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# SPATIAL STATISTIC MODELING FOR RICE FIELD AREA PREDICTION YEAR 2026 TO 2030 IN POLEWALI MANDAR REGENCY

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**ABSTRACT**

The sustainability of rice fields is fundamental to maintaining regional food security, particularly in agricultural production centers such as Polewali Mandar Regency, West Sulawesi, Indonesia. Rapid population growth and spatial development have intensified pressure on productive agricultural land, increasing the risk of long-term decline in rice field availability. This study develops a spatial statistical modeling framework to predict the distribution of rice field conversion for the period 2026–2030 using an integration of Frequency Ratio (FR) and Spatial Multi-Criteria Analysis (SMCA) within a Geographic Information System (GIS) environment. Land cover data from 2010 and 2020 were used to identify historical conversion patterns and to construct predictive variables. Ten driving factors—including topography, slope, geomorphology, soil type, rainfall, accessibility, settlement characteristics, and spatial policy direction—were evaluated alongside protected agricultural zones as limiting constraints. Model validation using the Receiver Operating Characteristic (ROC) curve produced an AUC of 0.83 (success rate) and 0.75 (predictive rate), indicating good and reliable model performance. The projection results demonstrate continued pressure on rice field areas, particularly in zones influenced by infrastructure and settlement expansion. By providing spatially explicit predictions, this study offers a decision-support tool for proactive land-use regulation, agricultural protection policies, and strategic planning interventions aimed at safeguarding food self-sufficiency in the medium term.

***Keyword:*** *Spatial Statistic Modeling; Rice Field Conversion; Land Use Prediction; GIS; Polewali Mandar*

## 1. INTRODUCTION

Food self-sufficiency is a strategic agricultural development program because it has a broad impact on people's lives. The availability of food in sufficient quantities, good quality food ingredients and high nutritional value has a broad impact on the economy and the quality of human resources. Rice as the main food ingredient is the main target agricultural commodity which is the availability will potentially decrease [1]. One of the factors that can trigger this is narrow land ownership which is exacerbated by uncontrolled land conversion [2] [3] [4]. Land conversion is closely related to increasing population and can cause a decrease in agricultural land [5] [6] [7]. Based on BPS data, the population of Polewali Mandar Regency is increasing from year to year, with population growth in Polewali Mandar Regency in the period 2016-2022 averaging 1.38%. Continuous population growth indicates a massive urbanization process and of course triggers the population's need for increasingly large amounts of land [8] [9], which encourages land conversion. Land conversion is the process of changing the use function,

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either partially or completely, into another function [5] [6] [10]. As a result of the massive urbanization process, this land conversion has created a significant change in rice fields into built-up land [11] [12] [13].
The conversion of agricultural land to land with other functions can certainly threaten the population's need for rice fields which produce rice as a staple food. Direct land conversion poses a serious threat to meeting people's food needs. In addition, the reduction in agricultural land can cause an imbalance between the population working in the agricultural sector in an area and the available area of wetland agricultural land. Thus, the conversion of wetland agricultural land can pose a threat to food self-sufficiency and can also threaten the population's source of focus of government sectors related to agriculture to achieve food self- sufficiency. The Polewali Mandar Regency area is one of the supporting areas in achieving food self- sufficiency in West Sulawesi Province. This is mainly because Polewali Mandar Regency is one of the rice storage centers for West Sulawesi Province [14]. As development becomes more massive in an area, food income. who work in the agricultural sector.
The dynamics of regional development have resulted in the conversion of agricultural (productive) land to built-up (physical) land is becoming more visible and will reduce the amount of agricultural area and will reduce the amount of agricultural production. In order to maintain consistent rice production, which is an important indicator of food self-sufficiency, regency government as local regulator need to develop policies and programs which will have positive impact to the increase rice production. Development of these policies and programs should be supported by identification and prediction of development of rice field area for certain span of time in the future. It is very urgent to identify the spatial distribution of future rice field area, because areas where rice fields are shrinking can be known so the government can determine strategic steps to address this issue. This research aims to model to model the development of rice fields in the future based on current existing conditions. It is hoped that the results of this research can become a basis for government to determine policies, programs and strategies related to increasing food self-sufficiency.

