SPATIOTEMPORAL ANALYSIS OF VIOLENT CONFLICT AND LAND COVER CHANGE IN LANAO DEL SUR FROM 2011 TO 2020

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ABSTRACT:

With Lanao del Sur historically being a setting for numerous violent conflict events, its land use and land cover (LULC) manifest the direct and indirect effects of conflict such as destruction and forced displacement that influences land cover change (LCC). Tracking LULC changes can determine the extent of damage induced by conflicts and support the crafting of policies toward sustainable development. To see how conflict has affected the land systems, Landsat-7, and -8 imagery from 2011 to 2020 were used to examine Lanao del Sur's periodic land covers and their trajectories. Barangay-level conflict incidence was also used to identify areas with both high conflict incidence and high rates of LCC. Trajectory analysis revealed patterns in land processes: afforestation coinciding with abandonment, and cultivation being bordered by deforestation as the connecting grassland cover decreases. Decreases in grassland cover were simultaneous with an increase in agricultural lands. Generally coinciding with conflict hotspots, areas with high conflict incidence and land cover change were typically found in urban centers, near water bodies, and provincial boundaries where there was a high volume of human activities. Meanwhile, areas with low conflict incidence and LCC were found in forested areas. Overall, there is a significant positive correlation between conflict occurrences and LCC (r = 0.388), with abandonment (r = 0.533) and cultivation (r = 0.546) having moderate strengths of association.

1. INTRODUCTION

The Philippines has a long history of destructive warfare and conflicts, especially in Mindanao where the prevalence and persistence of violent conflicts can be traced far back to the Spanish and American colonial periods (Capuno, 2017). Human-induced violent conflicts can originate from various issues including common crimes, governance, identity, politics, resources, shadow economy, and others (International Alert Philippines, 2022). The impacts of civil war and other forms of violent conflicts (e.g., feuds between tribes, clans, groups, or challenges against the government) can have adverse, and long-term consequences on human life and the surrounding environment. To determine the extent and magnitude of the effects of violent conflicts on the land systems, tracking LULC changes is imperative to aid in the crafting of policies toward sustainable development.

Remote sensing techniques have been applied to previous studies in Liberia and Syria to track conflict-driven land cover changes, using Landsat imagery to generate Land Cover Change (LCC) maps for analysis (Enaruvbe et al., 2019; Mohamed et al., 2018). Meanwhile, Geographic Information Systems (GIS) are also utilized to determine the land cover trajectories that an area has experienced over a long time such as abandonment, cultivation, or deforestation (Camargo et al., 2020; Gbanie et al., 2018). Various studies have also examined the linkages between LULC changes and violent conflicts (Landholm et. al, 2019; Rathnayake et. al, 2019).

In Lanao del Sur as well as the other parts of Bangsamoro, a study done by International Alert determined that violent conflicts mainly occur in capital cities and along political boundaries due to territorial claims among political clans (Quitoriano, 2022). Despite identifying the root causes and sources of violent conflicts, there has yet to be a study in Lanao del Sur looking at how the violent conflicts have driven changes in the land over time.

This study, therefore, aims to determine the spatiotemporal pattern of the LULC changes in Lanao del Sur and its correlation with violent conflict using satellite imagery and conflict data. The findings of this study attempt to address gaps in previous research and aid ongoing rehabilitation efforts by determining the extent of conflict's effects on the land cover of the province and by supporting the crafting of policies regarding land and peacebuilding management. This paper presents the following: (1) generation of land cover maps using random forest classification algorithm in Google Earth Engine (GEE), (2) assessment of LCC using change detection and trajectory analysis, (3) assessment of spatiotemporal dynamics of LCC and violent conflict using bivariate choropleth map, and (4) correlation between land cover trajectories and violent conflict.

Following the available conflict data managed by International Alert Philippines, the timeframe of this study has been limited to 2011 up to 2020. The conflict data considered in the analysis are limited to human-induced violent types of conflict consisting of common crimes, governance issues, identity issues, political issues, resource issues, and shadow economy issues. Furthermore, due to pandemic restrictions, accuracy assessment was done by getting validation data from higher-resolution imagery, specifically Google Earth's historical imagery.

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2. MATERIALS AND METHODS

2.1 Study Area

The study area is the province of Lanao del Sur located in the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM) in the Philippines (Figure 1). Among the numerous conflict events that occurred in the province in the last decade, a massive violent conflict happened in Marawi City, the capital of Lanao del Sur, in 2017 that may have consequently shaped the land cover changes in the provinces.

