

Spatial prediction of flood hazard susceptibility level in Majene urban area, West Sulawesi, Indonesia

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Abstract

This study models flood hazard susceptibility in the Majene urban area, West Sulawesi, Indonesia, for 2029–2049 using a GIS-based framework. It examines how land cover transformation associated with rapid urban growth and educational infrastructure expansion influences flood risk. A coupled Cellular Automata–Artificial Neural Network (CA–ANN) model was applied to simulate land cover change, while Multi-Criteria Decision Analysis (MCDA) was used to assess flood susceptibility. Land cover projections were derived from satellite imagery (2014, 2019, 2024). Validation against observed 2024 land cover produced an overall accuracy of 80.51% and a kappa coefficient of 0.62, indicating substantial predictive performance. Flood susceptibility was evaluated through weighted overlay of six biophysical parameters: land cover, slope, elevation, rainfall, distance to rivers, and soil type. Results indicate continued expansion of built-up and plantation areas, accompanied by reductions in grassland and open land. Susceptibility maps classify the area into low, medium, and high zones. Projections suggest a gradual decline in high-susceptibility areas and expansion of medium-susceptibility zones between 2029 and 2049. This shift is associated with increased vegetation cover from plantation growth, which may enhance infiltration and moderate runoff. The findings demonstrate the dynamic interaction between urban expansion and flood susceptibility, providing spatially explicit evidence to support risk-sensitive spatial planning, disaster risk reduction, and sustainable land management in rapidly developing coastal cities.

Keywords: flood susceptibility, land cover prediction, spatial, GIS, Majene urban area

Introduction

Majene Regency is an area in West Sulawesi Province that has experienced rapid development, primarily driven by the determination of Majene Regency to become the center for educational development in West Sulawesi Province, as outlined in West Sulawesi Provincial Regulation Number 1 of 2014 concerning the Spatial Plan of West Sulawesi Province for 2014-2034. Furthermore, in Majene Regency Regulation Number 12 of 2012 concerning the Spatial Plan of Majene Regency for the period 2011-2031, the areas prioritized for the development of education centers are the Banggae and East Banggae Districts. This has encouraged the development of several universities in the urban area of Majene, including West Sulawesi University (UNSULBAR), State Islamic College (STAIN), Open University, and several other private campuses. The presence of multiple university campuses functions as a catalyst for regional development by stimulating diverse socio-economic activities and increasing demand for land and services. Empirical studies consistently show that university-driven

development contributes to land-use transformation, population inflow, and intensified built-up expansion in surrounding areas (Rahman et al., 2024; Mohammed et al., 2022; Omollo, 2022; Mohammed & Ukai, 2021; Ambraini et al., 2020). The existence of several campuses can lead to an increase in the area's population (Institute of Economic Development & AtkinsRéalis, 2025; Awang et al., 2025; Wang & Tang, 2020) with the majority of the population comprising students. As student populations increase, supporting commercial and residential activities emerge, reinforcing spatial transformation dynamics.

Land cover change in Majene Regency is significant. Data from the Indonesian Geospatial Information Agency (BIG) show that built-up area coverage in Banggae and East Banggae Districts increased from 10.38% in 2012 to 12.54% in 2018 and 13.74% in 2022. This represents an overall increase of 3.36% in less than a decade. Limited land availability intensifies the conversion of non-built-up land into residential and service-oriented land uses (Adu et al., 2025; Imaduddin et al., 2025; Oktavilia et al., 2022; Ambraini et al., 2020)

Majene's urban expansion occurs predominantly along coastal zones, which are inherently vulnerable to

natural hazards and climate change impacts (Asensio-Montesinos et al., 2024; Zhang et al., 2024; Noor & Abdul Maulud, 2022; Nasution et al., 2020). With its rapidly growing population, concentrated socio-economic activities, and coastal characteristics, Majene faces heightened exposure to flood hazards. According to the Indonesian Disaster Risk Index (Bagaskoro et al., 2025), Majene ranks first among regencies in West Sulawesi Province in terms of disaster risk, with a particularly high flood hazard score of 21.9. Flooding frequently affects the Majene urban area, with significant events recorded in recent years, including a major flood in 2022 that damaged public facilities, schools, markets, and administrative centers (Syukri et al., 2025). The increasing conversion of natural land into built-up areas reduces water infiltration capacity and intensifies surface runoff, exacerbating flood risk.

Disaster mitigation efforts in Majene remain limited, often reactive rather than preventive (Mawan, 2021). Strengthening mitigation requires improved data availability, risk mapping, and predictive modeling (Wang et al., 2025; Khan et al., 2023; Nur et al., 2022; Jayawardene et al., 2021). Flood susceptibility prediction using spatial modeling and GIS-based analysis provides a valuable foundation for proactive disaster risk reduction. Consistent with previous research, GIS and spatial modeling techniques are effective for assessing current and future flood susceptibility (Khodaei et al., 2025; Nkonu & Antwi, 2024).

Therefore, this study aims to analyze how projected land cover dynamics driven by urban expansion influence the spatial-temporal evolution of flood hazard susceptibility in the Majene Urban Area over a 5-year interval period from 2029 to 2049 using integrated CA-ANN and MCDA approaches. The 5-years interval was chosen because, legally, national policy in Indonesia requires that disaster risk assessments in an area be updated every 5 years (BNPB Regulation No. 2 of 2012 on General Guidelines for Disaster Risk Assessment, 2012) and based on previous research (Qiu et al., 2024) indicates that using a five-year interval for hazard-susceptibility prediction effectively captures temporal fluctuations in hazard occurrence, thereby providing a more precise picture of the dynamic character of susceptibility. The findings are expected to support evidence-based planning and decision-making for flood mitigation in coastal urban environments.

Methodology

This study employs quantitative research approach that, in addressing its research questions, employs the post-positivist paradigm in developing science and utilizes research strategies focused on numerical data. (Emzir, 2019). According to the characteristics of quantitative research in general (Arikunto, 2006). This study employs variables and data expressed in numerical

units, which are processed from collection to the presentation of results, utilizing numerical values. The spatial approach employed in achieving the research objectives, using various methods to understand specific symptoms on the earth's surface through spatial media and spatial variables, takes a leading position in each analysis. (Yunus, 2010).

