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The Extent of Agricultural Land Cover Change: The Case of Bautista, Pangasinan

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Abstract

Urban Expansion in Bautista periodically alters its land cover, significantly diminishing agricultural land in favor of built-up areas. Therefore, a comprehensive investigation of past and future land cover changes is essential for sustainable development. The main objective of this research is to determine the extent of agricultural land cover change and its spatial pattern from 2018 to 2022 and in the year 2027 in Bautista, Pangasinan. This study employed a descriptive research approach integrating time series data, spatial analysis, and simulation tools to evaluate the dynamic changes in agricultural land cover. The extent of agricultural land cover change decreased from 3,480.95 hectares in 2018 to 3,417.04 hectares in 2022, primarily near road networks and within the identified urban barangays of the municipality. The change exhibited a clustered distribution, as per the summary report from the Average Nearest Neighbor using the Geographic Information System. In contrast, built-up land cover change expanded by 60.68 hectares from 2018 to 2022, following an increasing trend. Furthermore, the projected agricultural land cover change is expected to decrease continuously from 3,417.039 hectares in 2022 to 3,406.875 hectares in 2027. The results indicate a conversion of agricultural land to built-up areas between 2018 and 2022 and a further decrease in 2027, reflecting a shift from agriculture to man-made structures. This research underscores the importance of monitoring land conversions and provides a basis for sustainable solutions to address the growing demand for urbanization without compromising the future extent of agricultural land cover in Bautista, Pangasinan.

Keywords: Built-up areas, Geographic Information System, Spatial pattern, Urban planning, Urban expansion.

Introduction

Land, as defined by Ripke (2016), pertains to the distinguishable portion of the Earth's solid terrestrial surface, not submerged by water bodies. It includes all features of the biosphere, such as vegetation, bare soil, water, and man-made structures (Maina et al., 2020). It is a fundamental natural resource for human survival and development (Zhang et al., 2022). Land objects and key elements characterize the components of land, representing its unique properties and physical aspects. According to Ripke (2016), these elements correspond to a specific characteristic, such as a building serving as an element for a residential area. These elements link to the Earth's land cover and use, denoting surface features like trees and water and identifying the function of the land cover (García-Álvarez et al., 2022).

Both land use and land cover are subject to change over time due to natural and human-induced activities (Bekele et al., 2019). Drivers such as population growth and urbanization change land use and alter land cover (Kamran et al., 2023; Moniruzzaman et al., 2018).

Urbanization, as defined by the United Nations (2019), is a socio-economic process that transforms rural areas into urban settlements, altering the spatial distribution of the population. Global projections estimate that 66 percent of the world's population will reside in urban areas by 2050 (United Nations,2023). The urbanization trend, which has been occurring since 2007, raises concerns about overcrowded cities (Collymore, 2003). Examining population growth and its impact in South Asian countries, Ariani & Susilo (n.d.) focused on Yogyakarta City in Indonesia, where the increasing urban population demands the conversion of agricultural land for residential use.

Despite being an agricultural country with 47% of its land designated as such (FAO, 2023), the Philippines faces a threat to prime agricultural lands due to urbanization. Rapid urban growth demands buildable land to accommodate future development, resulting in agricultural land degradation (Peerzado et al., 2018). From 1988 to 2022, 46,339.38 hectares of agricultural land were approved for non-agricultural use (Marcos, 2023). The demand for land to accommodate population growth has increased land conversion frequency (Harewan et al., 2023).

These agricultural lands are the lands intended for farming activities as per Republic Act No. 6657 (also known as the Comprehensive Agrarian Reform Program Law of 1988) and are not to be used for mineral, forest, residential, commercial, or residential land (Official Gazette, 1998). Nowadays, agricultural lands tend to have high value, making them prime lands for urban development; previous studies showed that agricultural land in East Java, Indonesia, creates more economic value after being converted (Rondh et al., 2018). Sinaga & Dewata (2020) reveal that landowners permit agricultural land conversion for non-agricultural purposes to profit from the sale of their land rather than utilize the land for its intended purpose. In most cases, the low value of land triggers developers to encroach on agricultural lands (European Environment Agency, 2006) and boosts the demand from sectors such as industry, trade, and construction as preferred land for inefficient development for non-agricultural purposes that cause urban sprawl. The results of profit-driven development strategies contribute to continuous agricultural displacement and accelerated urbanization (Jimoh et al., 2020).

Zhang & Li (2022) mentioned that accurate and timely land use and land cover (LULC) maps play a vital role in the community, including urban and regional planning and environmental management. LULC generally refers to the categorization or classification of both human activities and natural elements on the landscape over a given period (SAPALDA, 2023). The LULC can be simulated, predicted, and projected using a multilayer perceptron artificial neural network (MLP-ANN) model (Dumdumaya & Cabrera, 2023) and can measure the distance of change using the Average Nearest Neighbor tool that measures the distance between each feature centroid and its nearest neighbor's centroid location (ESRI, 2005). The transformation of agricultural land into non-agricultural uses results in LULC change, exemplified by the Greater Jakarta Metropolitan Area in Indonesia where agricultural lands are converted into built-up areas like residential and industrial developments (Indrawan et al., 2022). The interconnected nature of land use and land cover is evident, where alterations in one can influence the other, leading to changes in the Earth's surface. Aside from tools to determine LULC, a framework like the Driver, Pressure, State, Impact, and State (DPSIR) model is used in research to link scientific findings with "real world issues'', how human society affects the environment (Kelble et al., 2013).

The Philippines has grappled with extensive land conversion, particularly in Luzon, accounting for 80.6% of approved land conversions, followed by Mindanao with 11.6% and Visayas with 7.8% (Simeon, 2019). The agricultural sector faces challenges due to widespread land conversion for new developments, driven by the creation of megacities in the Philippines, resulting in high-density settlements (Edelman, 2016). The construction acceleration is evident in the issuance of 37,329 building permits in 2022, with residential buildings dominating (Philippine Statistics Authority, 2023).

Manila, the capital, faces the pressure of rapid urbanization, leading to squatter residential areas and subdivision developments

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(Murakami & Palijon, 2018). The Mega Manila Dream Plan 2030 aims to address the effect of rapid urbanization by creating a polycentric region, but research predicts a substantial shift from agriculture, causing a 56% loss of agricultural land between 2010 and 2030 while 36% is gained in built-up areas (Shatkin & Mouton, 2020; Mishra et al., 2019).