Figure 1. Study area in red region indicating administrative boundary of Lanao del Sur, Philippines (Base map source: Google Maps, 2023)

2.2 Materials

2.2.1 Data Processing: The software applications, and their description, utilized in this study are the following:

Google Earth Engine (GEE): GEE is a cloud-based platform that stores historical and current Earth observation data while enabling users to execute geospatial analysis. Pre-processing of satellite imagery up to the classification and accuracy assessment were all performed in GEE.

Google Earth Pro: Training and validation data used for the image classification and accuracy assessment were sampled from the historical imagery of Google Earth Pro.

Geographic Information System (GIS): QGIS and ArcGIS were used for the subsequent analyses of the generated land cover maps and conflict data which include change detection, land cover trajectory analysis, and hotspot analysis, respectively.

2.2.2 Remote Sensing Data: In the study, satellite imageries from Landsat missions were used due to their long temporal record, spatial resolution, and spectral properties adequate for detecting historical changes of land cover in a given area (Gbanie et al., 2018; Mohamed, 2021). Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) with a 16-day repeat cycle, 30-meter spatial resolution, and a total of 8 to 11 spectral bands were used. All satellite missions have an available atmospherically corrected surface reflectance (Earth Engine, n.d.).

The satellite images were grouped by year to generate four cloud-free image collections for 2011, 2014, 2017, and 2020. Annual cloud-free composites were created by masking pixels identified as clouds, with value 3, or shadows, with QA value 4, based on the quality assessment (QA) bands and reducing it by taking the median value from all cloud-free pixels of the image collection (Phan et. al, 2020). Annual composites were used since a shorter timeframe led to significantly large holes in the image due to constant cloud cover over those areas.

2.2.3 Ancillary Data: The validation data were gathered from Google Earth Pro's historical imagery. Images from Google Earth have resolutions that can range from 15 meters to 15 centimeters which can provide high-quality details of the Earth's surface (Doyog et al., 2021). Other supplementary data used include land cover maps of the study area from the National Mapping and Resource Information Authority (NAMRIA).

2.2.4 Conflict Data: The study used the barangay-level conflict data from International Alert Philippines with temporal availability starting 2011 up to 2020. International Alert Philippines primarily obtains its conflict data in the Bangsamoro Autonomous Region of Muslim Mindanao (BARMM) from police blotters and media outlets for supplementary information and gets validated by consulting stakeholders consisting of various experts on conflict and crime monitoring (International Alert, n.d.).

2.3 Methods

The methodology was divided into four parts: (1) image classification, (2) change detection and trajectory analysis, (3) LCC and conflict overlay, and (4) hotspot and correlation analysis.

2.3.1 Image Classification and Accuracy Assessment: For this study, seven land cover classes were used for the image classification: (1) Agriculture: annual and perennial crops, (2) Bare land: bare soil, sand, and rocks, (3) Built-up: man-made infrastructure, specifically, standing buildings and roadways, (4) Forest, (5) Water: rivers, lakes, creeks, and irrigation canals, (6) Grassland: grass and small shrubs, and (7) Rubble: destroyed and demolished buildings.

Training and validation polygons were gathered by stratified random sampling through high-resolution satellite imagery as seen from Google Earth Pro. For each land cover class, a minimum of 60 training and 40 validation polygons were marked so that the confusion matrix would be adequately populated (Story & Congalton 1986, as cited in Congalton, 2001). A total of 2044 training and 1403 validation polygons were collected for the whole study period. Instead of pixels, polygons were used so that the total cumulative pixels per class for the whole region would be acceptable for classification since multiple pixels are captured in a single polygon.

The random forest (RF) classification algorithm was used for image classification since it has the highest accuracy among the algorithms in GEE (Yang et al., 2021). The algorithm classifies pixels using multiple decision trees and assigns a classification based on the most frequent prediction of the decision trees (Yiu, 2021). For this study, only the number of trees was specified and set to 100 which results are within a good accuracy range (Phan et. al, 2020; Pelletier et al., 2016; Yang et al., 2021).

For the accuracy assessment, the confusion matrix for the overall, user's, and producer's accuracy values were reported. The acceptable overall accuracy for classification using RF ranges from 77% to 90% (Pelletier et al, 2016). Cohen's Kappa statistic was also computed to determine the strength of agreement between the classified and reference images where a Kappa statistic value higher than 0.5 is considered satisfactory in modeling land use change (Adam et. al, 2023).

