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Dynamic trajectories of land use and land cover changes in Lombok Island, West Nusa Tenggara, Indonesia

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Abstract: This study investigates the dynamic trajectories of land use and land cover (LULC) changes in Lombok Island, West Nusa Tenggara, Indonesia, from 2013 to 2022. Utilizing Landsat satellite imagery and a combination of land cover classes from the Indonesian Ministry of Environment and Forestry (MoEF) with the machine learning-based Random Forest algorithm, we aimed to improve classification accuracy and model land cover transitions over time. Intensity analysis was used to measure the impact of population-related land use changes, while trajectory analysis quantified the directional shifts in land cover was employed to quantify and characterize these changes. The analysis highlights substantial transitions from primary and secondary forests to agricultural lands and urban areas, driven by urbanization, population growth, and infrastructure development. Specifically, the period saw a significant forest loss of 28,095 hectares, accounting for 24% of the total forest area, alongside a modest forest gain of 2,453 hectares, indicating ongoing environmental pressures. Despite conservation efforts, rapid economic growth continues to threaten Lombok's forest ecosystems. These findings underscore the urgent need for sustainable land management policies to balance development and ecological preservation while mitigating future forest losses.
Keywords: Land use and land cover, Lombok Island, Intensity analysis, Trajectory analysis

Endonezya'nın Batı Nusa Tenggara Bölgesi'nde bulunan Lombok Adası'ndaki arazi kullanımı ve arazi örtüsü değişimlerinin dinamik izleri

Öz: Bu çalışma, 2013-2022 yılları arasında Endonezya'nın Batı Nusa Tenggara Bölgesinde bulunan Lombok Adası'ndaki arazi kullanımı ve arazi örtüsü (AK/AÖ) değişimlerinin dinamik yörüngelerini incelemektedir. Çalışmada, Landsat uydu görüntüleri ve Endonezya Çevre ve Orman Bakanlığı'nın (MoEF) arazi örtüsü sınıfları, makine öğrenimi tabanlı Random Forest algoritması ile birleştirilerek sınıflandırma doğruluğunu artırmayı ve zaman içinde arazi örtüsü geçişlerini modellemeyi amaçladık. Nüfusla ilişkili arazi kullanımı değişimlerinin etkilerini ölçmek için yoğunluk analizi, arazi örtüsü değişimlerinin yönelimini belirlemek için ise yörünge analizi kullanılmıştır. Analiz, kentleşme, nüfus artışı ve altyapı gelişiminin etkisiyle birincil ve ikincil ormanlardan tarım arazilerine ve kentsel alanlara önemli geçişler olduğunu vurgulamaktadır. Özellikle, dönemde toplam orman alanının %24'üne denk gelen 28.095 hektarlık orman kaybı ve 2.453 hektarlık orman kazancı gözlemlenmiştir. Bu durum, çevresel baskıların hala devam ettiğini göstermektedir. Koruma çabalarına rağmen, hızlı ekonomik büyüme Lombok'un orman ekosistemleri üzerinde baskı oluşturmaya devam etmektedir. Bulgular, kalkınmayı ve ekolojik korumayı dengeleyerek gelecekteki orman kayıplarını azaltmayı hedefleyen sürdürülebilir arazi yönetimi politikalarının acil gerekliliğini ortaya koymaktadır.
Anahtar kelimeler: Arazi kullanımı ve arazi örtüsü, Lombok Adası, Yoğunluk analizi, Yörünge analizi

1. Introduction

Land cover change has been the subject of intense scientific investigation due to its significant implications for ecosystems, biodiversity and human livelihoods (Edith and Xue, 2020). In regions such as West Nusa Tenggara Province, Indonesia, an understanding of the dynamics of land cover change is crucial for effective natural resource management and sustainable development (Rijal et al., 2023). Over the past few decades, rapid population growth, urbanization, agricultural expansion, and other human activities have put significant pressure on the region's land cover, causing widespread transformations in its landscape (Karimov et al., 2023; Mariye et al., 2022). In addition, climate change impacts, such as changing rainfall patterns and increased frequency of extreme weather events, further exacerbate the vulnerability of West Nusa Tenggara's ecosystems to land cover change (Edith and Xue, 2020).

Remote sensing techniques combined with Geographic Information Systems (GIS) have become powerful tools for monitoring and analyzing land cover change over large spatial areas and long time periods (Çoban, 2009; Das and Angadi, 2022; Rawat and Kumar, 2015; Sameer and Hamid, 2023). By utilizing satellite imagery and sophisticated analytical methods, researchers can systematically quantify and characterize the spatial and temporal patterns of land cover change in West Nusa Tenggara Province. However, despite advances in technology and methodology, there is still

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a need for comprehensive studies that provide detailed insights into the drivers, trends and impacts of land cover change in the region (Edith and Xue, 2020). Such studies are important to inform evidence-based policy decisions and facilitate adaptive management strategies to mitigate the adverse effects of land cover change on ecosystems and human well-being.

In addition, the application of innovative visualization techniques, such as trajectories, offers a promising approach to synthesize complex spatial-temporal data on land cover change into easily accessible and interpretable visual representations (Zhou et al., 2008). The use of trajectories allows researchers to depict the flow and trajectory of land cover transitions across different categories through time, thus facilitating a deeper understanding of the underlying dynamics of land cover change (Mugiraneza et al., 2020; Van der Laan et al., 2018). By integrating quantitative analysis with visual narratives, the researchers were able to effectively communicate their findings to various stakeholders, including policy makers, land managers, and local communities, facilitating greater awareness and cooperation towards sustainable land use practices and conservation efforts in the region. The purpose of this study is to analyze the dynamics of land use/land cover (LULC) changes on the Lombok Islands in West Nusa Tenggara, Indonesia.

2. Materials and methods

2.1. Study area

Indonesia, as an archipelago, boasts a vast area of around 1.9 million square kilometers and is home to over 273 million people. It is a country of immense diversity, both culturally and geographically, consisting of thousands of islands, each with its unique characteristics and contributions to the nation's rich tapestry. Lombok Island, located in West Nusa Tenggara, is one of the many islands that make up Indonesia's diverse archipelago (Figure 1). This island, along with Sumbawa Island, forms the province of West Nusa Tenggara. Lombok covers an area of approximately 4,739 square kilometers and has a population of about 3.3 million people. The island is renowned for its stunning landscapes, including majestic mountains, fertile plains, and pristine beaches, making it a significant destination for tourism within Indonesia. Geographically, Lombok is characterized by its central volcanic range, with Mount Rinjani being the most prominent peak, standing at 3,726 meters above sea level. This stratovolcano is the second highest in Indonesia and a popular trekking destination. The island's diverse topography supports a variety of ecosystems, from lush rainforests to arid grasslands. In terms of land use, Lombok exhibits diverse patterns. Agriculture dominates the land cover, occupying approximately 61.4% of the total area. This sector is crucial to the local economy, with rice, tobacco, and coffee being the primary crops. Forests cover around 25.8% of Lombok's area, playing a vital role in maintaining ecological balance and biodiversity. However, the island has experienced significant land use changes over the years, particularly deforestation and forest degradation, resulting in the conversion of forests to agricultural land and shrubs (Kim, 2016).