In Bautista, Pangasinan, with limited land area and a growing population, linear development along roads has reduced agricultural land from 83.75% in 2010 to 80% in 2013. The municipality's land development pattern, characterized by institutional, commercial, residential, and industrial areas, has impacted agricultural activities. This study aims to determine the extent and spatial pattern of land cover change from 2018 to 2022 and its potential agricultural land cover changes in 2027.

Materials and Methods

This study employed a descriptive research approach integrating time series data, spatial analysis, and simulation tools to evaluate the dynamic changes in agricultural land cover within Bautista, Pangasinan, spanning from 2018 to 2022, with a projection for 2027. The detailed methodology is outlined below to fulfill the stated objective.

Agricultural Land Cover Change from 2018 to 2022. Raster files that are accessible were utilized and transformed into vector files to calculate the area of each designated polygon per land cover class in the attribute table. The process quantified and mapped changes in land cover from 2018 to 2022 in Bautista, Pangasinan. The documented alterations in land cover were presented in tabular form, while the geographical locations of changes can be visually examined through the creation of category maps.

The evaluation of agricultural land cover changes in Bautista, Pangasinan, between 2018 and 2022 was conducted using available Environmental Systems Research Institute (ESRI) Land Use/Land Cover (LULC) data. The study will leverage two types of Geographic Information System (GIS) data: raster and vector files. Raster files consist of pixels arranged in rows and columns, each cell holding a specific value. In contrast, vector files represent geometric data types such as points, lines, and polygons, visible in their attribute tables.

Each raster and vector dataset was comprised of at least three files: one storing the geometry of digital features, another containing an index for rapid access to spatial features, and the third holding attribute information. The fundamental distinction lies in the composition, where raster files consist of pixels, and vector files consist of paths.

Utilizing Land Use/Land Cover (LULC) data from the Sentinel-2 10m Land Use/Land Cover Timeseries Downloader is crucial for monitoring changes in a specific area. This data displays a global map of LULC derived from ESA Sentinel-2 imagery at a 10m resolution, predicting 10 classes throughout the year. However, for Bautista, Pangasinan, there are five identified classes, including water, trees, grass, crops, and built-up areas.

The available raster file can be downloaded and extracted using the Municipal boundary vector file of Bautista, Pangasinan. After reclassifying based on LC 2020 (Mature Support) values through Quantum Geographic Information System, the reclassified raster will be converted into vector files to calculate the area of each assigned polygon per land cover class in the attribute table.

Results of agricultural land cover changes and their extent from 2018 to 2022 were presented in time series maps and tables for differentiation. In these maps, various colors represent specific land cover types: red for built-up areas, orange for crops, yellow for grass, green for trees, and blue for water. The color scheme is based on the standard colors of the United States Geological Survey (USGS) in modeling Land Use/Land Cover (LULC) maps.

The five contextual land cover classifications for Bautista were based on the Life Cycle (LC) 2020 (Mature Support) and are defined as follows: 1. Water: Areas predominantly covered by water throughout the year, excluding sporadic water; little to no sparse vegetation; no rock outcrop or built-up features. 2. Trees: Significant clustering of tall, dense vegetation with a closed or dense canopy. 3. Grass: Open areas covered in homogeneous grasses with little to no taller vegetation. 4. Crops: Human-planted/plotted cereals, grasses, and crops not at tree height. 5. Built Area: Human-made structures, major road and rail networks, large homogeneous impervious surfaces.

Spatial Pattern of Changes in Agricultural Land from 2018 to 2022. Two

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crucial processes in understanding the spatial patterns of agricultural land cover changes from 2018 to 2022 involve quantifying the distribution of land cover and mapping points of change. The time series data on agricultural land cover changes, obtained from previous outputs, were pivotal in comprehending the spatial patterns of changes in agricultural land in Bautista, Pangasinan. The initial step involves quantifying spatial patterns to illustrate the shifting and distribution of land cover types in four specific periods. This analysis includes assessing and interpreting the transition of land cover changes by determining the net change. The quantified distribution was presented through transitional maps.

Transition maps, generated by intersecting the land cover of the preceding year with that of the succeeding year, determine the transitions of agricultural land to other land use types and vice versa. The resulting layer, displaying polygons indicating potential changes, was overlaid onto the preceding year's data to create a comprehensive map. Furthermore, mapping the points of change contributes to understanding the pattern of land cover changes from 2018 to 2022. The analysis of agricultural land use change patterns was processed through the Average Nearest Neighbor ArcGIS plugin. This tool measures the distance between each feature's centroid and the centroid location of its nearest neighbor (ESRI, 2005). The tool calculates distances between points, yielding five computed values that indicate whether the points are clustered or dispersed on the map.

The time series data of agricultural land cover changes from 2018 to 2022, derived from the previous output, were employed to understand the spatial patterns of changes in agricultural land in Bautista. Vector files for each period, spanning from 2018 to 2022, were imported into ArcGIS for the calculation of point distances. The distances of points were analyzed to provide insights into the patterns, indicating whether they exhibit a clustered or dispersed distribution. Vector datasets representing land cover changes from 2018 to 2022 were scrutinized to determine the average nearest-neighbor ratio. This ratio is computed by dividing the observed average distance by the expected average distance (ESRI, 2005), where the expected distance represents the average distance between neighbors in a hypothetical random distribution. The Average Nearest Neighbor ratio is given in Equation 1.

Given that Average Nearest Neighbor ratio:

$$\boldsymbol{ANN} = \frac{\bar{D}o}{\bar{D}e}$$

where Do is the observed mean distance between each feature and its nearest neighbor

$$\bar{\boldsymbol{D}}\boldsymbol{o} = \frac{\sum_{i=1}^{n} di}{n}$$

where Do is the observed mean distance between each feature and its nearest neighbor

$$\bar{\boldsymbol{D}}\boldsymbol{e} = \frac{0.5}{\sqrt{n/A}}$$

In the above equations, d equals the distance between feature i and its nearest neighboring feature, n corresponds to the total number of features, and A is the area of a minimum enclosing rectangle around all features, or its user-specific Area value

The average nearest neighbor z-score for the statistic is calculated as:

$$\% = \frac{\bar{D}o - \bar{D}e}{Se}$$

$$\boldsymbol{Se} = \frac{0.26136}{\sqrt{n^2/A}}$$

Interpretations of calculated values for the average nearest neighbor are as follows (see also Figure 1). 1). If the index (average nearest neighbor ratio) is less than 1, the pattern exhibits clustering; 2). and if the index is greater than 1, the trend is toward dispersion.