2.3.2 Change Detection and Trajectory Analysis: Change detection and land cover trajectory analysis were done on QGIS. For change detection, the land cover change tool of the semi-automatic classification plugin was used to determine the percentage of pixels that were converted before and after each temporal period.

Land cover trajectory analysis was executed to summarize the land cover changes of the study area for a long period of time. This was previously done in the study by Gbanie et. al (2018) upon which the study adopted the rules for the assignment of trajectories for each process. Using the raster calculator, a trajectory raster containing a four-digit value corresponding to each year's land cover was then created. The values of the trajectory were computed such that the first digit corresponds to the 2011 land cover, the second corresponds to the 2014 land cover, and so on. A total of 1,764 possible trajectories were identified, based on the possible land covers for each year. Table 1 shows the description and sample combinations for each trajectory.

	Process	Sample Trajectories	Description
1	No change	1111, 2222, 3333, 4444, 5555	Stable land cover
2	Urbanization	1373, 1133, 6133, 6113, 4663	Increase in built-up
3	Afforestation	6644, 1664, 1644, 2164, 2114	Densification of woody vegetation
4	Deforestation	4666, 4664, 6462, 1442, 1446	Removal and de-densification of woody vegetation
5	Abandonment	1166, 2116, 3377, 3376, 1376	Cultivated or occupied to bare land, grassland, or rubble
6	Cultivation	2121, 2112, 6151, 2151, 4261	Occupied lands used for agriculture
7	Improbable Transitions	3513, 4545, 6733, 4241, 3355	Not typically possible

Table 1. Land Cover Trajectories.

2.3.3 Conflict and LULC Intensity Map: A bivariate choropleth map was created by overlaying the conflict data and the percent land cover change within each respective barangay. The interval for both variables was divided into three classes according to the Jenks natural breaks classification method that determines the best arrangement of values into different classes by grouping similar values together and maximizing the differences between classes (Ahmad, 2019).

2.3.4 Hotspot and Pearson Correlation Analysis: Due to the sensitivity of Pearson's correlation to outliers, hotspot analysis was done to the barangay-level conflict data since several barangays in Lanao del Sur have zero or one recorded conflict incidence over the entire period. It is undetermined whether this was caused by a gap in the recording of conflict in the province. Hence, only the barangays identified to belong to the hotspot cluster were used for the correlation.

The Getis-Ord Gi* hotspot analysis on ArcGIS was used since it clusters high and low values of conflict incidences together (Nemeth et. al, 2014). The contiguity edges corners conceptualization of spatial relationships was also employed since it takes into account the neighboring barangays without relying on distance from the barangay centroids (Soleimnani and Bagheri, 2021). Out of 1,159 barangays in Lanao del Sur, there were 94 identified barangays with significant clustering of high conflict values.

Assuming a linear relationship between conflict incidence and LCC, Pearson's Product Moment Correlation analysis was utilized. Pearson correlation test is a statistical method that measures the linear association between two quantitative variables, ranging from -1 to +1 in increasing order of strength. The correlation function in Excel was used to compute the Pearson coefficient. Landholm et al. (2019) used $R^2 > 0.5$ as the benchmark to define a strong relationship between conflict-related variables and forest loss rate, which the study will also adopt. The level of significance used in the correlation was 0.05.

3. RESULTS AND DISCUSSION

3.1 Accuracy Assessment

Table 2 shows the confusion matrix for each annual classification. The overall accuracy (OA) of all classified maps reached the acceptable accuracy threshold. Furthermore, their kappa coefficients (κ) showed an almost perfect agreement between the classified and reference images making them suitable for subsequent analyses.

Misclassification among land cover classes as seen in the confusion matrix showed confusion between the built up and rubble classes, likely due to the relatively small areas of rubbles not covering an entire pixel which has an area of 900 sqm. There was also confusion between the agricultural and bare land land classes which may be attributed to agricultural land resembling bare land as it undergoes natural variations within the annual farming period. The annual compositing of images can possibly disregard paddy planting and the harvesting season and show only bare lands, thus leading to the misclassification of pixels.