2.2. Land cover datasets

The methodology for generating LULC data from the Indonesian Ministry of Environment and Forestry (MoEF) follows the guidelines outlined in Head of Forestry Planning P.1-VII-IPSDH-2015, which outlines the Land Cover Monitoring Guidelines (Pedoman Pemantauan Penutupan Lahan) (P.1-VII-IPSDH, 2015). Land cover was classified into nine categories (Kim, 2016). These classes were separated and combined into nine more general classes to facilitate data analysis and interpretation (Table 1).

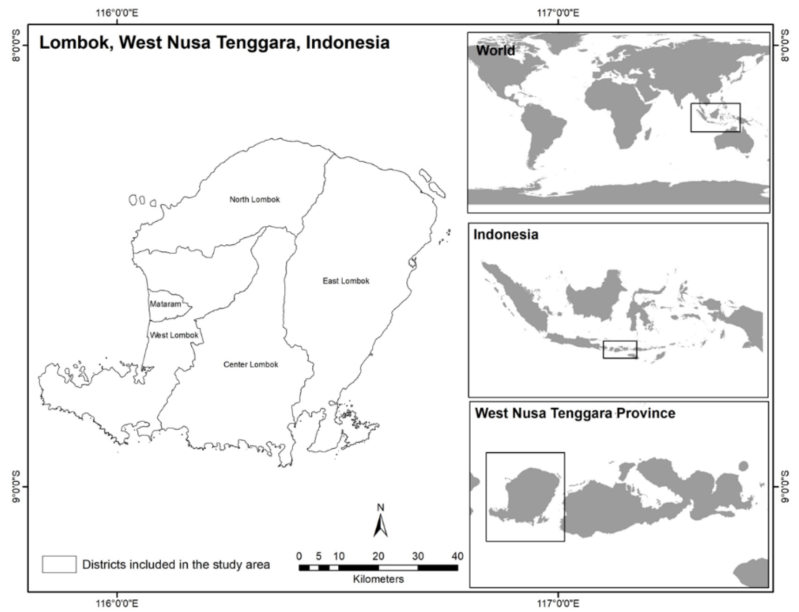

Figure 1. Study area (Lombok Island, West Nusa Tenggara, Indonesia)

Table 1. Land cover class codes

New land cover class	New class code	MoEF land cover class code
Primer forests	1 (PF)	2001 (Primary dryland forest) 2004 (Primary mangrove forest)
Seconder forests	2 (SF)	2002 (Secondary dryland forest/ opened forest) 20041 (Secondary/cut mangrove forest)
Dry land agriculture	3 (DLA)	20091 (Dryland agriculture) 20092 (Dry farming mixed shrubs/mixed gardens)
Paddy fields	4 (PFi)	20093 (Paddy fields)
Grasslands/Shrubland	5 (GS)	3000 (Savanna / Grassland) 2007 (Bushes)
Estate crop	6 (EC)	2010 (Plantation / Garden) 2006 (Plantation forest)
Wetlands	7 (W)	5001 (Water structures) 20094 (Ponds)
Settlement (Build up)	8 (SB)	2012 (Settlement / Inhabited land) 20121 (Airport/Port) 20122 (Transmigration)
Other	9 (O)	2014 (Bare Land) 20071 (Swamp shrubs) 20141 (Mine)

The land cover classification methodology uses a combination of land cover classes from the Ministry of Environment and Forestry (MoEF) that have been enhanced with a pre-trained Random Forest machine learning algorithm. The Random Forest algorithm achieved an overall accuracy of 0.82 and a ground truthing accuracy of 0.88 using several input variables, including Coastal Aerosol, Blue, Green, Red, Near Infrared (NIR), SWIR 1, SWIR 2, Normalized Difference Vegetation Index (NDVI), Soil-adjusted Vegetation Index (SAVI), Normalized Difference Water Index (NDWI), Enhanced Vegetation Index (EVI), Normalized Difference Built-up Index (NDBI), Elevation, Slope, Aspect, Soil Type, Population Density, Proximity to Roads, Proximity to Settlements, Proximity to Rivers, Proximity to Central Government, Average Temperature, and Average Rainfall.

In land cover classification, the Random Forest algorithm works by creating a large number of decision trees (Figure 2) using random subsets of training data and input variables. Each decision tree provides a prediction of the land cover class based on the data it receives (Breiman, 2001; Das et al., 2022; Purnama et al., 2024). The predicted results from all decision trees are then combined through a majority voting mechanism to determine the final class of each land cover instance. This approach improves classification accuracy by reducing overfitting and utilizing the collective power of many simpler models. The time series (Figure 3) used for this classification covers the years 2013, 2017, and 2022, utilizing land cover classifications from MoEF in combination with the Random Forest algorithm, allowing for a detailed temporal analysis of land cover change over almost a decade.