## 2. RESEARCH METHOD

This research was carried out by applying the principles and principles of a spatial approach. The spatial approach is a method for understanding certain phenomena in order to have deeper knowledge through the medium of space which occupies the main position in every analysis [15]. particular symptoms in question are the symptoms of the geosphere (surface layer of the earth) which includes the air layer (atmosphere), the water layer (hydrosphere), the rock layer (lithosphere), the living creature layer (biosphere) and the human layer (anthroposphere) which are related to the phenomenon of changes in use. land that affects the availability of agricultural land.
Data collection used two methods: a) institutional surveys for collecting secondary data and field surveys for collecting primary data. The data, types of data and collection methods can be presented as follows:

**Table 1.** Data, types of data and methods of collection

| No | Data | Data Type | Collection Method |
|---|---|---|---|
| 1 | Basic spatial data (administrative boundaries, roads, rivers etc.) | Secondary data | Institutional survey |
| 2 | Existing land use spans 10 years | Primary and secondary data | Digital interpretation of satellite imagery and field validation surveys |
| 3 | Land use change | Primary and secondary data | Digital interpretation of satellite imagery and field validation surveys |

Data analysis methods are carried out using several approaches including Frequency Ratio (FR) and Spatial Multi Criteria Analysis (SMCA) based on geographic information systems. This method is used to build a model to determine the distribution of rice field availability and the process can be presented in figure 1.

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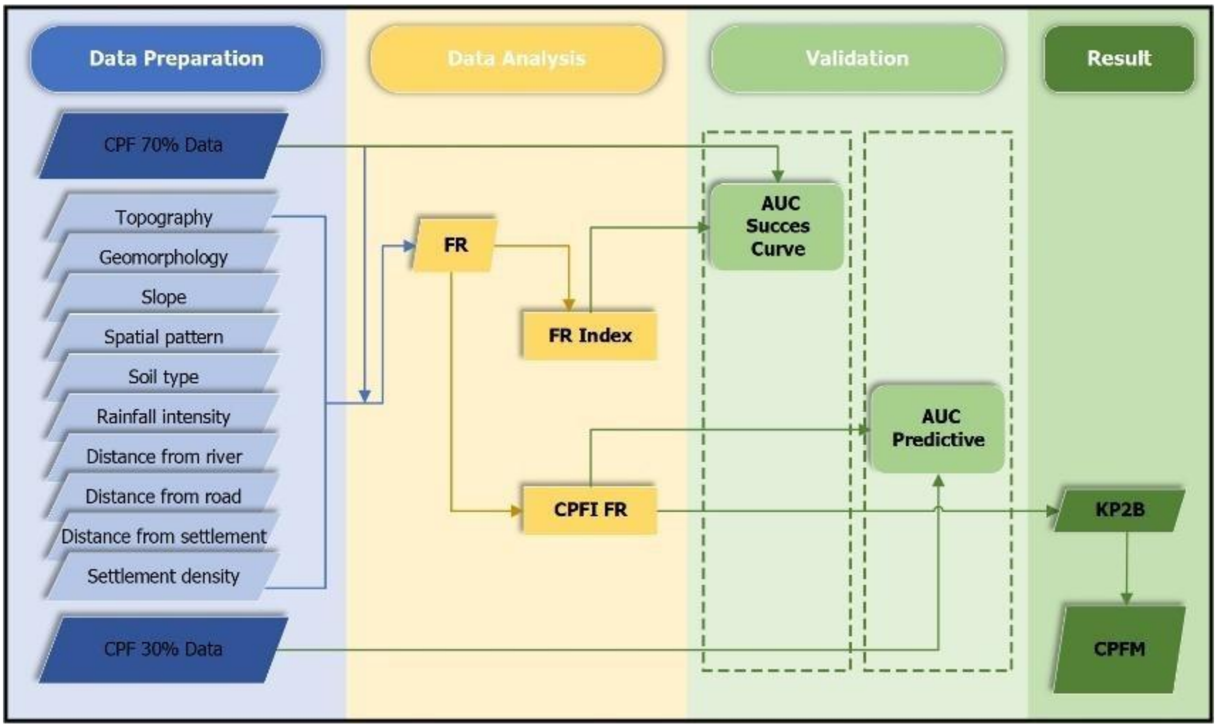