Year	OA	κ	Land Cover	Accuracy Type	
				UA	PA
2011	91.9%	0.85	Agricultural	73.6	53.9
			Bare Land	75	20
			Built-up	72.2	75.6
			Forest	95.7	93.6
			Water	97.2	99.6
			Grass	54.5	65
			Rubbles	-	-
2014	90.1%	0.84	Agricultural	77.1	81.6
			Bare Land	17.6	26.7
			Built-up	87.1	69
			Forest	92	95.3
			Water	99.9	99.9
			Grass	64.5	51.3
			Rubbles	-	-
2017	87.4%	0.81	Agricultural	77.8	74.2
			Bare Land	91.8	37.2
			Built-up	55.7	53.5

			Forest	92	84.9
			Water	99.9	99.9
			Grass	38.7	57.3
			Rubbles	67.7	72.2
2020	91.3%	0.87	Agricultural	83.7	77.6
			Bare Land	92.5	44.5
			Built-up	69	51.9
			Forest	91.7	95.5
			Water	100	99.8
			Grass	60.3	55
			Rubbles	25	8.3

Table 2. Accuracy assessment of land cover classification.

3.2 Land Cover Change Patterns

Changes in area of each land cover type are shown in Figure 2. On the other hand, Figure 3 shows the annual land cover maps indicating LCC for each 3-year period, while Figure 4 shows the trends or trajectory per land cover.

Water bodies mainly consisting of Lakes Lanao and Dapao maintained a relatively stable land area of around 9%. Meanwhile, forest lands had the largest land cover area and were mainly distributed in the north and southeastern portions of the region. Forest lands experienced slight fluctuations in its area, ultimately having a net gain of 7.31%, as seen in Figure 2. These fluctuations can be spatially attributed to construction of cemented roads, leading to an increased demand for housing due to accessibility. Furthermore, it can also be linked to the shifting of classification from forest land to agricultural land in the cultivated areas, particularly, in the case of perennial areas in the southwestern portion of the region.

Grasslands were concentrated on the edges of the forest lands and in the southwestern portion of the region. A decrease in grasslands that coincided with an increase in agricultural lands (50.69%) was observed in the southwestern part of the study area. The largest decrease in grassland area occurred from 2011 to 2014 with a 22.56% loss (~255.02 km^2) as shown in Figure 2. The majority of this change is located in the southwestern portion of the region which can be attributed to the cultivation of these areas into agricultural lands. The agricultural land class was mainly distributed around the Lake Lanao watershed and on the southeastern fringe of Lanao del Sur.

A steady increase in built up areas was also noted for all time periods except during peak conflict occurrence in 2017, when there was an increase in rubble due to the Marawi Siege. The increase of built-up areas is mainly located in Marawi City and the coastal municipality of Malabang, as well as the expansion of roads along the edges of Lake Lanao. The decrease from 2014 to 2017 can be attributed to the addition of a subclass of built-up which is rubble, or the demolished and damaged buildings and the majority of the changes occurred in Marawi City. Meanwhile, the substantial decrease in rubble from 2017 to 2020 can be attributed to rebuilding efforts in the region after the conflict.

Large fluctuations in the areas of bare soil also imply that it is a transitional land cover for other classes. As previously discussed in the accuracy assessment, bare lands were usually confused with agricultural land due to the nature of cultivated crops such as annual crops that live and die for only one season. Therefore, it is highly possible that some agricultural fields become bare before the planting season and after the harvesting season.

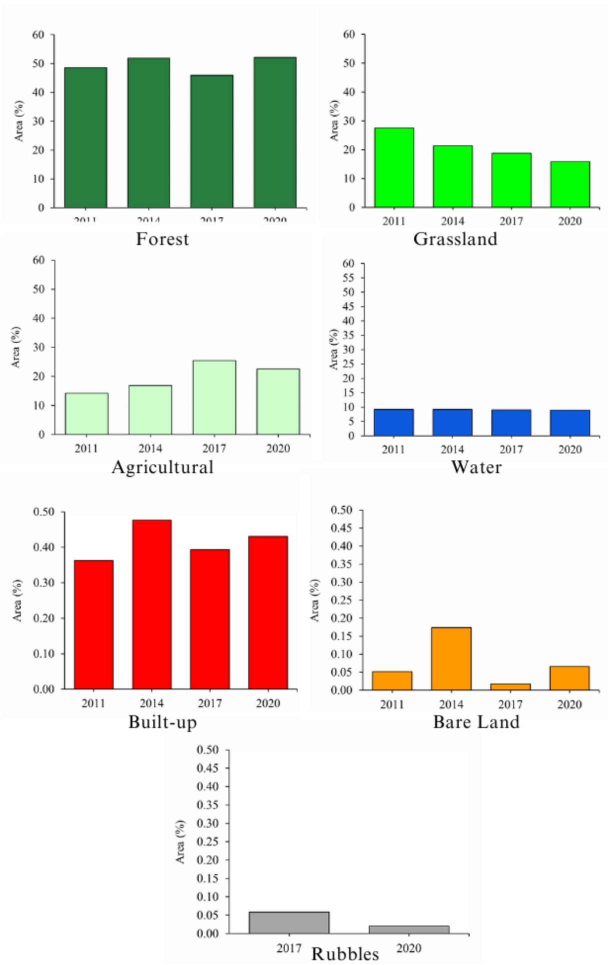

Figure 2. Proportions of each land cover class over the study period. Note that the y-axis in the graphs for bare land, built-up, and rubble are not uniform to the other four classes.