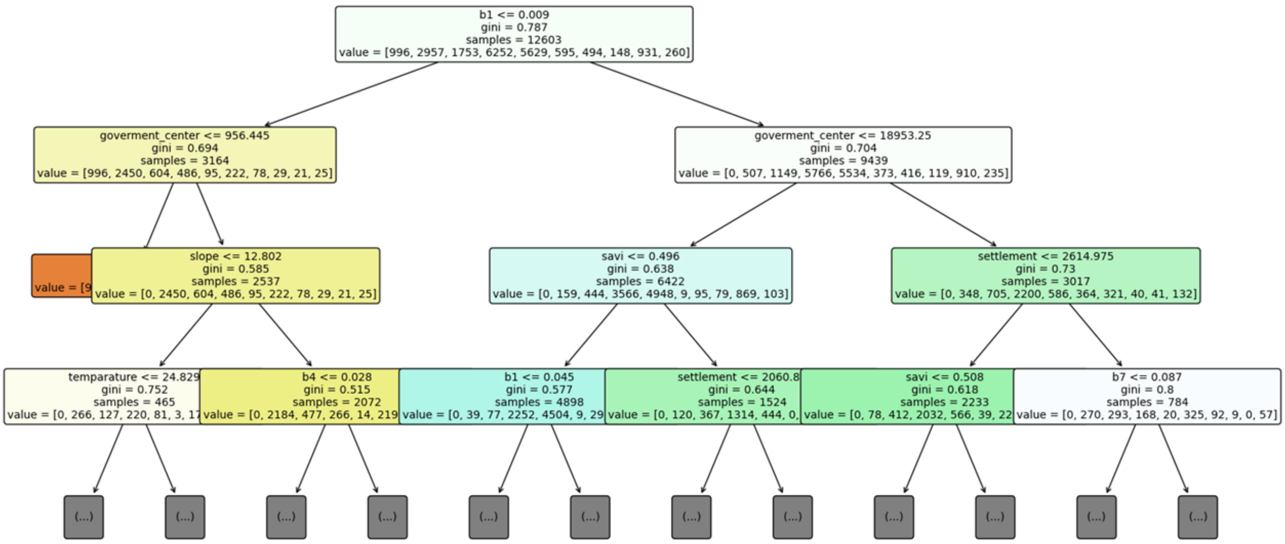

Figure 2. One of the decision tree examples in Random Forest algorithm

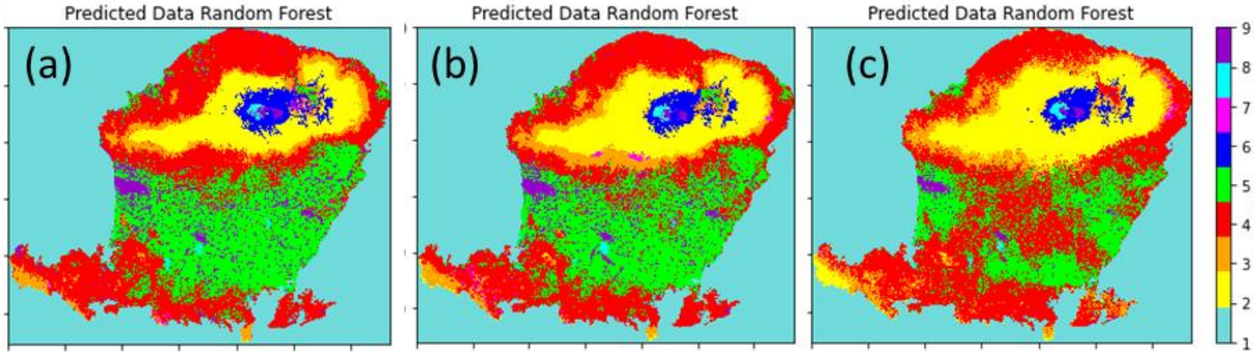

Figure 3. MoEF's and Random Forest land use/land cover classes: a) 2013, b) 2017, c) 2022 (1:Primary Forest, 2:Secondary Forest, 3:Dry Land Agriculture, 4:Paddy Fields, 5:Grassland/Shrubland, 6:Plantation, 7:Wetlands, 8:Settlement, 9:Others)

2.3. Intensity analysis

Intensity Analysis is a mathematical framework used to quantify and characterize changes in LULC over time. It decomposes the observed changes into different components to provide insights into the dynamics of LULC transitions (Akodéwou et al., 2020; Ouedraogo et al., 2023; Quan et al., 2020).

The first level determines how the annual change percentage (Equation 1) varies compared to a uniform annual change (Equation 2).

$$S_t = \frac{(size\ of\ change\ during\ [Y_t,Y_{t+1}])100\%}{(size\ of\ spatial\ extent)(duration\ of[Y_t,Y_{t+1}])} \quad (1)$$

$$U = \frac{(size\ of\ change\ during\ all\ intervals)100\%}{(size\ of\ spatial\ extent)(duration\ of\ all\ intervals)} \quad (2)$$

The second level compares, for each category, a uniform intensity S_t to the intensity of loss L_{ti} (Equation 3) and the intensity of gain G_{tj} (Equation 4) during each time interval $[Y_t, Y_{t+1}]$.

$$L_{ti} = \frac{(size\ of\ loss\ of\ i\ during\ [Y_t,Y_{t+1}])100\%}{(size\ of\ i\ at\ time\ Y_t)(duration\ of\ [Y_t,Y_{t+1}])} \quad (3)$$

$$G_{ti} = \frac{(size\ of\ gain\ of\ j\ during\ [Y_t,Y_{t+1}])100\%}{(size\ of\ j\ at\ time\ Y_{t+1})(duration\ of\ [Y_t,Y_{t+1}])} \quad (4)$$

The last level compares, during an analysed time interval, the transition intensity R_{tij} (Equation 5) from category i to category j to a uniform transition intensity W_{tj} (Equation 6), given the gain of category j (Akodéwou et al., 2020; Huang et al., 2018).

$$R_{tij} = \frac{(size\ of\ transition\ from\ i\ to\ j\ during\ [Y_t,Y_{t+1}])100\%}{(size\ of\ i\ at\ time\ Y_t)(duration\ of\ [Y_t,Y_{t+1}])} \quad (5)$$

$$W_{tij} = \frac{(size\ of\ gain\ of\ j\ during\ [Y_t,Y_{t+1}])100\%}{(size\ of\ not\ j\ at\ time\ Y_t)(duration\ of\ [Y_t,Y_{t+1}])} \quad (6)$$

2.4. Trajectory analysis

The analysis of land cover change trajectories in the study area covers time periods with year intervals (2013, 2017 and 2022). These intervals were chosen based on the availability of satellite imagery and land cover classes from the Ministry of Environment and Forestry (MoEF). Although the intervals are unequal, this does not affect the analysis, as the calculations focus on annual rates of change, ensuring consistent year-to-year comparisons. To ensure the representativeness of the sample and the accuracy of the spatial analysis, a fishnet (Figure 4) was systematically established across the study area (Zioti et al., 2022). GIS software, specifically ArcGIS, was used in this process. The grid size was set with a minimum distance of 100 meters between points. This aims to obtain land cover data that represents a random variety of land conditions and avoid biases caused by spatial data clustering. After the grid generation was completed, the land cover value for each point was extracted for each year using ArcGIS. With this technique, land cover data was obtained for each location at different time periods, making it possible to track land cover changes over time.