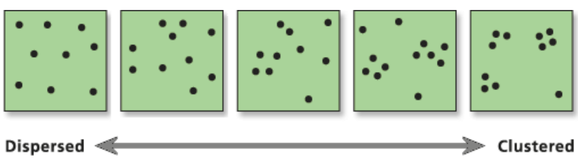

Figure 1. Illustration of dispersed and clustered distribution using the Average Nearest Neighbor Tool Source: Pro.Arcgis.co, n.d.

Moreover, in cases where points exhibit an average distance less than the expected average for a hypothetical random distribution, the distribution is categorized as clustered. Conversely, if the average distance exceeds

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that of a hypothetical random distribution, the features are deemed dispersed. The Average Nearest Neighbor tool interpreted the computed values to generate a diagram, illustrating the observed mean distance, expected mean distance, nearest neighbor index, z-score, and p-value. This diagram serves as a comprehensive representation of the spatial pattern analysis, aiding in the determination of whether the observed agricultural land cover changes display clustering or dispersion tendencies.

Projection of Agricultural Land Cover Changes by 2027. The previously obtained results from relative spatial maps were the basis to simulate the potential changes in agricultural land use development in 2027. This study aims to generate a prospective land cover map for Bautista in 2027, utilizing data from 2018 and 2022 along with selected variables. The variables considered in this analysis are: 1. Elevation, 2. Slope, 3. Aspect, 4. Distance from road network, 5. Distance from water bodies, 6. Population per barangay, and 7. Population density per barangay. The datasets for land cover changes in 2018 and 2020 were initially utilized to create the 2022 land cover map. This step serves to validate whether the chosen variables and parameters can yield a meaningful outcome for generating the 2027 land cover map.

To simulate the prediction of land cover change in 2022, the study employed the Artificial Neural Network (ANN) – Multilayer Perceptron (MPL) model through the Method of Land Use Change Evaluation (MOLUSCE) plugin in the Quantum Geographic Information System (QGIS), as illustrated in Figure 2.

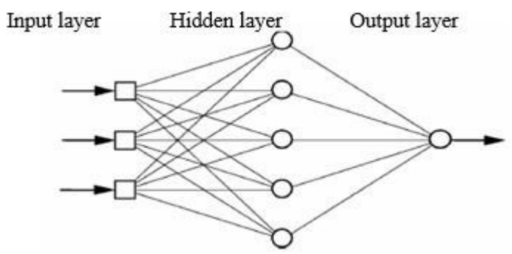

Figure 2. Artificial Neural Network (ANN) Multilayer Perceptron (MLP).

This modeling approach allows for a comprehensive analysis of land cover changes based on the specified variables, contributing to the projection of potential developments in agricultural land use in 2027 for Bautista.

The generation of the 2022 land cover map involved multiple iterations, each producing corresponding kappa values. In this context, iteration refers to the process of running the model multiple times to simulate potential land cover changes. The kappa statistic, a measure of inter-rater reliability, was employed to assess the correctness and accuracy between the generated 2022 land cover data and the actual 2022 land cover data. The kappa values obtained for each scenario with different iterations underwent validation, and the results were collected and interpreted using Cohen's kappa coefficient. This approach ensures a robust evaluation of the model's performance in predicting land cover changes and provides insights into the reliability and consistency of the simulated outcomes. Cohen, the creator of Cohen's kappa, suggested the following interpretations for kappa results:

value ≤ 0	no agreement
0.01 – 0.20	none to slight agreement
0.21 – 0.40	fair agreement
0.41 – 0.60	moderate agreement
0.61 – 0.80	substantial agreement
0.81 – 1.00	Perfect agreement

The differences in land cover area between the generated and actual 2022 land cover data were compiled in table form to facilitate a proper comparison in terms of area (hectares) across different iterations. If the results demonstrate strong evidence of reliability, such as high Cohen's kappa values, it can be concluded that the actual 2018 and 2022 land cover data is reliable for generating the 2027 land cover map under various iteration scenarios.

Simulation parameters for simulating the 2027 land cover map were set based on reliable data from the four iteration scenarios. These outputs were further validated by determining their kappa values, and the iteration with the highest kappa value was considered the most reliable for generating the 2027 land cover data. Subsequently, this reliable data was translated into a category map.

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Results and Discussion

This section presents the results and findings of the study about the three aims to determine the extent of agricultural land cover change from 2018 to 2022, the spatial pattern of changes, and the probable extent of agricultural land cover change in 2027.

The Extent of Agricultural Land Cover Change from 2018 to 2022. The ESRI 10x10m pixel land cover map was employed to assess agricultural land use in Bautista, Pangasinan. Figure 3 illustrates changes in land cover through five consecutive annual category maps from 2018 to 2022, offering visual insights into the study area's transformations ESRI identifies five land cover classes in Bautista, Pangasinan: built-up area (depicted in red), crops/agricultural area (in orange), water bodies (in blue), grassland (in yellow), and trees (in green).

The visual analysis of land cover changes in the municipality of Bautista indicates a moderate shift over the five consecutive years, from 2018 to 2022. Built-up areas exhibit minimal movement encroaching on agricultural lands but contribute to the decline of agricultural land cover in Bautista, Pangasinan.

Grass and tree classes show a gradual decrease based on the 2018 and 2022 land cover maps. Conversely, the land cover occupied by water has increased, particularly in the southeastern portion of the municipality's political boundaries. According to readings from PAGASA (n.d.), the notable changes in water in this area are attributed to the Poponto swamp, located at the confluence of the Agno and Tarlac rivers, marking the boundary of Tarlac and Pangasinan.

Table 1 displays the area statistics for Bautista, Pangasinan, from 2018 to 2022 in hectares and their corresponding percentages. Agricultural land dominates the land cover, constituting 82% or 3,417 hectares of the total land cover as of 2022, reflecting the municipality's predominantly agricultural nature. However, a gradual decrease in crop area is observed, with the total agricultural land cover decreasing from 84.25% to 82.68% over the five years, representing a 1.57% difference.