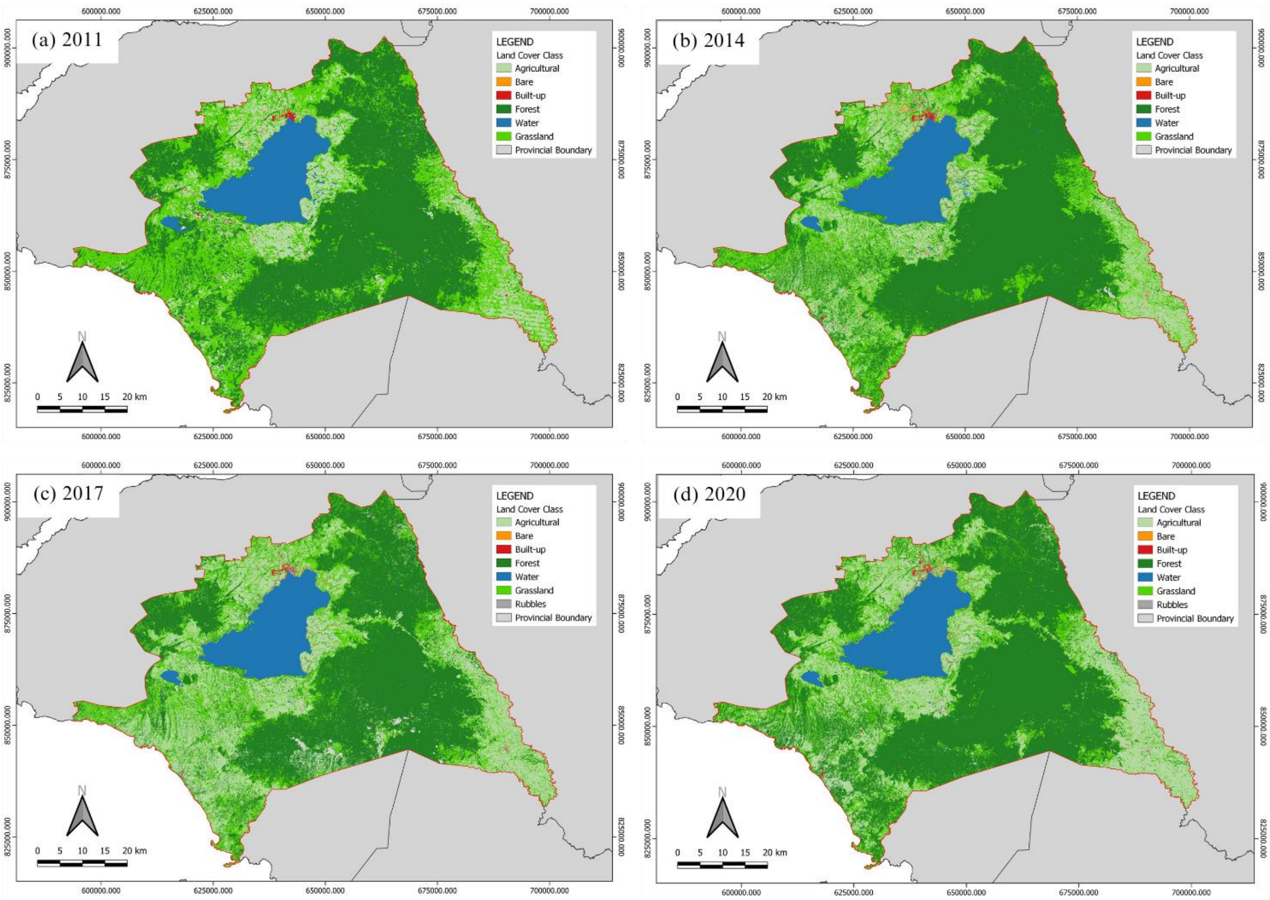

Figure 3. Land cover in Lanao Del Sur for the years: (a) 2011; (b) 2014; (c) 2017; and (d) 2020.