This study combines Cellular Automata – Artificial Neural Network (CA-ANN) and Multi-Criteria Decision Analysis (MCDA) to predict the susceptibility level of flood hazard in Majene. The analytical framework, as proposed in previous study by Nkonu & Antwi (2024), begins with CA-ANN analysis to predict land cover change in the Majene urban area over the coming years. The results will then be used in MCDA to map the spatial distribution of flood susceptibility levels within the area. The collection was carried out through primary and secondary data surveys, where the collected data have a spatial dimension that serves as a parameter in determining the level of susceptibility to flooding (Kusumo & Nursari, 2016). The data include land cover, rainfall, slope, soil type, elevation, and distance to the river. Land cover data is primary data acquired from very high-resolution vertical satellite imagery. To achieve the goal of flood susceptibility prediction, land cover prediction data are needed in the coming years, ensuring that the land cover data used spans different periods (Nuraeni et al., 2017). In this case, the data used are from satellite image recordings in 2014, 2019, and 2024. Slope and elevation data are primary data acquired from the Digital Elevation Model (DEM). Meanwhile, other spatial data are secondary data obtained from related agencies. The data analysis stages consist of three stages, namely:

a. Spatial Data Preparation

At this stage, the initial processing of the collected data is carried out. There are three initial processes carried out using ArcMap software, namely

1) On-screen digitization of high-resolution vertical satellite imagery recorded in 2014, 2019, and 2024 to obtain spatial data on land cover for each year. The accuracy of digitized data was analyzed using confusion matrix method (Congalton, 1991) which provides a comprehensive evaluation of the concordance between the sampled reference data and classification outcomes at designated locations, as well as an exhaustive account of misclassifications for each category (Stehman, 1997). Various statistical indices can be derived from the matrix to obtain accuracy metrics tailored to diverse requirements, including overall accuracy, kappa coefficient, user accuracy, and producer accuracy (Congalton, 1991);

2) Derivation of slope and elevation layers from DEM with spatial resolution of 8 m using spatial analyst tools;

3) Processing river network map using Euclidean Distance tools to obtain spatial data of area proximity to river network.

Furthermore, all spatial data were collected in one geodatabase.

b. Land cover prediction using Cellular Automata - Artificial Neural Network (CA-ANN)

Land cover prediction was conducted using the MOLUSCE plugin in QGIS. CA-ANN was selected due to its demonstrated effectiveness in simulating land cover dynamics (Sajan et al., 2022). The stages as follows:

• Inputs

The input stage involves entering spatial data on land cover in 2014 and 2019 as basic data, as well as road networks, which serve as driving factors for land cover changes, into the MOLUSCE tool. Land cover in 2014 is entered as initial data, and land cover in 2019 is entered as final data. Furthermore, geometry checks are carried out to ensure that all three datasets have the same geometry.

• Evaluating correlation

This stage involves determining the correlation between the variables that are driving factors.

• Area changes

This stage is conducted to identify changes in each type of land cover. This stage produces a transition matrix that contains information on the area of land cover changes from one type to another.

• Transition potential modeling

At this stage, training of the artificial neural network model is carried out using the following parameters: a neighborhood size of 1 px, a learning rate of 0.1, a maximum of 1000 iterations, a network topology with a multi-perceptron layer and 10 hidden layers, and a momentum of 0.05.

• Cellular automata simulation

Land cover prediction simulation is carried out using cellular automata with one iteration to produce an output in the form of a land cover prediction for 2024.

• Validation

The final step in land cover prediction is to evaluate the accuracy of the predicted land cover in 2024 against the actual land cover in 2024, as determined through digitization, which serves as the reference data. This test requires that the reference/comparator data used be more accurate. (Wiweka, 2014). Then, after the validation test meets the requirements, land cover prediction data for the five years interval from 2029 to 2049 are obtained by carrying out the CA simulation using two to six iterations.

c. Flood Susceptibility Prediction Analysis

Flood susceptibility prediction analysis is conducted using the Multi-Criteria Decision Analysis with overlay technique in ArcMAP 10.4. This technique, which involves multiple map datasets containing information with distinct characteristics, aims to gain new insights into the data. The overlay technique used is a weighted overlay in which spatial data that flood susceptibility parameters are given a certain weight that describes the extent of the variable's influence on the measurement object. (Karana & Supriharjo, 2013). Data analysis begins by providing scores and weights to all parameters. Scoring and weighting are based on the principle that the greater

the influence of a parameter on flood susceptibility, the higher the score given, with the highest score being nine and vice versa. If the impact on flooding is lower, the score will be lower, with the lowest score being 1 (Matondang et al., 2013). Scoring for each parameter can be presented in the following table:

Table 1. Flood Susceptibility Parameters

No.	Parameter	Weight	Class/grade	Score
1.	Rainfall	15	>2500	9
			2001 – 2500	7
			1501 – 2000	5
			1001 – 1500	3
			≤1000	1
2.	Slope gradient	10	0 – 8 %	9
			8 – 15 %	7
			15 – 25 %	5
			25 – 40 %	3
			>40 %	1
3.	Soil type	10	Vertisol, Oxisol	9
			Alfisol, Ultisol, Molysol	7
			Inceptisol	5
			Entisol, Histosol	3
			Spodosol, Andisol	1
4.	Land cover	25	Open space – Water Bodies – Ponds	9
			Settlements – Rice Fields	7
			Plantation – Fields	5
			Mixed Garden – Shrubs	3
			Forest	1
5.	Distance of the area to the river	20	0 – 25 m	9
			25 – 50 m	7
			50 – 75 m	5
			75 – 100 m	3
			>100 m	1
6.	Elevation	20	0 – 20 m	9
			21 – 50 m	7
			51 – 100 m	5
			101 – 300 m	3
			>300 m	1