In terms of area, agricultural land declined from 3,480.95 hectares in 2018 to 3,417.04 hectares in 2022. Conversely, built-up areas experienced steady growth, increasing from 12% or 509.85 hectares to almost 14% or 570.18 hectares of the total land area in 2022. The 2% increase in built-up areas is concentrated near identified urban barangays in Bautista and encompasses impervious areas, residential, commercial, and other infrastructure. The percentage of built-up areas in the municipality rose from 12.34% in 2018 to 13.80% in 2022, marking a 1.46% increase over the same period. In terms of area, built-up areas increased from 509.85 hectares in 2018 to 570.13 hectares in 2022.

Other identified land covers, namely grass and trees, exhibit a continued decrease, while the water area expands. Grassland decreased from 10.51 hectares in 2018 to 3.07 hectares in 2022, and trees decreased from 20.83 hectares in 2018 to 18.51 hectares in 2022. Meanwhile, the water area in the municipality expanded from 109.70 hectares in 2018 to 123.91 hectares in 2022.

Table 2 details the area changes per period and the corresponding percentage changes that occurred from year to year. Built-up areas exhibited a steady increase from 2018 to 2022, with a total growth of 60.28 hectares or 11.39%. The most significant change, 5.85%, transpired in 2018-2019, while the least change of 1.20% occurred in 2020- 2021, attributed to the COVID-19 pandemic causing development delays and a decline in building permits.

Crops, overall, showed a declining trend, except for a temporary increase from 2019 to 2020. The total crop area decreased by 64.01 hectares or -1.84%. Climatic conditions and drought in 2019 influenced this decline, affecting agricultural land expansion. Grass cover displayed a decreasing pattern from 2018 to 2020 but increased from 2020 to 2022, possibly due to pandemic-related disruptions in land activities. The grass cover increased by 120.89%, with a significant 176.84% change in 2020-2021 during the height of the pandemic. Trees experienced an overall decrease of 6.62%, with a slight increase observed during the pandemic in 2020-2021.

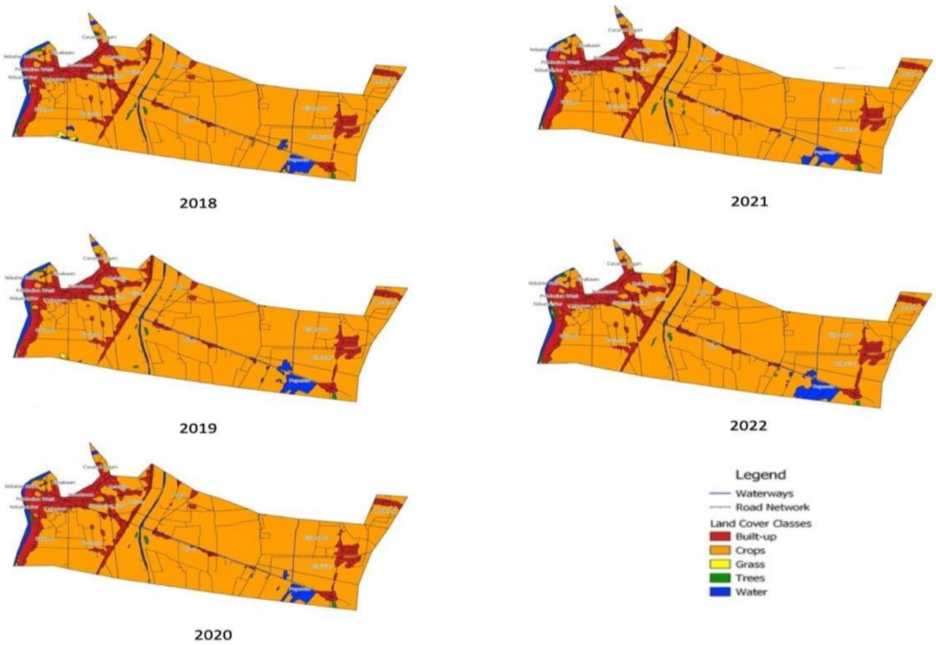

Figure 3. The extent of land use from 2018 to 2019

Table 1. Area in hectares of the identified extent of land cover in Bautista from 2018-2022

Class	2018	%	2019	%	2020	%	2021	%	2022	%
Built-up	509.85	12.34	539.68	13.06	552.55	13.37	559.16	13.53	570.13	13.80
Crops	3480.95	84.25	3444.29	83.35	3457.89	83.68	3455.26	83.61	3417.04	82.68
Grass	10.51	0.25	4.31	0.10	0.95	0.02	2.63	0.06	3.07	0.07
Trees	20.83	0.50	15.74	0.38	16.80	0.41	19.62	0.47	18.51	0.45
Water	109.70	2.65	128.11	3.10	103.94	2.52	95.84	2.32	123.91	3.00

Table 2. Percent change in land cover from 2018 to 2022

	2018-2019		2019-2020		2020-2021		2021-2022		Total	Total %
Class	∆A (ha)	%	∆A (ha)	%	∆A (ha)	%	∆A (ha)	%	∆A	
a. Built-up	29.83	5.85%	12.87	2.38%	6.61	1.20%	10.97	1.96%	60.28	11.39%
b. Crops	-36.66	-1.05%	13.60	0.39%	-2.63	-0.08%	-38.22	-1.11%	-64.01	-1.84%
c. Grass	-6.20	-58.99%	-3.36	-13.69%	1.68	176.84%	0.44	16.73%	-7.44	120.89%
d. Trees	-5.10	-24.48%	1.06	6.73%	2.82	16.79%	-1.11	-5.66%	-2.33	6.62%
e. Water	18.41	16.78%	-24.17	-18.87%	-8.10	-7.79%	28.07	29.29%	14.21	19.41%

To correlate the extent of agricultural land cover results with the farmers-to-agricultural land ratio, Table 3 presents the distribution of the total number of farmers across the 18 barangays in Bautista, Pangasinan. As of 2022, the Office of the Department of Agriculture in the municipality recorded 1,792 farmers, with Barangay Diaz having the highest number and Barangay Nibaliw Norte having the lowest.