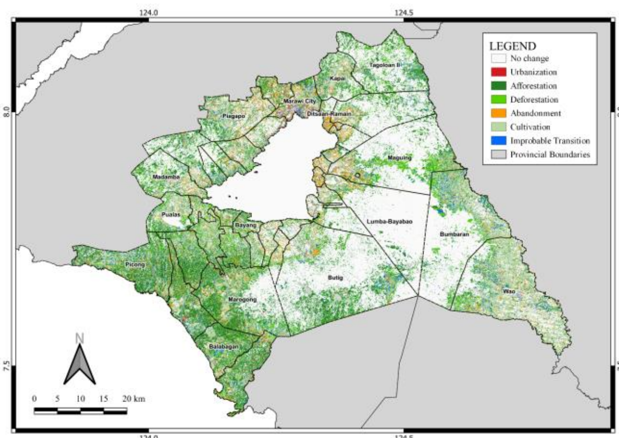

Figure 4. Land cover trajectory map of Lanao del Sur.

No.	Process	Area Percentage (%)
1	No change	55.28
2	Urbanization	0.34
3	Afforestation	16.25
4	Deforestation	5.79
5	Abandonment	4.35
6	Cultivation	13.89
7	Improbable Transitions	3.67

Table 3. Land cover trajectories in Lanao del Sur by percentage.

3.3 Trajectory Analysis and Change Detection

Figure 4 shows the corresponding process experienced by each pixel in the study area based on its land cover trajectory while Table 3 shows the relative area of each process. Despite the numerous conflict incidents in the area, over half of Lanao del Sur did not experience any LCC. Unchanged areas were mainly unpopulated areas, particularly water bodies such as Lake Lanao or forested areas in the municipalities of Lumba-Bayabao and Bumbaran. The two most prevalent LCC processes, afforestation (16.3% of total area), and cultivation (13.9% of total area), were consistently present throughout the study area.

In Marawi City, abandonment was seen in the destruction of built-up areas into rubble in the most affected area (MAA) of the 2017 siege. Areas that experienced abandonment outside of Marawi City were cultivated lands that became grasslands, such as in Gauan and Ditsaan-Ramain. Pixels that experienced abandonment were clustered around water bodies as shown in Marawi City, Ditsaan-Ramain, and the eastern part of Lanao Lake. Coincidentally, these areas were also identified as conflict hotspots.

Less than a percent of the study area was found to have experienced urbanization, mostly found in Marawi City where it could be associated with the rebuilding of the city after the 2017 siege, and in the municipality of Malabang where it could be associated with the expansion of the town proper.

Improbable transitions are also spread throughout the study area. The increased frequency of improbable transitions in Marawi City is due to destroyed built-up areas being classified as either agricultural, bare soil or grassland. Inspection of satellite imagery from 2020 revealed that rubble areas in the most affected area of Marawi City that were being demolished were classified as bare soil while abandoned buildings that have not been developed were either classified as agricultural or grasslands. Due to the confusion between bare and agricultural lands during image classification, several of the rubble were being classified as agricultural lands in 2020 instead of bare land, making the transition improbable (i.e. built-up to agricultural, rubble to agricultural) instead of being classified as abandonment.

In examining the potential impacts of conflict on the land cover processes, certain processes were identified to coincide with each other. Processes involving afforestation and abandonment were often found together, as seen in the municipalities of Picong, Malabang, and Balabagan in eastern Lanao del Sur. This aligns with the observations of Gbanie et al. (2018) where lessened anthropogenic activities in conflict-affected areas led to an increase in forest cover. The decrease in human activities could then be attributed to the abandonment of those areas.

Meanwhile, areas that experienced cultivation were usually bordered by deforested pixels, as seen in municipalities Wao, Bumbaran, and Madamba. These coincide with the observations in Section 4.2 where there was an inverse relationship in the increase of grassland and agricultural areas. Since grasslands serve as the transitions between cultivated agricultural lands and forests, the decrease in grassland cover could also coincide with the decrease in forest cover.

3.4 Spatiotemporal Variation of Conflict and LULC

Barangays with high conflict but low LCC were found to share boundaries with forested areas, as observed in Figure 5. Since forested areas can be hard to access, the changes that happen in these barangays can only be limited to the edges of the forests and the populated areas which can be observed in the municipalities of Tagoloan II, Mamba, and Madalum. This inference can also be applied to the barangays that have moderate conflict but low percent land cover change.