Source: Kusumo & Nursari, 2016

Rainfall data used in this study were obtained from official meteorological records and represent long-term average annual precipitation (1501–2000 mm/year). Soil type data were sourced from the national soil database and categorized according to permeability characteristics relevant to runoff generation. The flood susceptibility value is determined by summing the scores of all six parameters that affect flooding (land use, altitude, distance of the area to rivers, rainfall, slope, and soil type), each weighted according to its importance. The analysis was carried out using ArcGIS software with the Weighted Sum Overlay tool. (Wahyuni et al., 2021). The susceptibility value is obtained using the following equation:

$$H = \sum (W_i \times X_i)$$

where,

H = Susceptibility value

W_i = Weight for the parameter

X_i = Class score on the parameter

The stage of the analysis can be presented as follows:

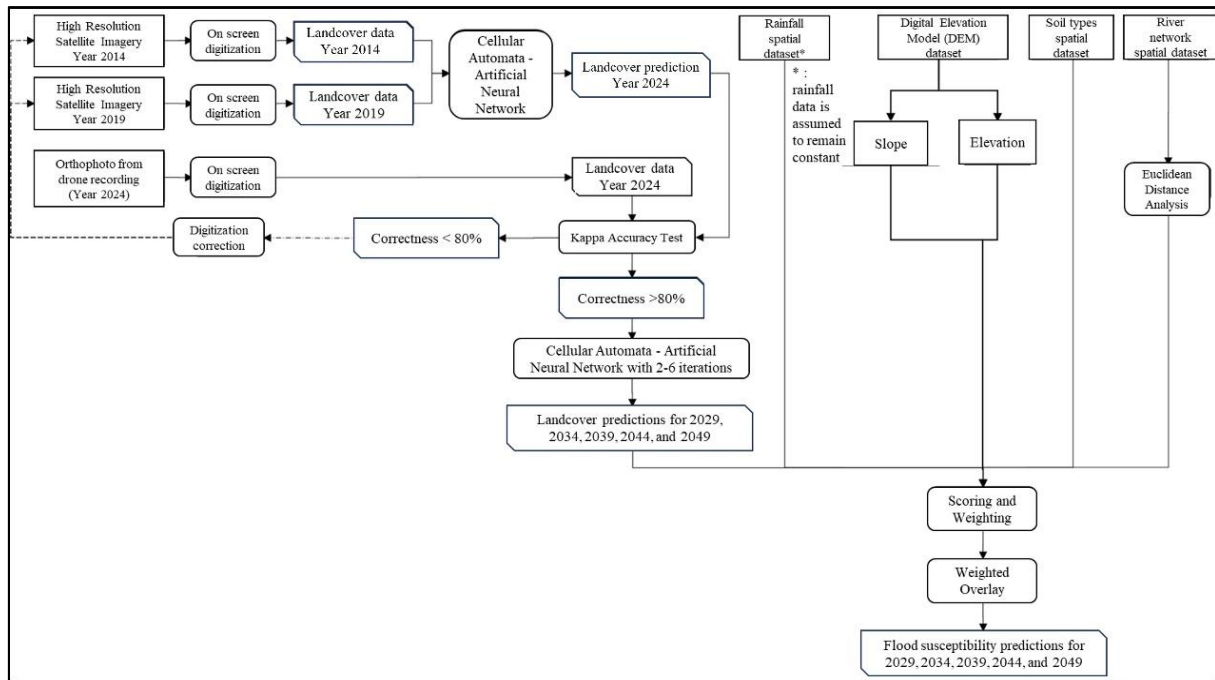


Figure 1. Data analysis process flow

Results and discussion

Land Cover Development in Majene urban area 2014-2024

The change in land cover from non-built land to built-up land is directly proportional to population growth in an area. With an increasing population in an area, the need for housing and land to support livelihoods will also increase. (Pimentel et al., 1997), which can lead to land conversion. In addition to occurring due to population concentration, land conversion can also result from the development of a new activity center, which can trigger the development of other supporting activities. (Chromicco, 2016). In the Majene urban area, the increase in population was triggered by the determination of the Majene urban areas, namely the Banggae and East Banggae Districts, to be centers of education. The spatial data of land cover of Majene urban area were obtained

using on-screen digitization in ArcGIS software. The accuracy assessment of on-screen digitized land cover maps for the Majene Urban Area across 2014, 2019, and 2024 carried out using confusion matrix method and the result as shown in Table 2 demonstrates a consistently robust classification performance. Overall accuracy values of 84%, 79.69%, and 81.31%, respectively, exceed widely accepted thresholds for land cover mapping derived from visual interpretation of remote sensing imagery. Correspondingly, Kappa coefficients ranging from 0.68 to 0.69 indicate a substantial level of agreement between the classified outputs and reference data, confirming the reliability of the digitization process beyond chance effects, in line with contemporary land cover accuracy assessment guidelines (Tyukavina et al., 2025). The marginal decline in accuracy observed in 2019 is attributable to increased urban landscape heterogeneity and the introduction of additional land cover classes, such as bare or open land, which intensified class confusion during interpretation.

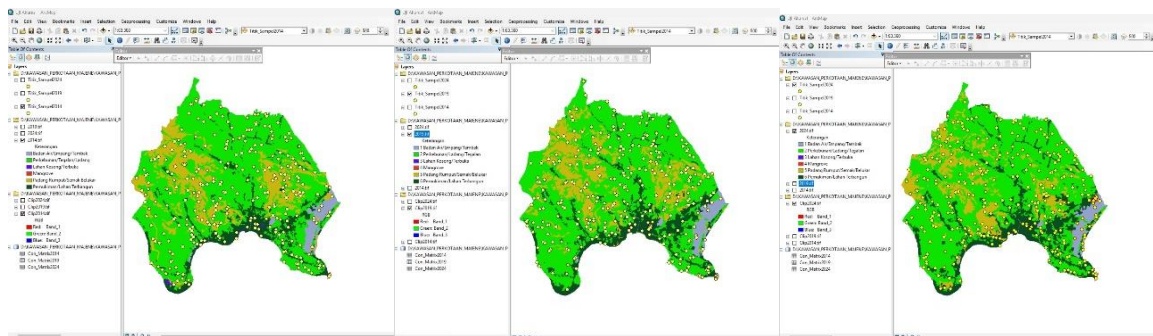


Figure 2. Accuracy assessment process in ArcGIS for digitized land cover data year 2014, 2019 and 2024