The agricultural land cover from 2018 to 2022 was reported to be 82%, equivalent to 3,417 hectares out of the total land cover in 2022. The Office of the Department of Agriculture in Bautista indicated an increase in the number of farmers, rising from 1,125 in 2010 to 1,792 in 2022. Based on the gathered data, the estimated farmers-to- agricultural land ratio stands at 1:2, signifying one farmer for every two hectares. This indicates a decline in the ratio from 1:3 in 2010 to 1:2 in 2022. The ratio is calculated by dividing the total agricultural land by the total number of farmers.

The Spatial Pattern of Agricultural Land Cover Change from 2018 to 2022. Land cover changes over time, driven by underlying spatial processes that influence its distribution. Accurate quantification of the dynamics of spatial patterns is crucial to comprehend the implications, such as the outcomes of land cover changes and the services it provides. Analyzing spatial patterns involves identifying the arrangement of individual entities in space and understanding the geographic relationships among them. In the case of Bautista from 2018 to 2022, the research quantifies and locates the changes in agricultural land cover to determine their spatial patterns.

Table 4 reveals that areas transitioning from crops to other land covers surpass those transitioning to crops. Notably, the increase from crops to built-up areas is more significant than other transitions, indicating the ongoing conversion of agricultural areas to built-up spaces each year

Table 3. The number of farmers distributed in 18 barangays of Bautista, Pangasinan 2022

BARANGAY	NUMBER OF FARMERS
Artacho	130
Baluyot	134
Cabuan	52
Cacandungan	29
Diaz	346
Ketegan	61
Nadacan	22
Nibaliw Norte	17
Nibaliw Sur	10
Palisoc	119
Poblacion East	27
Poblacion West	26
Pogo	134
Poponto	87
Primicias	174
Sinabaan	17
Vacante	128
Villanueva	249
Total No. of Farmers	**1,792**

Table 4. The quantification of land cover shifting and their distribution from 2018 to 2022

2018-2019 Transition	Area (ha)	2019-2020 Transition	Area (ha)	2020-2021 Transition	Area (ha)	2021-2022 Transition	Area (ha)
Crops to Built-up	35.51	Crops to Built-up	25.67	Crops to Built-up	23.17	Crops to Built-up	27.26
Crops to Grass	0.41	Crops to Grass	0.19	Crops to Grass	1.10	Crops to Grass	0.03
Crops to Trees	2.46	Crops to Trees	2.86	Crops to Trees	5.15	Crops to Trees	2.99
Crops to Water	27.31	Crops to Water	3.65	Crops to Water	9.01	Crops to Water	34.27
Grass to Crops	5.73	Grass to Crops	3.13	Grass to Crops	0.50	Grass to Crops	0.05
Trees to Crops	6.37	Trees to Crops	2.99	Trees to Crops	3.34	Trees to Crops	4.97
Water to Crops	9.09	Water to Crops	25.79	Water to Crops	14.19	Water to Crops	5.98

Notably, the increase from crops to built-up areas is more significant than other transitions, indicating the ongoing conversion of agricultural areas to built-up spaces each year. Although a substantial portion of croplands is converted to built-up areas, the areas converted to crops are comparatively smaller. Studies indicate that agricultural land expansions lead to a decline or negative growth in land covers dedicated to agriculture, such as trees, grass, and water (Daba & You, 2022, p.20). Figure 4 illustrates the transition maps of land cover changes from 2018 to 2022, supporting the recorded data in Table 4.

Transition maps in Figure 4 visually present the distribution of one land cover type transitioning to another. The depicted land cover change transitions include crops to built-up; crops to grass; crops to trees; crops to water; grass to crops; trees to crops; and water to crops. The clear transitions of crops to built-up areas and crops to water are visually evident on the transition maps, indicating a decrease in agricultural land cover from 2018 to 2022.

