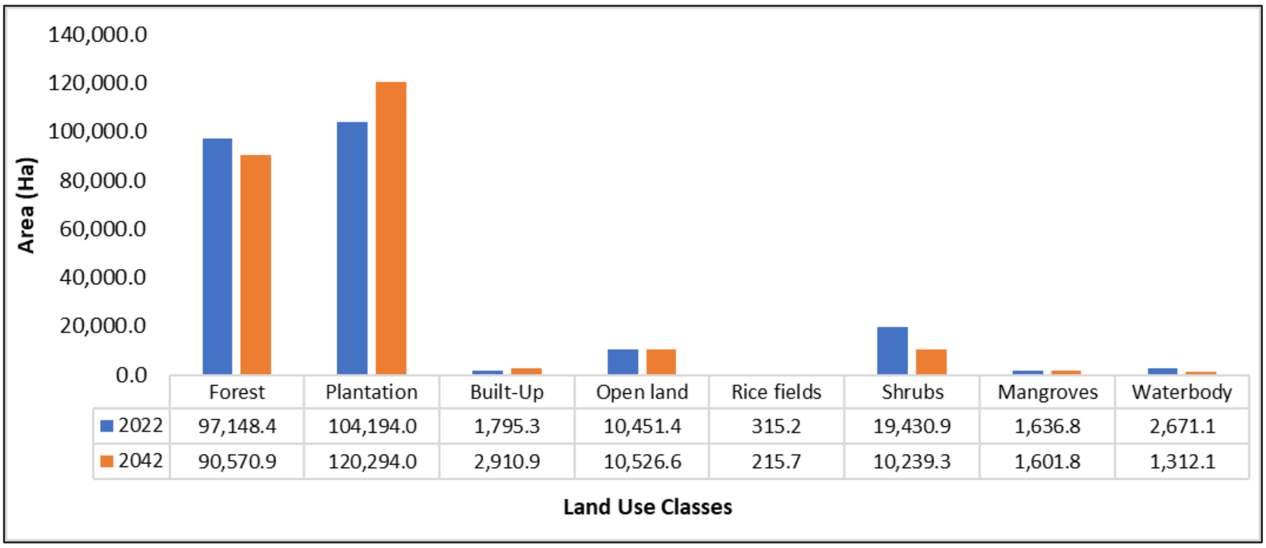

Figure 6. Projected pattern of LULC in 2042.

Table 6. Projected land use and land cover change in Banggai Island Regency in 2042.

No	Land use and land cover	Land area					
		2022		2042		Land change	
		ha	%	ha	%	ha	%
1	Forest	97,148.4	40.9	90,570.9	38.1	-6,577.5	-2.77
2	Plantation	104,194.0	43.8	120,294.0	50.6	16,100.0	6.77
3	Built-up	1,795.3	0.8	2,910.9	1.2	1,115.6	0.47
4	Open land	10,451.4	4.4	10,526.6	4.4	75.2	0.03
5	Rice fields	315.2	0.1	215.7	0.1	-99.5	-0.05
6	Shrubs	19,430.9	8.2	10,239.3	4.3	-9,191.6	-3.87
7	Mangroves	1,636.8	0.7	1,601.8	0.7	-35.0	-0.01
8	Waterbody	2,671.1	1.1	1,312.1	0.6	-1,359.0	-0.57
Total		237,671	100	237,671	100	237,671	100