Table 2. Confusion matrix of landcover digitized data year 2014, 2019 and 2024

Year	Number of Sample	Number of Classes	Overall Accuracy	Producer's Accuracy Range	User's Accuracy Range	Kappa Coefficient
2014	320	5	0.84	0.64 – 1.00	0.64 – 1.00	0.692
2019	320	6	0.797	0.74 – 1.00	0.74 – 1.00	0.682
2024	320	6	0.813	0.73 – 1.00	0.79 – 1.00	0.695

Misclassification was predominantly concentrated within non-forest vegetation categories, particularly grassland/shrubland and plantation or dryland agriculture, due to their overlapping visual characteristics and frequent occurrence as spatial mosaics in urban–peri-urban transition zones. This source of uncertainty is consistent with recent land cover classification studies identifying mixed vegetation classes as a principal contributor to classification error, despite overall

accuracy and Kappa values remaining within acceptable limits for urban spatial analysis and land-use planning applications (Gülci et al., 2025; Rwanga & Ndambuki, 2017; Congalton et al., 2014)

A comparison of land cover in 2014, 2019 and 2024 in the Majene urban area, which encompasses the Banggae and East Banggae Districts, is presented in Table 3 and Figure 3.

Table 3. Changes in land cover in the Majene urban area in 2014, 2019 and 2024

No	Land cover	Area (ha)			Area Difference (ha)		
		Year 2014	Year 2019	Year 2024	2014-2019	2019-2024	2014-2024
1	Water Body/ Pond / Fishpond	158.02	160.39	153.17	2.37	-7.22	-4.85
2	Plantation/ Dry land / Field	3,427.9	3,325.6	3,393.8	-102.28	68.24	-34.04
3	Vacant / Open Land	7.92	0.97	2.55	-6.95	1.58	-5.37
4	Mangrove	2.01	3.02	10.37	1.01	7.35	8.36
5	Grassland / Bushland	980.02	948.11	765.25	-31.91	-182.86	-214.77
6	Residential / Built-up Land	565.21	702.97	815.89	137.76	112.92	250.68

Source: Data analysis, 2024

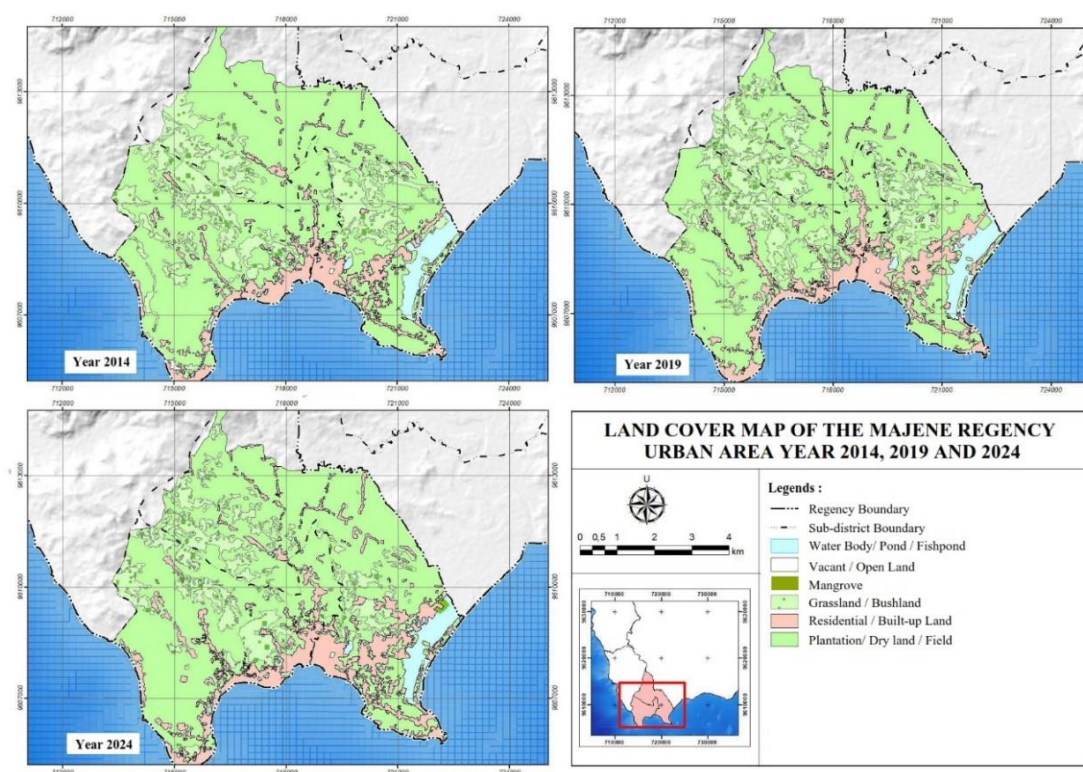


Figure 3. Land cover map of urban areas in Majene Regency years 2014, 2019 and 2024 (Source: Data analysis, 2024)

In the period 2014-2024, there was a change in non-built land cover to built land of 4.87% or an area of 250.68 ha, whereas in 2014-2019, there was a change in non-built land cover to built land of 137.75 ha and in 2019-2024 there was a change in non-built land cover to built land of 112.92 ha. The change in land cover over the 10 years (2014-2024) was primarily driven by changes in land cover of empty or open land, resulting in a total reduction of open land of 67.79%. The increasingly massive change in non-built land cover to built land in the urban area of Majene Regency is also confirmed by the results of compiling land cover maps in 2014, 2019 and 2024, as presented in Figure 3. Based on the maps in the figure, the area of residential land cover (marked in pink) has increased significantly.