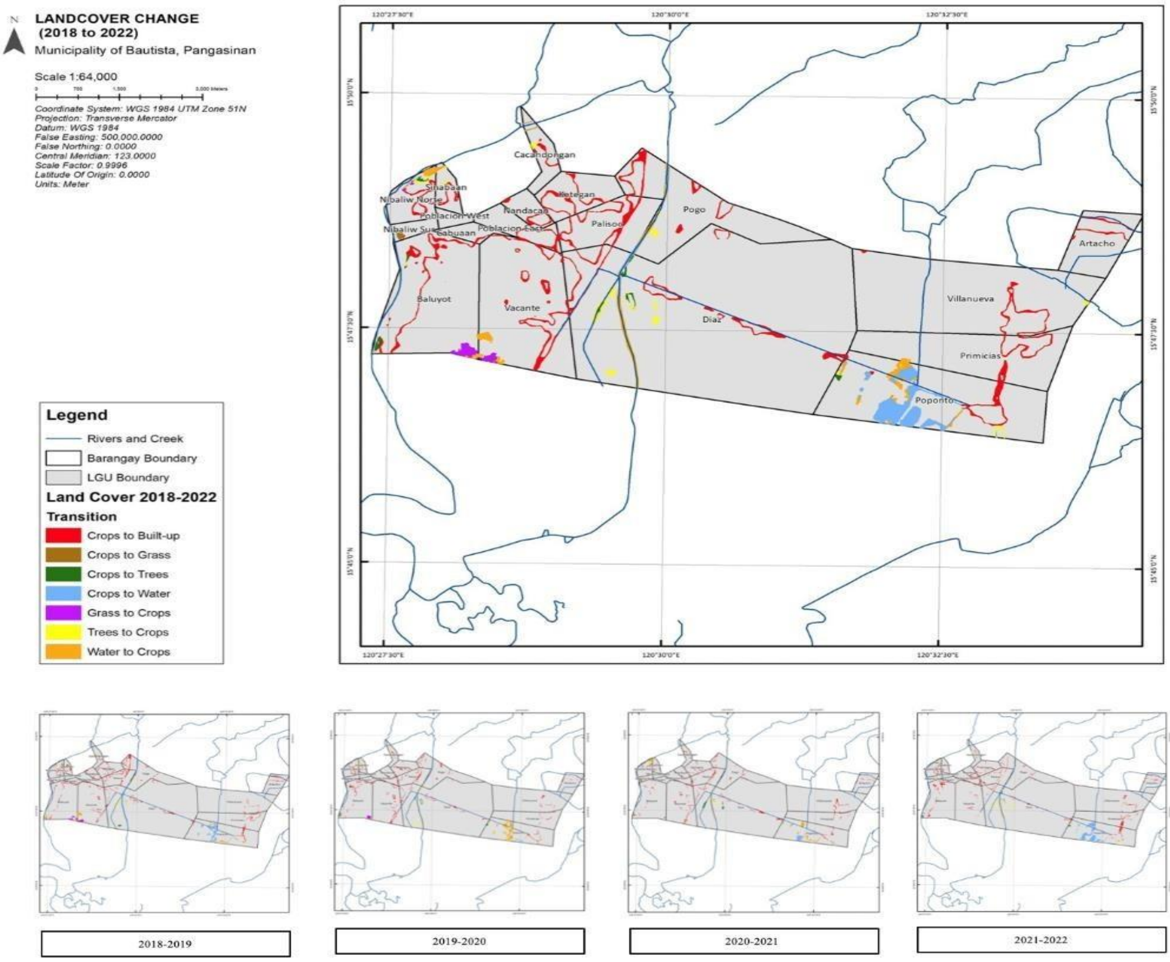

Figure 4. Transition map of land cover changes from 2018 to 2022

To further analyze the transitions concerning agricultural land cover, net changes of land covers to crops and vice versa are presented in Table 5. Positive values indicate that there was a net increase in crop areas, while negative values indicate a net decrease.

The total crop areas converted to built-up ones totaled 111.61 hectares, reflecting a decrease in areas dedicated to agriculture in favor of man-made infrastructure. The most significant conversion occurred 2018 to 2019, coinciding with the Build-Build-Build program of the incumbent president during those years. There were increases in crop areas converted from grass and trees, indicating efforts to enhance land productivity or explore alternative areas for agriculture. While some grass and tree lands were converted to crops, certain croplands were transformed into water (swamps), with the most substantial conversion observed from 2021 to 2022. This suggests that while the productivity of some croplands have been reduced to water, there is potential for restoring their productivity, thereby increasing agricultural areas in the future.

Table 5. Net changes concerning crops

Net Changes in Crop Areas	2018-2019 (ha.)	2019-2020 (ha.)	2020-2021 (ha.)	2021-2022 (ha.)	Total 2018-2022 (ha.)
Crops to Built-up	-35.51	-25.67	-23.17	-27.26	-111.61
Grass to Crops- Crops to Grass	5.32	2.94	-0.6	0.02	7.68
Trees to Crops- Crops to Trees	3.91	0.13	-1.81	1.98	4.21
Water to Crops- Crops to Water	-18.22	22.14	5.18	-28.29	-19.19
Total net changes (ha.)	-44.5	-0.46	-20.4	-53.55	-118.91

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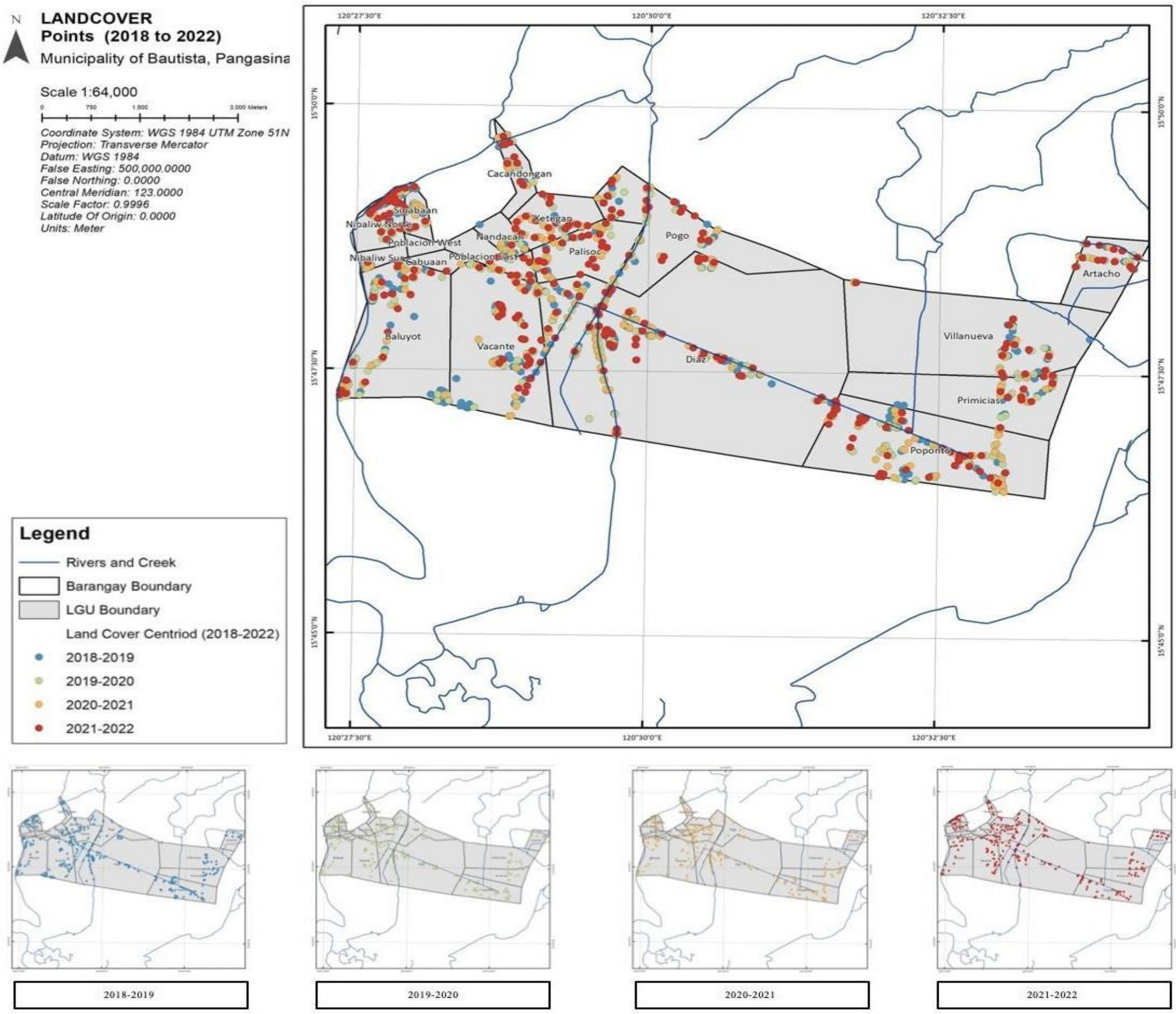

Figure 5. The physical location of changes in land cover from 2018 to 2012

Each point on the map in Figure 5 represents a specific distance generated by the Average Nearest Neighbor tool in ArcGIS, measuring the distance between each feature and its nearest neighbor's centroid location. Four distinct colors differentiate four specific periods: blue (2018 to 2019), green (2019 to 2020), yellow
(2020 to 2021), and red (2021 to 2022).