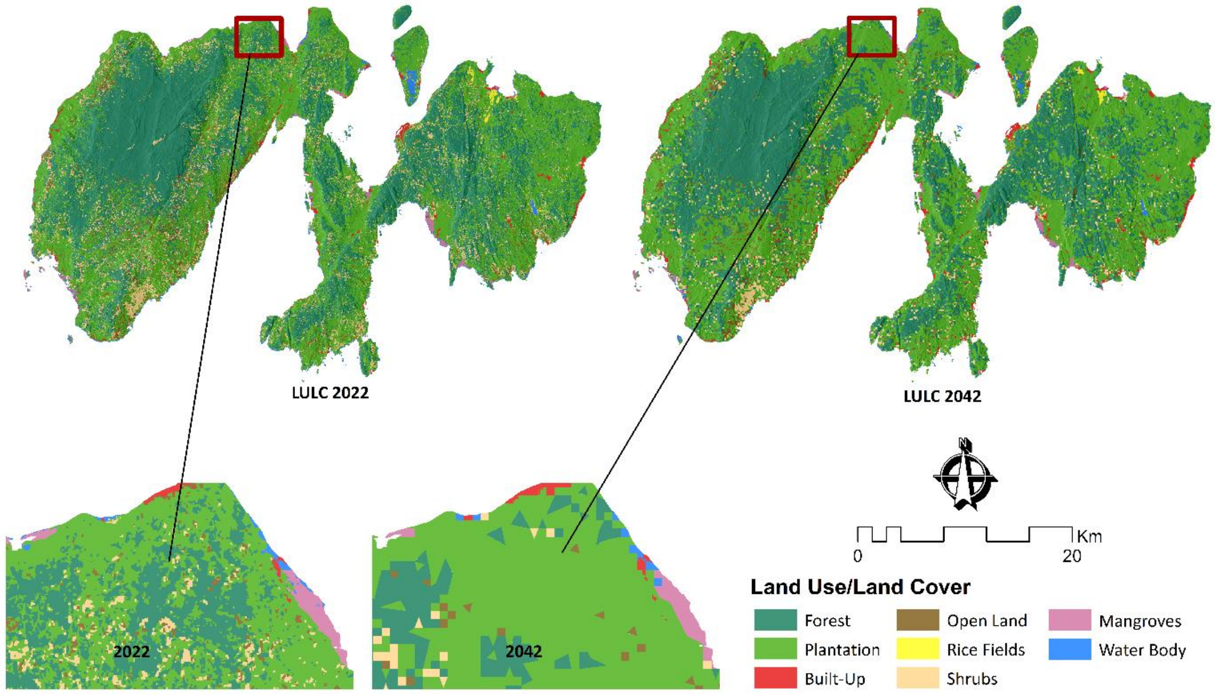

Figure 7. Predicted LULC in Banggai Islands Regency in 2042.

According to LULC predictions for 2042, the area of forest and shrubs is estimated to decrease by 6,577.5 ha and 9,191.6 ha, respectively. Conversely, the plantation area is projected to increase by 16,100 ha due to the conversion of forest and shrub lands. Additionally, residential land in the Banggai Islands Regency is anticipated to grow by 1,115.6 ha, driven by population growth, with the population growth rate in Banggai Islands Regency reaching 0.96% per year. However, paddy fields are expected to decrease by 127.6 ha, as local farmers face challenges in rice cultivation due to high costs and low yields. Furthermore, water body areas will decline by 1,359 ha, with much of this land transitioning to open land and shrubs. This shift can be attributed to seasonal variations in the region; during the rainy season, lake areas may expand, causing adjacent open land and shrubs to be classified as water bodies.