Land cover prediction model

The change in non-built land cover to built land is influenced by road infrastructure (Liem & Purwanto, 2022; Rusdi, 2013; Moore et al., 2007). A transportation system supported by good infrastructure will increase the movement of goods and services, which will also lead to changes in land cover. Specifically, land located in areas with good accessibility will tend to be more easily converted. Land cover prediction for the Majene urban area is preceded by making a land cover prediction in 2024, which will then be tested against digitized 2024 land cover spatial data as a reference. The probability of changing one land cover type to another between 2014 and 2019 is evident from the Transition Probability Matrix, which was generated using the MOLUSCE plugin in QGIS software and is presented in the following table.

Table 4. Transition Probability Matrix (TPM) of land cover 2014 – 2019

	Water Body/ Pond / Fishpond	Plantation/ Dry land / Field	Vacant / Open Land	Mangrove	Grasslands / Shrubs / Thickets	Settlement / Built-up Land
Water Body/ Pond / Fish- pond	0.9115	0.0357	0	0	0.0023	0.0504
Plantation/ Dry land / Field	0.0017	0.8457	0	0.0003	0.0974	0.0548
Vacant / Open Land	0	0.5169	0.1236	0	0	0.3595
Mangrove	0	0	0	0.9565	0	0.0435
Grassland / Bush / Thicket	0.0059	0.3554	0	0	0.6255	0.0132
Settlement / Built-up Land	0.0049	0.1169	0	0	0.0044	0.8737

Source: Data analysis, 2024

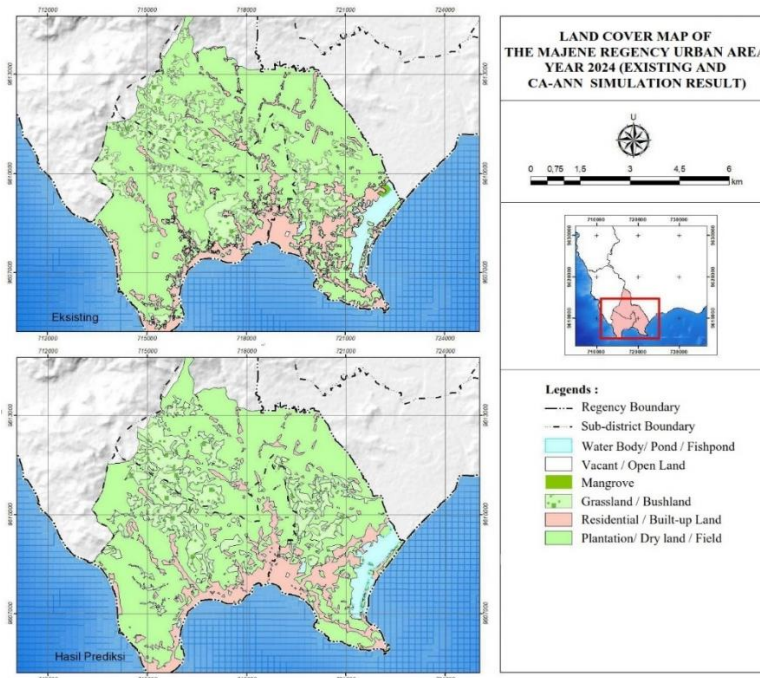


Figure 4. Land cover map of Majene urban area in 2024, existing and predicted results (Source: Data analysis, 2024)

Several types of land cover tend not to change into other types of land cover, as indicated by a TPM value of

zero (0). Land cover that tends to change quite significantly into built-up land is open land with a probability value of

0.3595. The results of land predictions in 2024, obtained through the processing of the Cellular Automata-Artificial Neural Network (CA-ANN) method, and their comparison with the land cover in 2024 from the digitization results are shown in Figure 4.

Based on the comparison of existing land cover in 2024 with the predicted results from CA-ANN processing presented in Table 5, it is evident that the difference in area for each type of land cover between the existing 2024 data and the predicted results is relatively small. This indicates that CA-ANN processing based on land cover data from 2014 and 2019 for the Majene urban

area yields fairly accurate land cover predictions. This is also supported by the analysis results' correctness percentage of 80.51% and a kappa value of 0.62, which is classified as good to strong. (Jenness & Wynne, 2005; McCoy, 2005), so that CA-ANN processing can continue to predict land cover development in the coming years, with road data serving as a driving factor.

The predicted results of land cover in the Majene urban area for 2029, 2034, 2039, 2044, and 2049 are presented in Figure 5, and the area of each type of land cover is shown in Table 6.