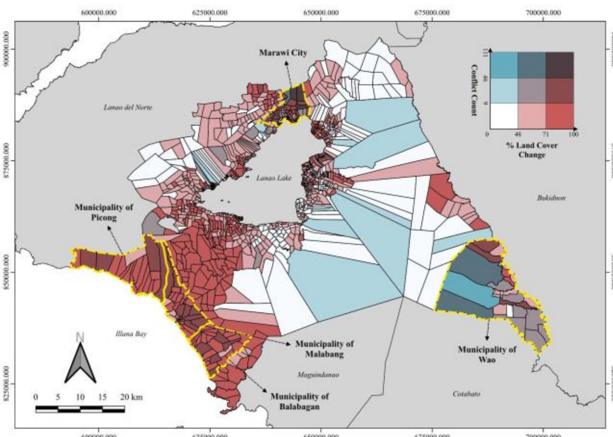

Figure 5. Bivariate choropleth map showing the relationship between conflict count and relative land cover change.

Barangays with low conflict count but moderate to high LCC were mostly in the north- and southwestern portion of Lanao del Sur where majority of the lands are cultivated. Some of these municipalities have barangays that have zero conflict count while some have had low recorded conflict count for the whole decade. Therefore, these land cover changes can occur naturally since these areas are sites for agricultural activities where cultivated crops including annual and perennial crops are planted. However, there are also barangays with moderate conflict and moderate percent land cover change facing the Illana Bay. Food supply is an important economic factor to supply armies in violent conflicts. A study by Weldegiargis et. al (2023) discussed that in a recent and rapid assessment by the Agriculture Bureau in Ethiopia, their findings show that crops and animals were looted or destroyed as also stated by Kemmerling et. al (2022).

Areas with moderate conflict and moderate to high percent land cover change occur primarily along the edges of water bodies such as Lanao Lake and Illana Bay as well as in the eastern and northern fringes of Lanao del Sur. International Alert Philippines (2022) found that municipalities including Wao in the eastern part and Malabang that are facing Illana Bay had an increase of 41% in the average incidents in 2019 compared to the previous years since these are among the areas that are geographically strategic. The municipality of Wao is located at the tri-boundary of Lanao del Sur, Bukidnon, and the province of Cotabato while the municipality of Malabang faces Illana Bay. According to Diakona International Humanitarian Law Centre (2023), water resources can become a source of tension and a critical point for violence between conflicting parties because it is an important resource for survival and coercion. Furthermore, water bodies are also a medium for transportation if transportation by land is avoided, hence, areas near the shores are sites for access. Several studies have found that armed conflict can cause an increase in water pollution (Gbanie et. al, 2018).

Lastly, areas with high conflict counts and moderate to high percent land cover change were primarily found in Marawi City and the municipality of Wao. As previously mentioned, the municipality of Wao is strategically located since it shares the boundary with Bukidnon and the province of Cotabato. Therefore, it can be an entry site among three provinces where violent encounters can occur. Marawi City, on the other hand, is the capital city of Lanao del Sur which is the site of resources and economic activity. The high percent land cover change can be attributed to the fact that the city was a site of urban expansion as well as the battleground for the 2017 Marawi City Siege which resulted in the modification of the landscape in the city. Buildings in the city became damaged and demolished in the aftermath of the conflict. During the post-conflict period, there was an intense rebuilding effort and decreased forest cover in the northern part of Marawi City. Also, upon a visual comparison between the 2017 and 2020 land cover maps, previously agricultural and grassland areas in 2017 were converted into bare lands as rebuilding efforts still continue.

3.5 Conflict Hotspot and Correlation Analysis

Figure 6 shows the barangays identified as conflict hotspots or where high conflict incidence tended to cluster. Comparing the location of conflict hotspots with barangays in Figure 5, hotspots generally coincide with the areas identified with both high magnitudes of land cover change and conflict incidence, as seen in the municipalities of Wao, Malabang, and Marawi City.

However, barangays with low magnitude of LCC did not follow this trend since these municipalities are mainly forests, with populated areas only having a small area relative to the size of the barangays.