Discussion

The identification of LULC changes in the Banggai Islands Regency over the past 20 years (2002–2022) reveals a clear decline in forest and shrub areas, while other land uses have increased. A similar study on land use change conducted by Yulianto et al. [7] in Tondano, North Sulawesi, found a decrease in forest and shrubland area over 20 years. Meanwhile, research identifying land use changes conducted over 15 years found that forest area continued to increase. This increase in forest area was due to conversion to plantations and rice fields [9]. The most significant decline in forest area in the Banggai Islands occurred between 2002 and 2012, primarily attributed to human activities driven by population growth, which increased land demand for purposes such as agriculture and plantations (notably coconut and clove cultivation) and illegal logging. This decline was exacerbated by inadequate local government oversight of forest management and land use practices. However, from 2012 to 2022, there was a slight increase in forest area, albeit only by 1%. This uptick was facilitated by more active government oversight and improved planning, though it still lagged other regions. The decline in forest cover during the earlier period was largely a result of extensive development initiatives by both central and local governments, as the region had established itself as a new district capital. Consequently, the central government developed office facilities in the district's urban center, leading to the conversion of land into built-up areas within Banggai Islands Regency. Additionally, the rapid conversion of forests to plantations is driven by farmers' needs for agricultural land to support their families [67]. The substantial decrease in forest areas is largely due to land being repurposed for agriculture, with plantations accounting for 47,411.81 ha. This is because the indigenous people of Banggai do not hesitate to convert forests if their income increases, resulting in a very significant decline of 15% of the total forest area. This study is similar to research conducted by Juniyanti et al. [66] in analyzing LULC changes on Bengkalis Island, Riau, where the sharp decline in forest cover converted to plantations reached 10% of the total. According to Meyer and Turner [68], Halim et al. [69], Dibaba et al. [11], population growth is a critical factor influencing this conversion, as it increases the demand for housing and agricultural activities. While the expansion of plantations may economically benefit farmers by potentially increasing their income, the loss of forest cover poses significant environmental risks, including damage to ecosystems and biodiversity [70] the conversion of forested areas into other land uses can lead to detrimental impacts on the environment and the land's ecological potential [71].

Plantations in the Banggai Islands Regency saw significant growth from 2002 to 2022, largely due to the use of agricultural land for mixed plantations that include food and horticultural crops such as pepper, tomatoes, taro, and Banggai yam, which are cultivated alongside clove, coconut, and nutmeg trees (Agriculture Office of Banggai Islands Regency 2022). This expansion is driven by the annual increase in the local population, necessitating that farmers enlarge their agricultural and plantation areas to meet their needs. The community employs a rotational agricultural system, resulting in a relatively high presence of open land and shrubs in the region. According to Mulyani and Agus [72], Jin et al. [73], this open land and shrub area holds considerable economic potential if developed for agricultural purposes, which could enhance local incomes. According to McNicol et al. [74], the shifting cultivation practices are vital for the regeneration of native plants, contributing to the abundance of open land and shrubs. In this context, based on information from Banggai yam farmers and agricultural extension workers, that Banggai yam farmers in Banggai Kepulauan Regency usually return to using previously cultivated land after about ten land rotation cycles, reflecting the tradition of shifting cultivation that persists today.

In the Banggai Islands, farmers practicing shifting agriculture believe that land left fallow for several years can regain fertility without the need for fertilizers upon reuse. Consistent rotation and resting of land can promote ecosystem maturity and enhance land stability over time [75]. This agricultural pattern is crucial as it facilitates soil recovery [74]. Similarly, rice fields in the study area are mostly rainfed, which are usually suited to lowland conditions. However, their management is often ineffective due to individual land ownership, leading to cultivation at specific times and leaving fields idle for extended periods without alternative crops [76]. Utilizing rain-fed paddy fields for replacement crops, such as Banggai yam, could benefit farmers; otherwise, neglect may lead to the conversion of these fields. Additionally, mangrove areas in the region have significantly increased from 2002 to 2022, largely due to local government initiatives since 2016 aimed at monitoring and replanting mangroves to protect the ecosystem. According to Marois and Mitsch [77], mangroves are very important because they can withstand storm surges and wind, thus protecting beaches, housing, and other infrastructure, such as those in the Banggai Islands Regency.

LULC in Banggai Islands Regency in 2042 is predicted to decrease in forest land use by 2.77%. This underscores the need for effective regulation and monitoring of forest areas to prevent disturbances, crimes, and threats [78]. Forests are crucial for oxygen production and play a vital role in maintaining water systems, preventing floods, controlling erosion, and sequestering carbon. Additionally, locally managed forests provide significant economic and social benefits to communities [79]. Given the critical importance of forests for the residents of Banggai Islands, enhancing oversight of these areas is essential for ensuring their integrity and sustainability, particularly regarding ecosystem services and biodiversity [80]. Considering the current degradation of forest areas, such as illegal logging and land conversion, one viable alternative is to designate these lands for agroforestry, which can create jobs, optimize land use, and increase farmers' income in the Banggai Islands. This approach is supported by the Regulation of the Minister of Environment and Forestry of the Republic of Indonesia Number 4 of 2023 concerning the management of social forestry in forest areas with special management, through social forestry with special management, including areas with potential for agrosilvopastoral activities. Although this regulation does not specifically promote agrosilvopastoralism, it regulates social forestry more broadly. Furthermore, changes in plantation land use are projected to increase by 120,294 hectares (6.77%) by 2042.