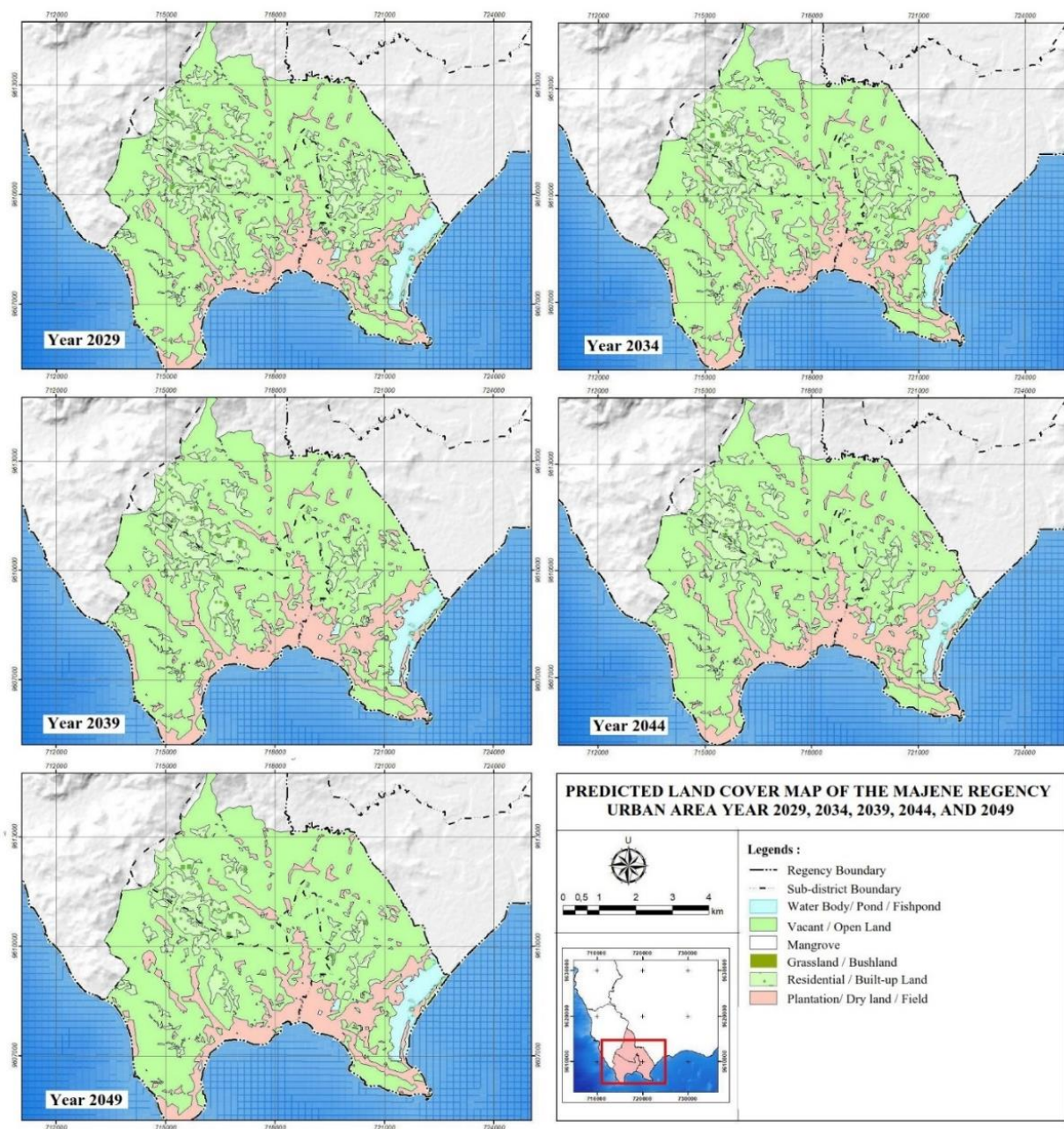


Figure 5. Predicted land cover map of the Majene urban area in 2029, 2034, 2039, 2044 and 2049 (Source: Data analysis, 2024)

Table 5. Comparison of existing and predicted land cover in 2024

Land cover	Area (ha)	
	2024 (existing)	2024 (prediction)
Water Body/ Pond / Fishpond	153.169	159.107
Plantation/Field/ Dry Field	3,393.808	3,407.260
Vacant/Open Land	2.550	0.913
Mangrove	10.367	2.958
Grassland / Bush / Thicket	765.246	804.910
Residential / Built-up Land	815.889	765.641

Source: Data analysis, 2024

Table 6. Area of land cover types predicted for 2029, 2034, 2039, 2044 and 2049

Land cover	Area (ha)				
	Year 2029	Year 2034	Year 2039	Year 2044	Year 2049
Water Body/ Pond / Fishpond	158.551	158.165	157.536	157.411	157.126
Plantation/Field/ Dry Field	3,471.837	3,518.886	3,555.747	3,583.855	3,603.281
Vacant/Open Land	0.913	0.913	0.913	0.913	0.913
Mangrove	2.958	2.958	2.958	2.958	2.958
Grassland / Bush / Thicket	694.246	613.331	552.450	505.173	471.166
Residential / Built-up Land	812.284	846.537	871.185	890.480	905.345

Source: Data analysis, 2024

The results of this prediction are consistent with the theory and results of previous studies, which state that infrastructure and regional development have a very close and continuous relationship, where infrastructure can be a force that forms regional development (Adisasmita, 2011), where, in terms of the development of the Majene urban area, road infrastructure can serve as a trigger for changes in land cover. Road development will trigger the growth of new economic activities, which can lead to population movement to these new centers of economic activity, ultimately encouraging an increase in the number of requests for residential and other built-up land to meet socio-economic needs. This is what characterizes the development of urban areas, where there is a change in land cover from non-built-up land to built-up land.

Prediction of flood susceptibility

The flood susceptibility pattern in Majene in this study is modelled based on six variables: rainfall, slope, elevation, soil type, land cover, and proximity to rivers, which are widely recognized as the dominant climatic, morphometric, and land-surface drivers of pluvial and fluvial flooding.

This study emphasizes on modelling of relative flood susceptibility mapping, not physically based hydrodynamic flood depth simulation. While hydrodynamic models require discharge measurements, drainage network density, channel geometry, and

boundary conditions, susceptibility mapping aims to identify spatial likelihood patterns under prevailing environmental conditions (Alcântara et al., 2025; Shrestha et al., 2025). Within this framework, the selected six parameters adequately capture the dominant climatic, topographic, pedologic, and land-surface controls of pluvial and fluvial flooding at the urban scale. Tidal influence and groundwater dynamics were also not considered in modelling process due to the absence of long-term tidal gauge and hydrogeological datasets. Consequently, the model primarily captures relative pluvial and fluvial susceptibility rather than compound coastal–tidal flooding. Rainfall acts as the triggering factor, while slope and elevation regulate runoff concentration in low-lying terrain. Soil properties influence infiltration and sediment transport, land cover modifies surface permeability, and river proximity captures floodplain exposure. Similar predictor dominance identified terrain, rainfall, land use, and river distance as statistically robust flood susceptibility determinants across machine-learning and GIS-based frameworks (Jumadi et al., 2024; Farhadi & Najafzadeh, 2021; Khosravi et al., 2019).

The key contribution of this study lies in integrating CA–ANN-based land cover prediction with MCDA flood susceptibility assessment under multi-temporal urban growth scenarios (2029–2049). Unlike static susceptibility analyses, this framework embeds projected land-use transitions into hazard modelling, enabling dynamic evaluation of how urban expansion reshapes flood risk

distribution. Compared with previous CA-ANN applications that primarily focus on static land cover prediction, this study advances the methodological integration by linking multi-temporal land cover projection with future flood susceptibility modelling.