The findings reveal that most agricultural land cover changes occurred near road networks, particularly in urban barangays, as depicted in Figure 5. Preceding the expansion of built-up areas in urban barangays, there was a notable reduction in agricultural land cover. Bagarinao's study (2015) noted that the conversion of agricultural land and the establishment of large-scale built-up areas primarily took place in barangays experiencing significant changes in population sizes.

For instance, Barangay Canlubang, identified as an urban barangay with the highest population change between 2003 and 2010, witnessed approximately 19% of total land conversion from annual cropland to built-up areas in 2010.

Additionally, the 'Sector Theory' by Homer Hoyt in 1939 suggests that sectors tend to grow along transportation routes as they represent lines of least resistance (McDonagh, 2007). Research by Fakhruddin and Gultom (2021) supports this notion, indicating that the construction of the Trans Java toll road led to an expansion of built-up land, signifying that economic forces drive increased urbanization (McDonagh, 2007).

The spatial pattern of land use change from 2018 to 2022 was examined using the Average Nearest Neighbor Summary results, based on the earlier extent of land cover change data. The summary results present five values for each period: observed mean distance, expected mean distance, nearest neighbor ratio, z-scores, and p values. Generally, when the average

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distance is less than the average hypothetical random distribution, it signifies a clustered pattern. This suggests that the physical location of land cover changes occurred in contiguous areas from 2018 to 2022.

The Potential Extent of Agricultural Land Cover Change in 2027. Table 6 presents the kappa values obtained for each scenario involving different numbers of iterations using the Multilayer Perceptron - Artificial Neural Network (MLP-ANN).

The process employed utilized prior land use data, specifically spanning from 2018 to 2019, to simulate the 2022 land cover map. Various iteration scenarios—(A) 500; (B) 1000; (C) 1500; and (D) 2000—were adjusted within the Modules for Land Use Change Evaluation (MOLUSCE) plugin to generate the 2022 land cover map, along with corresponding kappa value results. All iteration scenarios produced acceptable kappa values in the Multilayer Perceptron - Artificial Neural Network (MLP-ANN) context, ranging from 0.77 to 0.96. These values indicate substantial agreement (0.60 – 0.80) to almost perfect agreement (0.81 – 1.00), as per the Cohen kappa values interpretation.

The generated land cover data results and the actual land cover data were validated to determine the percentage of accuracy for each iteration scenario, as illustrated in Table 7.

This validation aimed to assess the accuracy of simulating the 2027 land cover map. The results of each iteration scenario consistently yielded a correctness/accuracy value of 97%.

Based on the result of the different simulation parameters, it shows minimal variation in area size between the simulated and actual 2022 land cover maps. Table 8 exhibits the difference between the generated 2022 land cover maps compared to the actual land cover map in different iteration scenarios.

Since the results indicate that the actual and generated land cover maps in 2022 have minimal area differences and a high accuracy percentage, the actual land cover maps from 2018 and 2022 can be used as a basis to generate the 2027 land cover map across all given iteration scenarios. Figure 6 displays the generated 2027 land cover map for Bautista, Pangasinan, across different iteration scenarios

Table 6. Kappa Value of the four scenarios in MLP-ANN

Scenario	Number of Iterations	Kappa Value
A	500	0.77255
B	1000	0.80517
C	1500	0.96467
D	2000	0.80960

Table 7. Kappa Value of the four scenarios upon validation

Scenario	Number of Iterations	Kappa Value
A	500	97.22249
B	1000	97.22249
C	1500	97.22443
D	2000	97.21717

Table 8. Comparison of the generated 2022 land cover map and the actual land cover map

Class	Actual Area of 2022 Land Cover (ha)	Area generated in 2022 (ha) based on the number of iterations			
		A. 500	**B. 1000**	**C. 1500**	**D. 2000**
Built-up	570.13	552.551	552.551	551.329	552.551
Crops	3417.039	3458.12	3457.891	3459.114	3457.891
Grass	3.072	0.948	0.948	0.948	0.948
Trees	18.507	16.716	16.802	16.802	16.802
Water	123.907	103.802	103.944	103.944	`103.944

Table 9 illustrates substantial results in scenarios A, C, and D, ranging from 0.61 to 0.80. Notably, Scenario B stands out with the highest kappa value of 0.83832, indicating almost perfect accuracy. In 2027, Scenario B projects growth in built-up area from 570.13 hectares in 2022 to 596.761 hectares, a decrease in agricultural land from 3,417.039 to 3,406.875 hectares, affecting the farmers-to-agricultural land ratio. Additionally, grass area is projected to decrease from 3.072 to 1.972 hectares, trees from 18.507 to 2.134 hectares, and water area to increase from 123.907 to 124.913 hectares.

The projection spans a 5-year interval from 2022 to 2027, aligning with the typical timeframe in land cover change studies (Roy et al., 2021). Notably, urban barangays in the municipality witness a shift from agricultural land to built-up areas. Considering the potential conversion of the nearby municipality, Bayambang, into a component city (Pasiliao, 2021), there is a possibility of expanded built-up areas between their political boundaries.