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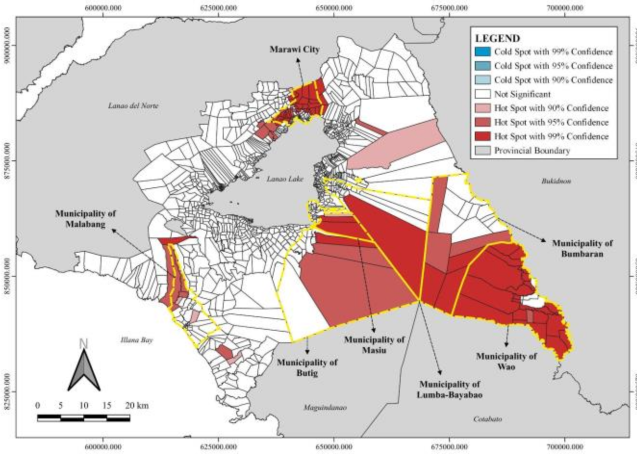

Figure 6. Conflict hotspots in Lanao del Sur

Three clusters of conflict hotspots with different primary land covers were identified. In the mainly built up Marawi City, the construction of housing facilities manifested as urbanization if it is completed before 2020 and as abandonment if it continues after the study period. In primarily cultivated municipalities such as Malabang, afforestation was the main process present. On the ground, this translates to the cultivation and increase in canopy cover of tree plantations. In primarily forested municipalities such as Wao, forests remained unchanged despite the high conflict incidence. These forested areas are mountainous and cannot be easily accessed due to the lack of road infrastructure which may explain why these areas are not affected by conflict. Abandonment manifested from agricultural lands not being cultivated and being converted to grasslands while urbanization heavily depended on the construction of concrete roads and the subsequent construction of more housing structures.

Statistically, the high conflict incidence in these hotspots had a significant positive correlation with land cover change. Table 3 shows the correlation coefficient values for the land processes.

Process	**R**	**P-value (* if p > 0.05)**
Changed	**0.388**	**0.0001**
No change	0.139	0.1822*
Urbanization	0.508	0.0000
Afforestation	0.167	0.1074*
Deforestation	0.265	0.0099
Abandonment	0.533	0.0000
Cultivation	0.546	0.0000
Improbable Transitions	0.427	0.0000

Table 3. Correlation between land processes and conflict count.

Based on the computed area of each process per barangay, all processes except afforestation and no change had a significant positive correlation with conflict occurrences. The total land cover change had a moderate to weak correlation with conflict, with r = 0.388. Non-specific land cover changes are impacted by the direct and indirect effects of conflict (IUCN, 2021). For specific processes, moderately strong relationships with conflict were also found for abandonment (r = 0.533) and cultivation (0.546). Forced displacement causing people to relocate and cultivate other areas has also been observed in Colombia by Camargo et al. (2020). With abandonment and cultivation having similar coefficient values, it is possible that internally displaced persons could have cultivated the areas that they relocated to.

On the other hand, deforestation had a weak correlation with conflict (r = 0.265). Correlating with conflict incidents over the span of a decade, the weak correlation may indicate that conflict mainly affects populated areas and leaves forests relatively unchanged, also evidenced in Figure 4. Gbanie et al. (2018) also noted that deforestation actually slowed down during conflict events due to lessened economic activities and only increased during post-conflict rebuilding efforts, which in this study, only happened from 2017 to 2020.

4. CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

The study analyzed the spatiotemporal variations in Lanao del Sur's land cover using Landsat imagery and conflict incidence data. Temporal analysis of the land cover maps revealed a steady increase in agricultural lands concurrent with a decrease in grasslands, indicating that cultivation converts grasslands adjacent to existing agricultural lands. The steady increase in built-up land was only disrupted by an increase in rubble during peak conflict incidence, coinciding with abandonment that occurred during conflict events.

Spatial analysis of the LC trajectory map showed that areas that underwent afforestation usually also experienced abandonment while areas that underwent cultivation were typically bordered by deforestation. Integrating conflict into spatial analysis, conflict hotspots generally coincide with areas with a high rate of land cover change. The conflict and LULC intensity map also showed that barangays with both high conflict incidence and high magnitude of LCC were located near water bodies and administrative boundaries where transportation may be easily facilitated. However, areas that are mainly forested did not experience a large magnitude of LCC, even when identified as hotspots. Hotspot analysis and correlation showed that land cover change had a significant positive correlation with conflict incidence, especially for the abandonment and cultivation processes.

4.2 Recommendations

For further studies when higher-resolution satellite imagery may be available, it is recommended to use finer spatial resolution in the classification of land cover changes and to use field data for validation to minimize errors and improve accuracy. In correlating conflict events and land cover changes, using different types of clustering methods or spatial relationships in the hot spot analysis of conflict count per barangay and doing pixel-based correlation if possible are recommended. The indirect effects of conflict on the changing landscape may also be explored by incorporating socioeconomic factors.

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