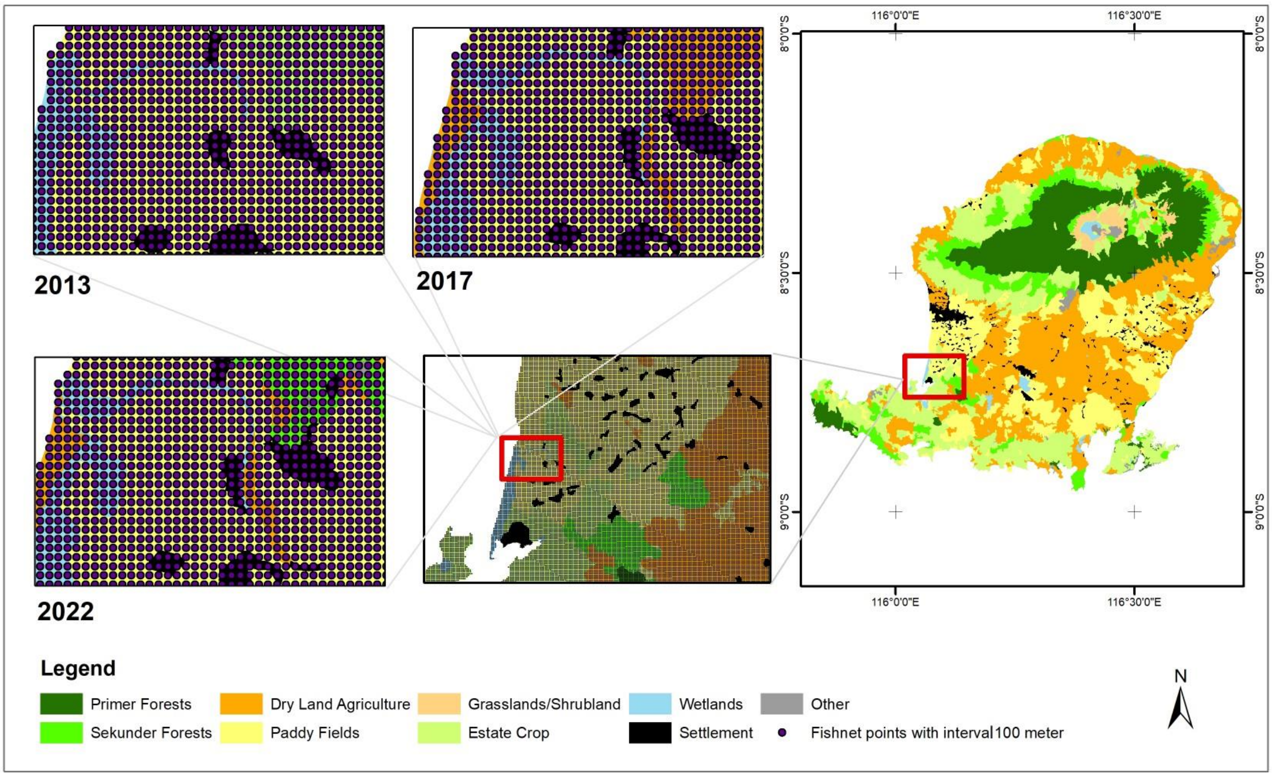

Figure 4. Distribution of sample points (with intervals 100 x 100 m)

The next step is the creation of alluvial sankey diagrams to visualize the flow of land cover change trajectories and identify transition patterns between land cover classes (Akodéwou et al., 2020; Gong et al., 2022; Zioti et al., 2022). Google Colab, a web-based computing platform, was used as an analysis environment. The "plotly.graph.objects library" was imported to enable the creation of the sankey diagram visualization.

The land cover data that had been extracted from ArcGIS was then converted to a format suitable for the creation of sankey diagrams. This process involved creating two main data structures: dictionary nodes and dictionary links. The node dictionary contained information about the land cover classes, which were redefined using the "label_mapping" dictionary to improve readability. In addition, a "class_colors" dictionary was created to assign different colors to each land cover class, thus facilitating visual interpretation. The link dictionary, on the other hand, stores information about transitions between land cover classes. This information includes the start (source) and target (destination) points of the transition, the number of data points undergoing change, and the label describing the transition.

3. Results and discussion

3.1. Intensity analysis

The LULC change rate in Lombok from 2013-2017 (30.27%) was higher than from 2017-2022 (18.55%) due to rapid urbanization and agricultural expansion driven by increased tourism and population growth in 2014-2015 (Figure 5). The construction of new residential areas and tourist facilities accelerated the conversion of natural areas into agricultural and urban uses. The 2018 earthquake caused significant land use changes, and the slower rate during 2017-2022 can be attributed to post-earthquake reconstruction and the COVID-19 pandemic, which restricted activities and slowed economic and social activities. Despite the slowdown in LULC changes in Lombok, it is essential to address the challenges of controlling and monitoring the environmental dynamics associated with these changes.

Government policies in West Nusa Tenggara (WNT) province have significantly impacted LULC changes in Lombok. The Green WNT Movement aims to restore degraded lands and improve land management, involving various stakeholders to reforest approximately 77,760 hectares by 2023 (DLHK NTB, 2021). However, rapid urbanization in cities like Mataram increases demand for housing and infrastructure, leading to the conversion of agricultural and natural lands into urban areas, contributing to deforestation and landscape fragmentation. Informal settlements spread unchecked due to high housing costs, adding pressure on natural resources and reducing the effectiveness of reforestation efforts (Bohensky et al., 2016; Gokarn et al., 2023).