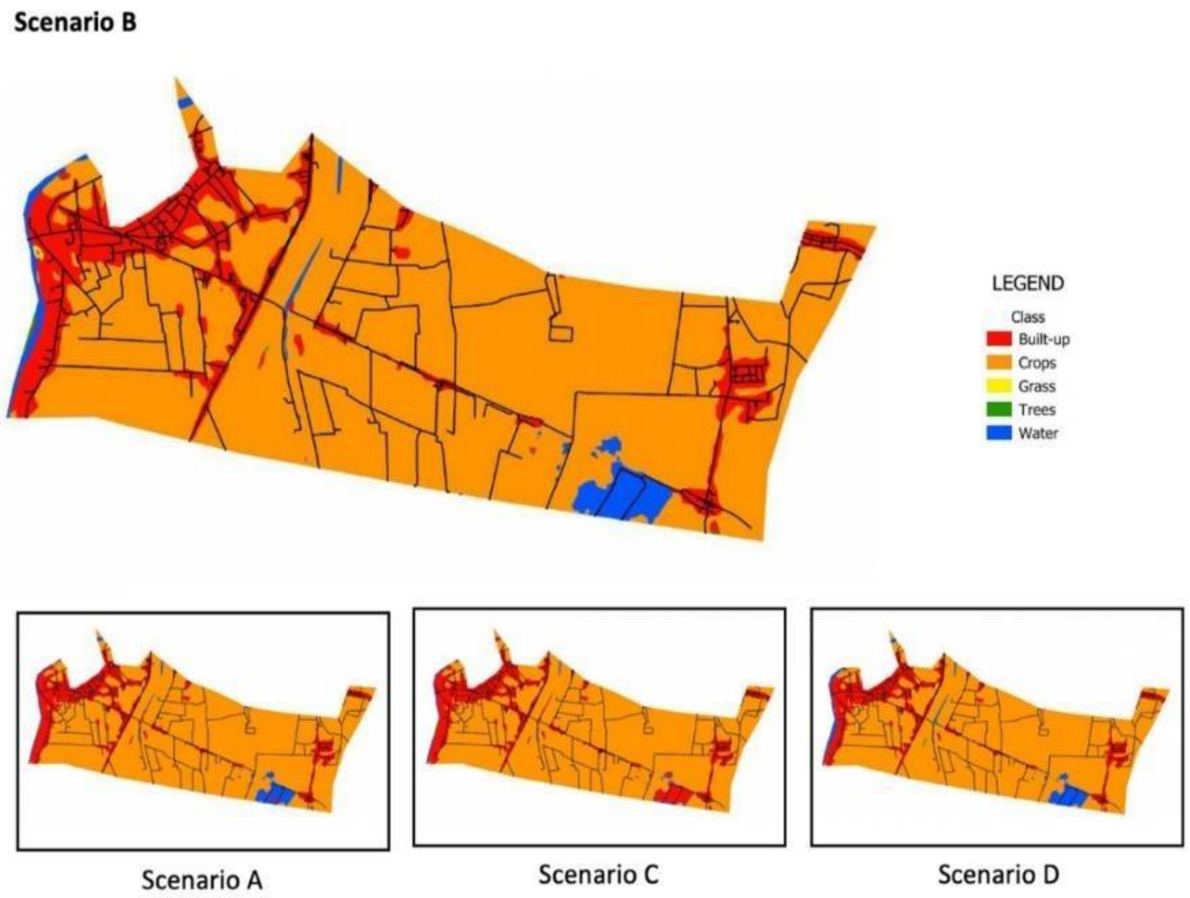

Figure 6. Predicted 2027 Land Cover Map in (4) four iteration scenarios

Table 9. Area per hectare of the 2027 land cover map generated from different iteration scenarios

Class	Area ha. (Based on the number of iterations)							
	A 500	Kappa Value	B 1000	Kappa Value	C 1500	Kappa Value	D 2000	Kappa Value
Built-up	619.678	0.76204	596.761	0.83832	684.056	0.76509	584.344	0.74619
Crops	3409.052		3406.875		3409.1381		3416.730	
Grass	0		1.972		0		0.306	
Trees	3.518		2.134		3.653		8.118	
Water	100.406		124.913		35.807		123.157	

The result of the generated 2027 land cover data was further explored using regression analysis, Table 10. The regression analysis was done through Jamovi analytical software (2022) to determine the land cover classes that are associated with crops.

The regression analysis indicates that the land covers built-up, grass, and water jointly have an effect on the size of crop areas as indicated from the data.

An increase in built-up areas decreases crop areas, a decrease in grass areas increases crop areas, and an increase in water (swamp) areas decreases crop areas. Tree land cover changes do not have a significant effect on the changes in croplands. Both regression analysis results and the generated 2027 land cover data provide the same findings.

Table10. Predictor variables of crop areas

Land Cover	P-value	At 5% Significance level
Built-up	0.012	Significant
Grass	0.044	Significant
Water	0.012	Significant
Trees	0.478	Not Significant

Conclusion

The study assessed agricultural land cover changes in Bautista, a key agricultural municipality in the Philippines. Mapping these changes provides a baseline for studying the local and global impacts of anthropogenic activities altering the Earth's surface. Urban expansion in Bautista poses a threat to agricultural land, leading to its conversion for non- agricultural purposes. The recorded change in agricultural land cover from 2018 to 2022 was a decrease from 3,480.95 to 3,417.04 hectares. Urban expansion, driven by increased demand for buildable areas, resulted in a 5.85% change rate in built-up areas from 2018 to 2019, with a consistent increasing trend to 2022, totaling 60.68 hectares. A significant 111.16 hectares of agricultural land was converted to built-up areas, primarily occurring along road networks and near urban barangays.

Spatial analysis revealed clustered patterns of agricultural land cover changes, emphasizing the need for further assessment to understand and anticipate future impacts. Using MPL-ANN, the research projected a continued decrease in agricultural land cover from 3,417.039 to 3,406.875 hectares from 2022 to 2027, influencing the expansion of built-up areas from 570.13 to 596.761 hectares. Anthropogenic activities significantly contribute to ongoing land cover alterations, necessitating sustainable solutions to balance urbanization demands and agricultural land preservation in Bautista, Pangasinan.

Urban expansion, driven by anthropogenic activities, poses a threat to agricultural lands in Bautista. Policymakers and stakeholders must be vigilant and enforce policies from agencies like DA, DAR, and DENR to address land conversion issues. Further research should focus on specific agricultural land typologies and land usage changes (e.g., agricultural to residential) to quantify and map shifts effectively. This comprehensive approach will aid in developing proactive measures for sustainable land use in the face of rapid urban development.

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