Similar studies (Nkonu & Antwi, 2024) demonstrate the effectiveness of CA-ANN for spatial prediction; however, few explicitly connect projected land transformation trajectories with evolving hazard susceptibility classes in a coastal secondary city context.

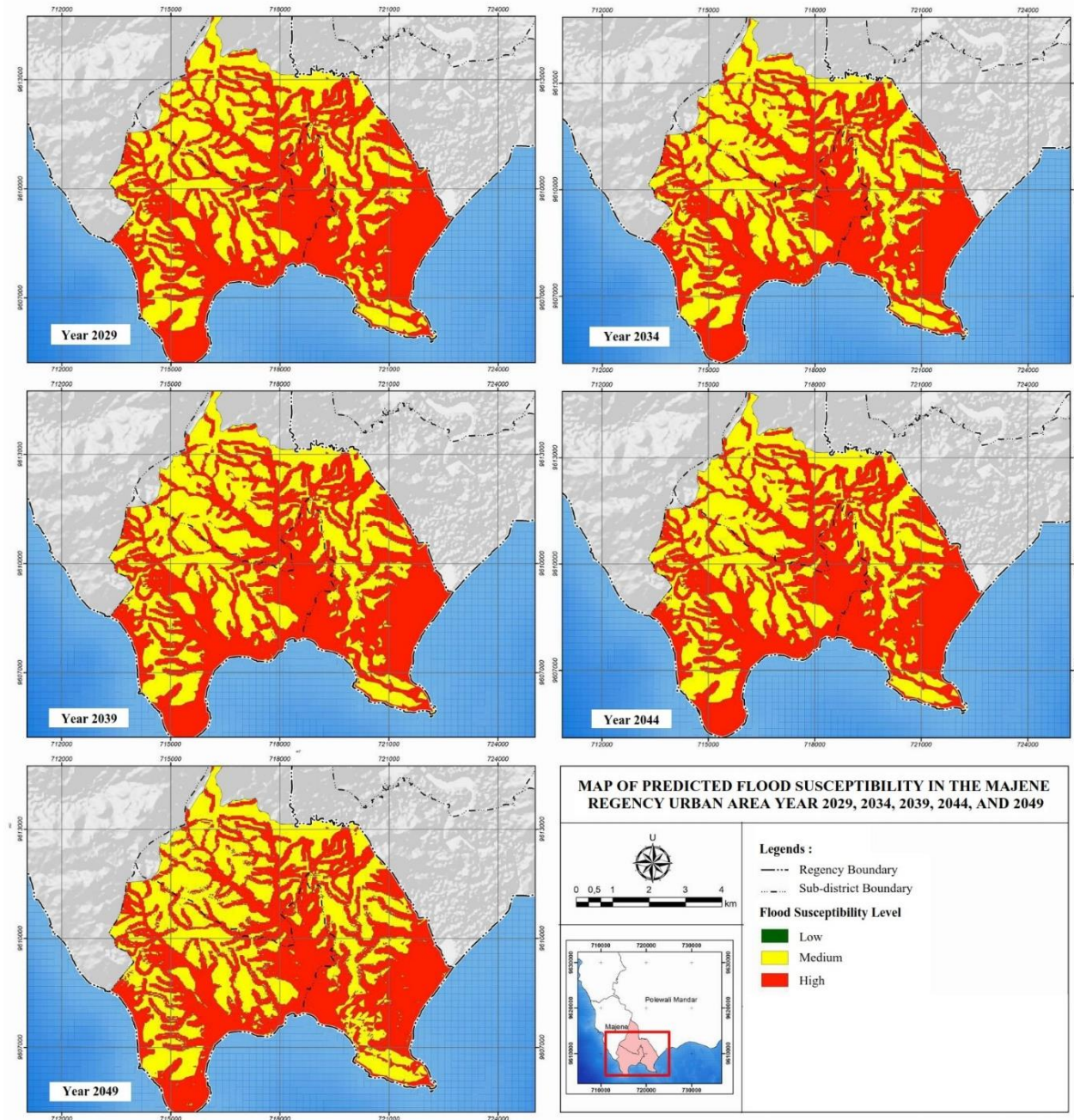


Figure 6. Map of predicted flood susceptibility in the Majene urban area in 2029, 2034, 2039, 2044 and 2049
(Source: Data analysis, 2024)

The urban area of Majene has an average rainfall classified as moderate, ranging between 1501 and 2000 mm per year. This rainfall can cause flooding if supported by other factors, such as the lack of water catchment areas and river shallowing triggered by sedimentation, either from eroded soil or waste disposal into rivers.

Most urban areas in Majene have developed in coastal areas with slopes ranging from 0% to 8%. Flat areas are more prone to flooding than areas with a greater slope. This is related to the nature of water, which tends to accumulate in low-lying and poorly drained flat areas, resulting in most water flow leading to urban areas. In terms of

regional altitude, most urban areas in Majene have areas with varying altitudes. Areas with low altitudes are primarily located in coastal regions, which eventually develop into centers of regional activity. The type of soil that predominates in the urban area of Majene is red-yellow Mediterranean and rendzina, which is found in almost all areas. This type of soil is characterized by further development from the parent material of limestone, with the following characteristics: a soil solum of 1-2 m, a brown to red color, a clay to loamy texture, a lumpy structure, and a loose consistency at the top and a firm consistency at the bottom. The level of sensitivity of this type of soil to erosion is moderate to high, so that if erosion occurs. The eroded soil is transported by surface flow and then deposited in places where the water flow slows down, such as rivers, irrigation channels, reservoirs, lakes, or river mouths. This can cause river shallowing, leading to increased flood intensity during the rainy season. The Majene urban area is traversed by several rivers, which results in some of its areas being within a very close radius of the river. This area should be designated as a local protected area, such as a river boundary area; however, in reality, cultivated land is being used for various purposes, including development, in this area.