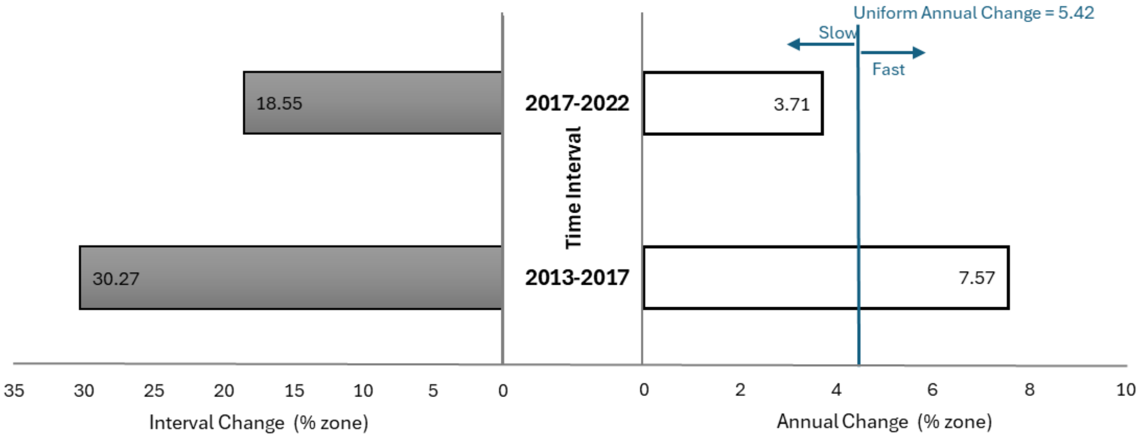

Figure 5. Intensity analysis interval level

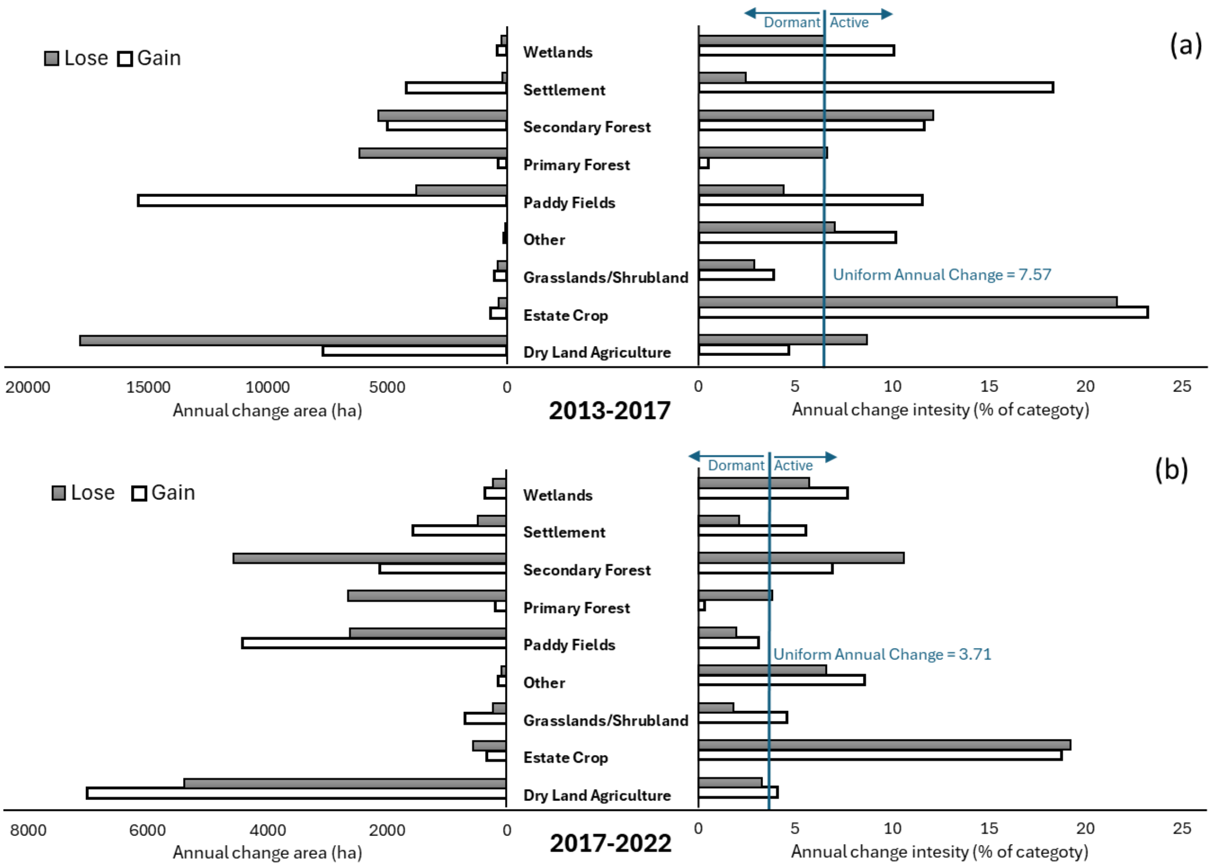

Figure 6. Intensity analysis of category level a)2017-2022 years, b) 2013-2017 years

The intensity analysis of category changes reveals variations in growth and decline rates across different time periods. During the 2013-2017 period, there was a significant increase in the Paddy Fields category, likely due to the expansion of rice cultivation or changes in agricultural practices (Figure 6). Conversely, there was a notable decrease in the Dry Land Agriculture category, which could be attributed to the conversion of dry lands to other land uses such as residential development (Masril, 2018). Additionally, the Secondary Forests category experienced significant losses, possibly due to deforestation activities (Sinurat and Arifien, 2021). On the other hand, during the 2017-2022 period, there was a substantial increase in the Estate Crops category, likely influenced by the expansion of commercial agriculture or changes in planting patterns. However, Secondary Forests showed a significant decline, which may be a result of ongoing deforestation activities or unsustainable land use practices. In both periods, the intensity analysis indicates a more uniform pattern with lower uniform values during the 2017-2022 period. This suggests greater stability or regulation in land use during this period or conservation efforts implemented after the more significant changes recorded in the previous period (Gokarn et al., 2023; Masril, 2018; Sinurat and Arifien, 2021).

The transition intensity analysis for primary and secondary forests on Lombok Island reveals significant dynamics in land cover changes between 2013-2017 and 2017-2022 (Figure 7). During 2013-2017, primary forests experienced substantial transitions to dry land agriculture (1,204 hectares, intensity 0.73) and secondary forests (4,275 hectares, intensity 9.97). In 2017-2022, these transitions significantly decreased to 622 hectares (intensity 0.36) and 1,516 hectares (intensity 4.95), respectively, indicating effective deforestation prevention efforts. Similarly, transitions from secondary forests to dry land agriculture decreased from 568 hectares (intensity 0.28) to 446 hectares (intensity 0.27). Transitions from primary to secondary forests also dropped from 4,275 hectares (intensity 4.60) to 1,516 hectares (intensity 2.18). This analysis suggests a more stable and reduced frequency of land cover changes in 2017-2022, likely due to improved land management practices such as the Green WNT Movement's reforestation efforts. However, the pressures from ongoing urbanization and agricultural expansion continue to pose challenges to Lombok's forest ecosystems.

The transition intensity data for Dry Land Agriculture, Plantation, and Paddy Fields from 2013 to 2022 highlight significant land cover changes in Lombok driven by socio-economic factors (Figure 8). From 2013 to 2017, Dry Land Agriculture saw notable transitions from Secondary Forests (568 transitions, intensity 0.28) and Primary Forests (1,203 transitions, intensity 1.29), reflecting an expansion to support the growing population and tourism. This trend reduced from 2017 to 2022, suggesting regulatory measures or sustainable development policies mitigated land conversion pressures. Similarly, Paddy Fields experienced high transitions from Dry Land Agriculture (14,975 transitions, intensity 7.32) from 2013 to 2017, with a decline in intensity by 2022, indicating improved land management or a focus on other economic activities like tourism. Lombok's urbanization and development as a tourism zone have significantly impacted land use patterns, contributing to these transitions. Projects like the Mandalika Urban Tourism and Development Project have boosted economic growth but also present social and environmental impacts (Just Finance, 2023; The Diplomat, 2023).

From 2013 to 2017, there were notable transitions from Dry Land Agriculture to Grassland/Shrubland, indicating agricultural expansion, which decreased slightly during 2017-2022 (Figure 9). The "Other" category showed significant transitions from Grassland/Shrubland and Wetlands, likely due to urban and infrastructural developments. Settlement areas experienced high transition intensities from Dry Land Agriculture, reflecting Lombok's urbanization through projects like the Mandalika Urban Tourism Project. Wetlands showed shifts towards conservation, though development pressures persist. These dynamics underscore the complex interaction between development and ecological preservation, necessitating careful land management to balance growth with ecological protection.