Based on the Spatial Plan for the Banggai Islands Regency, agricultural areas generally cover 136,900.02 ha of the total land area. This growth is driven by economic and social factors, including limited land resources, population growth, and economic development [81]. In the Banggai Islands Regency, the rising population exacerbates land scarcity, while economic growth encourages plantation activities at a pace that often exceeds land availability. The heightened demand for plantation land, fueled by socio-economic pressures, has led to rapid expansion in this sector [67]. Therefore, the implementation of sustainable agricultural systems, such as agroforestry (integration of trees and agriculture), organic farming, and LEISA (Low External Input Sustainable Agriculture), can support sustainable land use. Plantation expansion can be carried out in tandem with biodiversity conservation through the implementation of local agroforestry practices. Agroforestry is a system that integrates plantation crops with trees and other natural vegetation, thereby helping to reduce deforestation, increase community resilience, and preserve biodiversity. This approach utilises traditional practices that have long been applied by local farmers in the Banggai Islands, such as planting various species of plants in the same field.

Additionally, the increase in settlements in the Banggai Islands is expected to reach 0.47% by 2042. Although this growth is relatively slow compared to other regions, proactive measures are necessary to manage it effectively. Converting land to settlements can negatively impact soil properties, particularly in terms of water absorption. According to Kurowska et al. [82], changes from green spaces to built-up environments can disrupt runoff and water infiltration, resulting in the loss of plantation, forest, and agricultural lands. To mitigate land conversion, particularly of underutilized rice fields, farmers could cultivate more profitable crops such as horticultural products, taro, and Banggai yam. Rotating crops on the same land can optimise its use, reduce costs, and increase revenue. Furthermore, several previous studies, such as [83–85], have stated that the application of progressive taxes on land use can encourage the maximum utilization of existing land without the need to develop new land, thereby minimizing environmental damage. Reducing settlement rates can also be achieved through land-saving principles, such as promoting the construction of multi-story buildings. However, these policies require revitalization of land conversion regulations to support sustainable development. This can be accomplished by reformulating policy directions, objectives, and instruments, ensuring alignment between land use and spatial patterns as established by regional regulations in the Banggai Islands Regency.

Conclusions

The results of this study achieved a kappa value of 89% for LULC in 2022, with model validation yielding a kappa of 93%, indicating its suitability for land change predictions through 2042. Over the 20 years from 2002 to 2022, the Banggai Islands Regency experienced a 15% decrease in forest area, primarily due to human activities such as agricultural expansion and illegal logging, particularly between 2002 and 2012, when 47,411.81 hectares were converted to plantations. Projections for 2042 indicate further declines in forest, shrubs, rice fields, mangrove, and water body areas by 7.27%, while plantation land is expected to increase by 6.77% due to socio-economic factors. Built-up growth is anticipated at 0.47%, necessitating proactive management to mitigate negative impacts on soil and water absorption. Strategies to optimize land use include planting profitable crops on land that has not been optimally utilized. The involvement of stakeholders in implementing agroforestry systems can lead to a sustainable land management system, providing economic, social, and environmental benefits to the community. Further research on the alignment between LULC and the Regional Spatial Plan is essential to evaluate the effectiveness of the planning efforts of the Banggai Islands Regency.

Author Contributions

HAK: Conceptualization, Software, Formal Analysis, Resources, Initial Drafting, Visualization; **S**: Conceptualization, Methodology, Validation, Investigation, Resources, Data Curation, Writing - Review & Editing, Supervision; **FI**: Conceptualization, Validation, Investigation, Writing - Review & Editing, Supervision; **W:** Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing - Review & Editing, Supervision.

Conflicts of Interest

There are no conflicts to declare.

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