Parameters that form flood susceptibility, including land cover predictions, are processed using the Weighted Overlay method with ArcMap software to produce a 5-year flood susceptibility prediction for the period 2029-2049. In this process, each parameter is given a score and weight based on its influence on the level of flood susceptibility. Based on the total number of

multiplications of the scores and weights of each parameter, the level of flood susceptibility in Majene urban area determined and mapped as in Figure 6. The level of flood susceptibility is divided into three classes ranging from low to high. Based on the prediction results, most urban areas in Majene are characterized by a high level of flood susceptibility. Most areas with high levels of susceptibility are primarily concentrated in regions dominated by settlement or built-up land cover.

The predicted flood susceptibility map (2029 baseline) was visually compared recent flood susceptibility modelling from previous study (Pratama et al., 2025). Result from previous study as seen in Figure 7 shows that flood inundation is concentrated in low-elevation coastal plains and estuarine areas, which correspond directly to zones classified as high susceptibility in Figure 6. Flood patterns following river corridors align with high-susceptibility areas generated from the river proximity parameter, confirming the model's ability to capture fluvial exposure. Transitional inland areas with moderate inundation in Figure 7 correspond to medium susceptibility classes in Figure 6, reflecting the influence of slope and elevation. Nevertheless, the consistent overlap across coastal lowlands and floodplain corridors indicates that the model effectively reproduces the dominant flood-prone of the study area, strengthening confidence in its 2029–2049 projections.

The prediction results indicate that flood susceptibility in the Majene urban area is expected to decrease from 2029 to 2049 as in Table 7.

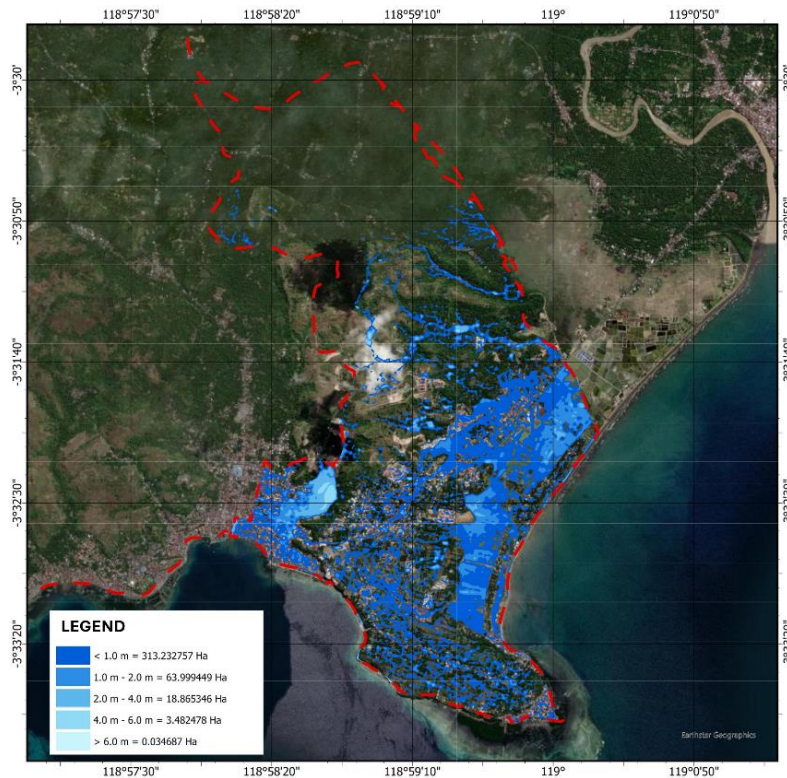


Figure 7. Flood susceptibility modelling from previous study (Source: Pratama et al., 2025)

Table 7. Distribution of flood susceptibility level in Majene urban area

Susceptibility level	Area (ha)				
	Year 2029	Year 2034	Year 2039	Year 2044	Year 2049
Low	18.86	18.86	18.86	18.86	18.86
Medium	2098.17	2199.06	2170.83	2150.04	2240.27
High	3040.91	2940.02	2968.24	2989.03	2898.81

Source: Data analysis, 2025

The results indicate a gradual shift from high to moderate susceptibility zones, although the changes are not strictly linear from year to year. Overall, areas with high susceptibility show a net decrease between 2029 and 2049, while areas with moderate susceptibility show a net increase over the same period. This is primarily related to the results of land cover predictions, where, although built-up land has increased, on the other hand, the use of plantation has also increased quite significantly, indicating that there is more vegetation cover that can pass or absorb rainwater into the soil and reduce the amount of rainwater that becomes surface runoff. This coupling of predictive land dynamics and susceptibility mapping strengthens forward-looking spatial planning relevance in medium-sized coastal cities experiencing accelerated development.

The observed reduction in high flood susceptibility despite continued built-up expansion should not be interpreted solely as a direct effect of plantation-driven infiltration. Urban hydrology is influenced by multiple interacting factors. In the Majene urban area, a drainage improvement program implemented in 2025 (Dinas Perumahan dan Permukiman Provinsi Sulawesi Barat, 2025) including channel normalization, culvert enlargement, and localized drainage upgrading in flood-prone corridors likely contributed to improved surface runoff conveyance capacity. However, because hydraulic infrastructure is not explicitly represented in the susceptibility model, these improvements should be understood as a contextual factor rather than a direct driver of the modeled redistribution from high to moderate susceptibility zones.

Conclusions

Majene's rapid urban development, driven by educational expansion and infrastructure improvement, has significantly transformed land cover patterns over the last decade. Using CA-ANN and MCDA, this study successfully modeled land cover change and flood susceptibility from 2029 to 2049.

Key findings include:

- Built-up and plantation areas will continue to expand through 2049;
- Grassland and open land will continue to decline;
- High flood susceptibility areas will gradually decrease, while medium susceptibility areas will expand;

- Increased vegetation cover contributes to reduced runoff and moderated flood risk.

The integration of GIS-based modeling with spatial multi-criteria analysis provides valuable insights for disaster risk reduction and sustainable spatial planning in coastal urban areas. Policymakers can use these findings to guide land-use regulation, infrastructure development, and flood mitigation strategies.

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Author contribution

Conceptualization, RM and AP; methodology, NRS; formal analysis, AP, AM and NFM; investigation, MAE; writing—original draft preparation, RM, NRS and AP; writing—review and editing, AM, NFM and AW. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

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