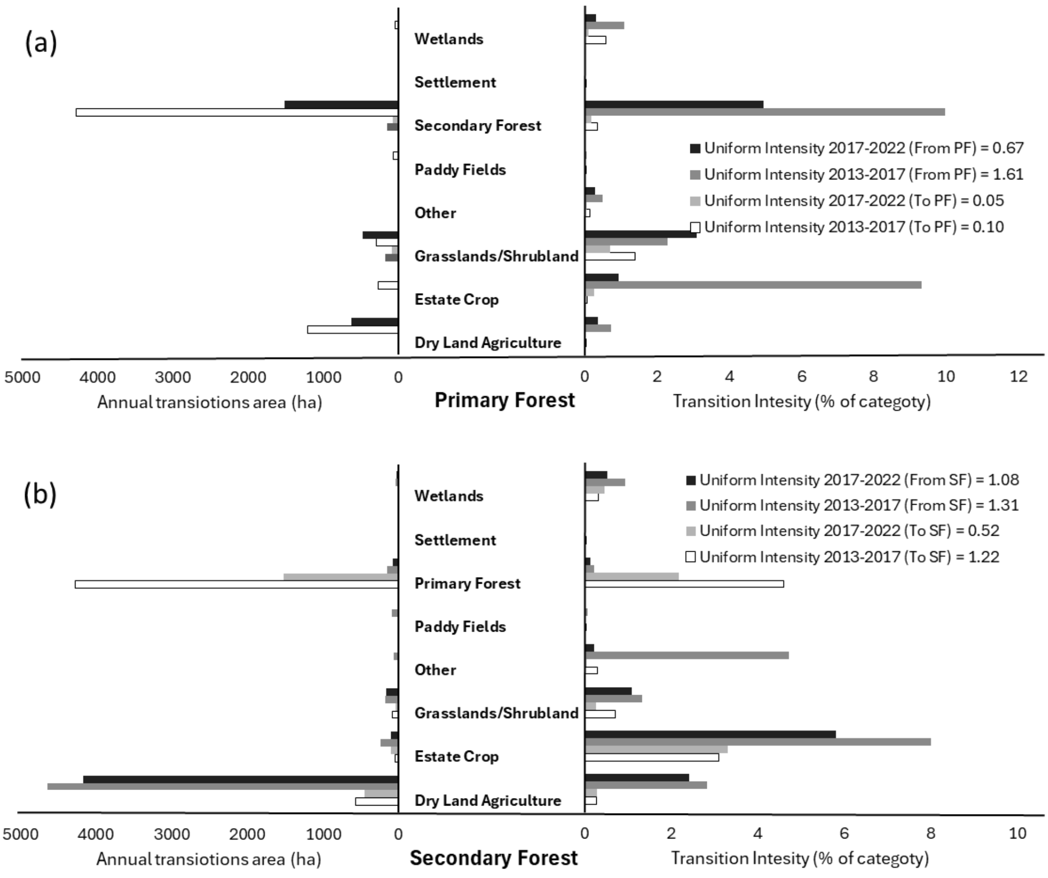

Figure 7. Intensity analysis transition level: a) primary forest b) secondary forest

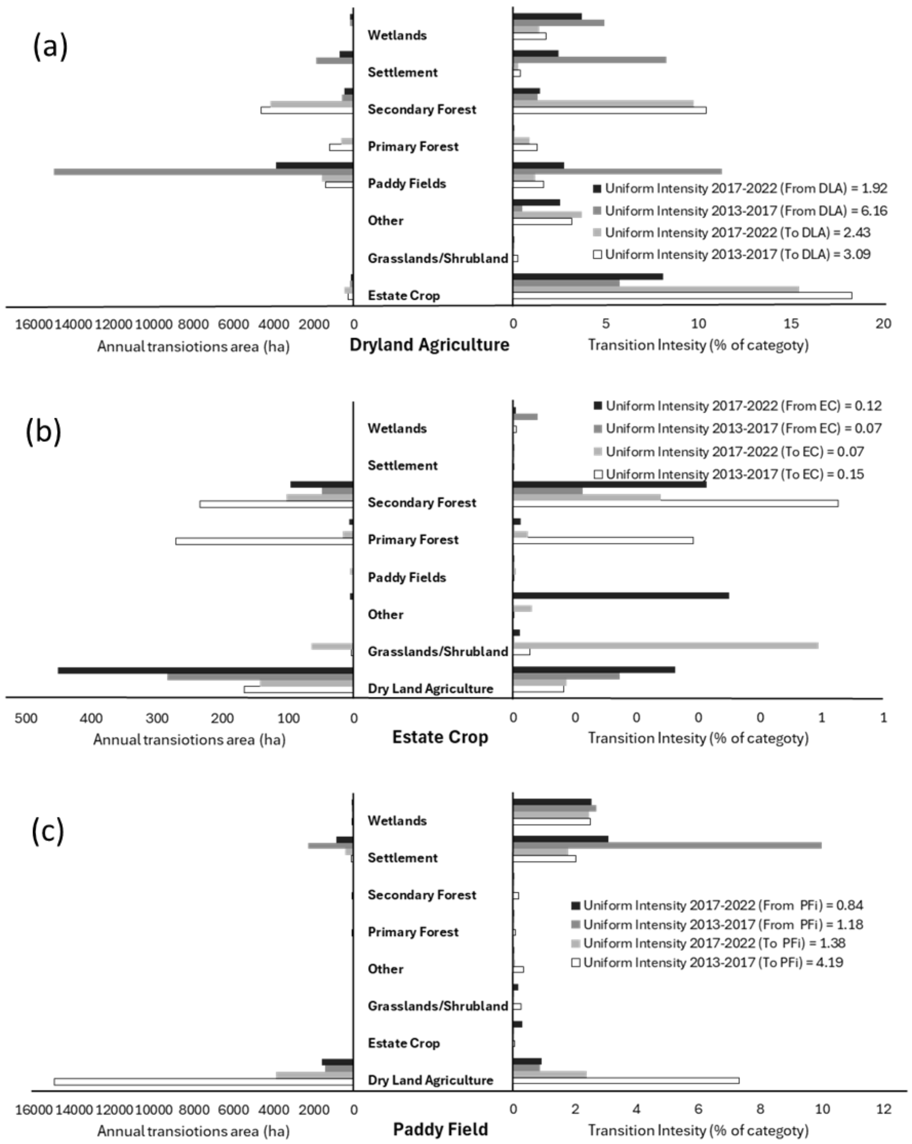

Figure 8. Intensity analysis transition level: a) dryland agriculture b) estate crop c) paddy fields

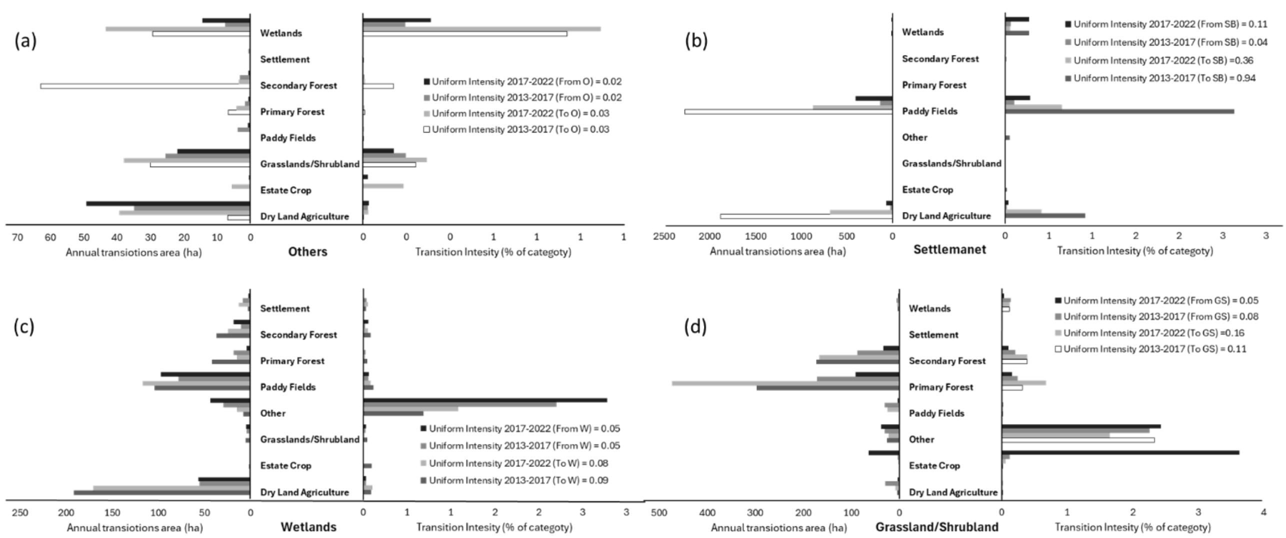

Figure 9. Density analysis transition level: a)others b)settlement c)wetlands d)grasslands/shrublands

The transition matrix of land use and land cover from 2013 to 2022 (Table 2) for Lombok Island highlights significant dynamics and changes driven by socio-economic factors. Dry land agriculture in 2013 saw a substantial conversion into paddy fields (68,671 ha) and settlements (10,843 ha) by 2022, reflecting the growing demand for agricultural land and urban expansion. Primary forests, initially covering 14826 ha, experienced significant reduction, transforming into secondary forests (17,838 ha) and paddy fields (333 ha), indicative of deforestation and agricultural encroachment. Grasslands/Shrublands largely persisted but also transitioned into other categories such as paddy fields (75 ha) and primary forests (440 ha), suggesting shifts in land use priorities. These transitions illustrate the impact of agricultural expansion, urbanization, and infrastructure development on Lombok's land cover.

3.2. LULC Trajectories

Yearly changes in land cover dynamics indicate complex alterations in the structure and composition of the study area. Primary and secondary forests tend to remain stable or experience minor changes annually, but transitions between these categories suggest changes in forest sustainability. Data shows primary forests converting to secondary forests and other categories, indicating degradation (Figure 10). Significant shifts towards more intensively used lands like dryland agriculture, paddy fields, plantations, and settlements are notable. From 2017 to 2022, there was a marked increase in land use for dryland agriculture and settlements, reflecting economic and social dynamics driven by population growth and development policies. These changes often occur at the expense of forest land, negatively impacting environmental sustainability.

Studies on deforestation in Indonesia support these findings (Miettinen et al., 2011) identify agricultural and plantation conversions as primary deforestation drivers in Southeast Asia, including Indonesia. Significant declines in primary natural forests from 2000-2012 due to conversions for plantations and agriculture (Margono et al., 2014). These land use changes do not always align with the policies in the West Nusa Tenggara Province Spatial Plan 2009-2029 (Regional Regulation of West Nusa Tenggara Number 3, 2010). Despite emphasizing optimal, balanced, and sustainable spatial planning, the dynamics of land use change highlight challenges in policy implementation. The significant shifts towards intensive agriculture and settlements suggest that economic development often outweighs environmental and sustainability concerns. This indicates the need for a more holistic and sustainable approach to ensure economic growth does not compromise long-term environmental sustainability. These findings underscore the importance of stricter policy oversight and enforcement to balance economic development and environmental conservation.

Table 2. LULC Transition Matrix from 2013 to 2022

LULC class in 2013	LULC class in 2022								
	Dry Land Agriculture (ha)	Estate Crop (ha)	Grasslands/ Shrubland (ha)	Other (ha)	Paddy Fields (ha)	Primer Forests (ha)	Seconder Forests (ha)	Settlement (ha)	Wetlands (ha)
Dry Land Agriculture	**121561**	683	56	121	68671	5	1402	10843	1196
Estate Crop	1163	**20**	1	0	5	1	331	31	3
Grasslands/Shrubland	111	295	**11072**	206	75	440	134	2	21
Other	172	5	104	**771**	11	2	1	3	26
Paddy Fields	3476	22	4	0	**71254**	1	21	11015	496
Primer Forests	14826	157	2829	15	333	**56608**	17838	29	283
Seconder Forests	30620	578	1184	177	379	223	**10830**	111	276
Settlement	41	0	0	1	581	0	1	**6055**	24
Wetlands	192	1	22	270	298	35	80	22	**2173**

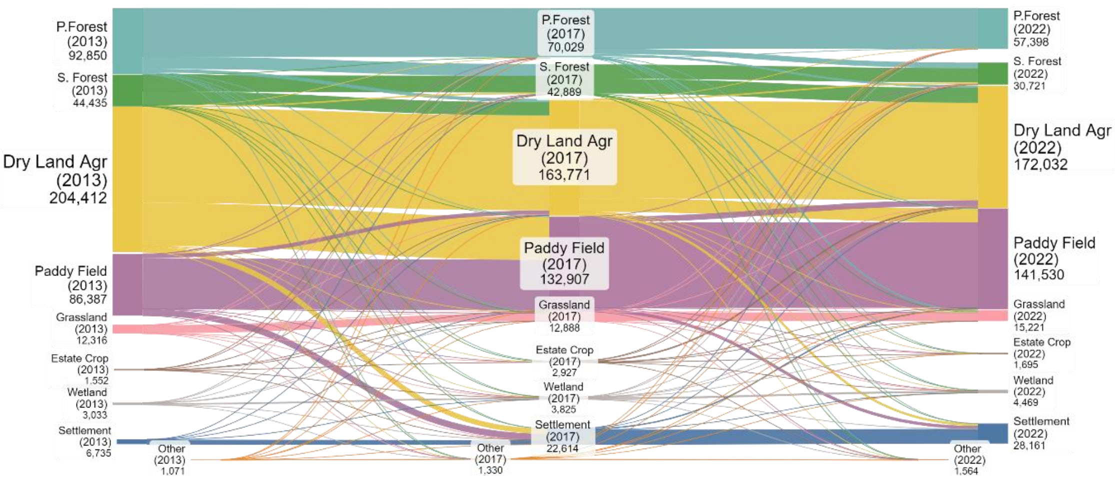

Figure 10. Lombok’s land use/land cover trajectories

The Sankey diagram (Figure 11) details how primary and secondary forest cover in Lombok transitions into various land use classes. The diagram illustrates these changes based on sample points. In 2013, most primary forests remained in their class. However, by 2017, a small portion had shifted to secondary forests, dryland agriculture, paddy fields, grasslands, plantations, wetlands, settlements, and other categories. By 2022, much of the primary forest that had changed in 2017 remained as primary forest, though some continued to transition to other classes. This data shows the dynamic nature of forest land use changes over the years, highlighting both conversions to more intensive land uses and restorations to more natural uses. This transition is crucial for understanding Aboveground Biomass (AGB) dynamics, as different land uses can significantly alter AGB, accurate AGB equations are essential for assessing carbon sequestration potential, with land use changes affecting biomass distribution among foliage, branches, and stems (Eker et al., 2017).

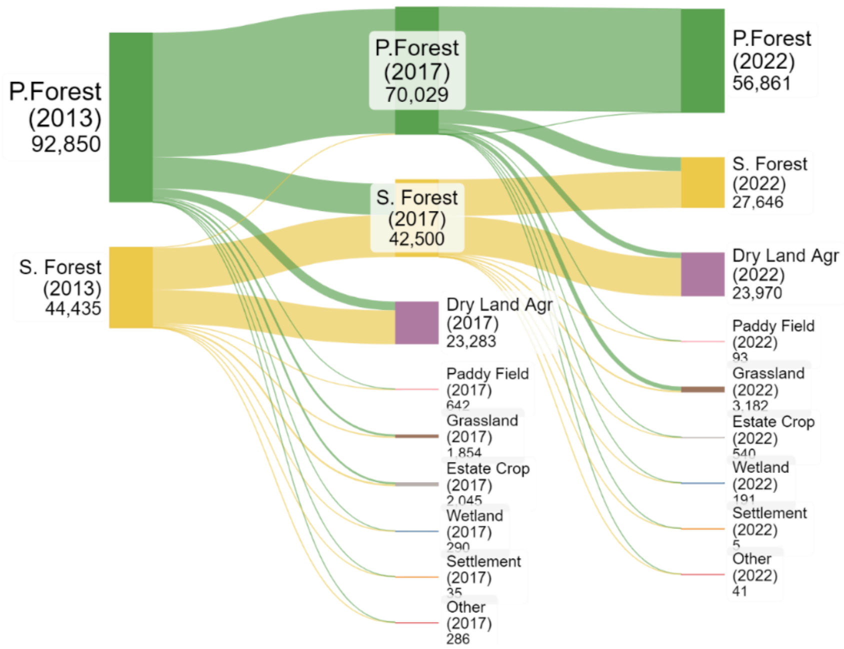

Figure 11. Direction and intensity of changes in forest classes

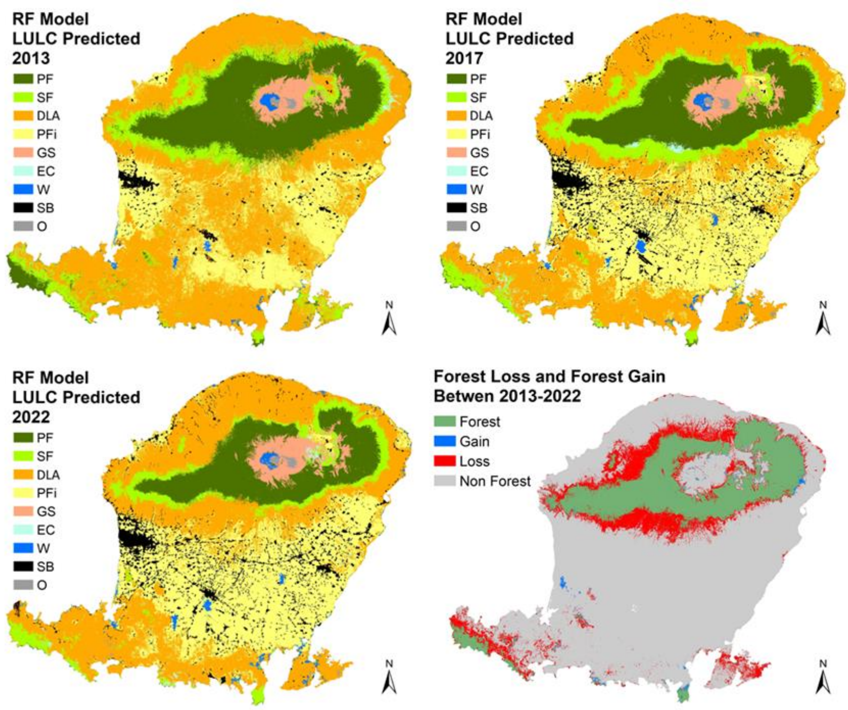

Figure 12. Temporal change of land use/land cover classes generated by Random Forest Algorithm a) 2013, b) 2017, c) 2022 and d) changes in forest areas between 2013-2022

During the period 2013-2022, forest loss amounted to 28095 ha, representing 24% of the total forest area (Figure 12). This loss was largely due to the conversion of primary and secondary forests to dry agricultural land, as well as other land uses. At the same time, there was a small increase in forest cover of 2,453 hectares, indicating reforestation and rehabilitation efforts, but not yet able to offset the rate of deforestation. The trajectory of forest cover change on Lombok Island reflects a complex interaction between various factors, including environmental policies, socio-economic dynamics, and natural disaster events. In recent years, primary forest conservation and rehabilitation policies have been strengthened to maintain ecosystem sustainability. However, rapid economic growth and urbanization have driven the conversion of forest land into residential areas and commercial infrastructure (Markum and Rahman, 2024). Natural disaster events such as the Lombok earthquake in 2018 have also had an impact on forest cover, with damage and land use changes occurring in the affected areas (Latifah et al., 2020). To face these challenges, a holistic approach that considers environmental sustainability, socio-economic needs, and disaster risk mitigation is needed in the management of forest cover on Lombok Island.

4. Conclusions

Regarding land cover dynamics in Lombok Island from 2013 to 2022, the data shows significant forest loss compared to forest gain. This reflects the substantial pressure on the island's forest ecosystems due to land use changes, urbanization, and population growth. Infrastructure development activities, such as road construction, also have the potential to accelerate land cover changes. The combination of data analysis and field research findings provides a more comprehensive understanding of the complex dynamics of land cover change in Lombok Island. This information is crucial for designing sustainable conservation and management policies to protect the island's ecosystems and biodiversity in the long term. Additionally, the scale of land cover change during the period is notable, with significant forest loss (28,095 ha, 24% of the total forest area) from 2013 to 2022 due to urbanization, population growth and infrastructure development. The distribution of LULC classes in Lombok showed that dry land agriculture (27.56%) and paddy fields (24.22%) cover the largest areas, followed by primary forest (13%) and secondary forest (7.68%). This highlights the need for sustainable conservation and management policies. Recommendations include implementing strict land use regulations, promoting reforestation programs, monitoring urban expansion, encouraging sustainable agricultural practices, raising environmental awareness, and enhancing policy enforcement. Utilizing advanced technologies for real-time monitoring and supporting continuous research can further aid in protecting Lombok's forest ecosystems and balancing development with ecological preservation.

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