**Figure 1.** Model development flow

The stages of data analysis in this research are as follows :

1) Inventory of agricultural land (rice fields)
   The agricultural land inventory process was carried out using land cover data for 2010 and 2020 as a result of interpretation of medium resolution satellite imagery. This spatial data was validated by conducting ground checks in several sample areas (agricultural land). Based on the data obtained, it describes the occurrence of agricultural land conversion.
2) Determining parameters in building the model
   Data analysis carried out using geographic information system approach which employs spatio-temporal data of land cover year 2010 and 2020. This data became basic reference in determining the dependent variable, namely rice fields converted within a period of 10 years and the independent variable, namely the total area of rice fields. Based on the results of the literature study, 10 indicators have been determined that influence the occurrence of rice field conversion that has occurred, including: topography and rainfall [16], slope [17], geomorphology [18], soil type [19] [20], distance from rivers [21], distance from roads and distance from settlements [22], settlement density [23] [24] and the direction of local government spatial plan policy [25]. In addition to determining the indicators that influence the occurrence of rice field conversion, the process of determining this model prediction also considers the limiting factors for the occurrence of rice field conversion, namely government policies in the form of the distribution of rice fields that have been designated as sustainable food agriculture areas [25]. This limiting factor is intended to limit the possibility of predicting the distribution of rice field conversion.
3) Data analysis
   The initial stage of the analysis process for spatial modelling was carried out using a statistical frequency ratio (FR) approach [26] [27] [28]. The frequency ratio is a simple statistic by dividing the ratio of factors involving the conversion of rice fields to the ratio of the total area of rice fields. FR is calculated using the following equation [29]:

$$Fr = \frac{PxcL(nm)/\Sigma PnxL}{Pixel\ (nm)/\Sigma Pnx} \quad (1)$$

   where, PxcL represents the number of class pixels in the incidence factor of parameter m (nm), and Pixel is defined as the number of class pixels of parameter m (nm). In Frequency ratio Pxcl and Pixel are each divided by the total pixels of parameter m (ΣPnxL) and the total pixels of the study area (ΣPnx).

4) Data validation
Measuring the performance of modeling algorithms is an important step in all model-basedpredictions. This method was also used to validate the results of the prediction model for rice field conversion in Polewali Mandar Regency. In this research, Receiver Operating Characteristic (ROC) is used to assess algorithm performance. ROC graphs a plot of sensitivity (ratio of 27 true positives) against 1-specificity (ratio of false positives) with various thresholds. The index is calculated as follows:

$$\text{AUC} = \sum TP + \sum TN\ P + N \qquad (2)$$

where, P is the total number of converted rice fields and N the total number of existing rice fields. The area under the curve (AUC) is used to evaluate the performance of the model being analyzed (Sahin et al., 2020). A rate change curve was created with the value of rice fields as the x-axis and the cumulative percentage of converted rice fields as the y-axis [30] [31]. The classification of validation results is then grouped into several value ranges, namely 0.5 – 0.6 is declared failed, 0.6 – 0.7 is declared bad, 0.7 – 0.8 is declared adequate, 0.8 – 0.9 is declared good, and 0.9 – 1 is considered very good [32].

5) Integration of Frequency Ratio and Spatial Multi Criteria Analysis (SMCA)
SMCA is a multi-criteria-based spatial evaluation method that integrates various factors within a single spatial analysis framework using Geographic Information Systems (GIS). The weighted values obtained from FR modeling of all causative variables are combined with overlay techniques to produce a rice field conversion index. The process of combining all these layers is added with limiting factors in the form of sustainable food agriculture areas (or KP2B) to obtain more realistic results in accordance with applicable regional development policies.

6) Classification of model results
After going through the validation process, the prediction results of the rice field conversion model were classified into 10 classes using the geometrical interval method to see land changes every year within a 10 years period. Determination of classification is based on the results of overlaying the FR values for each causative factor and taking into account the sustainable agriculture areas area as a limiting factor in the possibility of converting rice fields.

## 3. RESULT AND DISCUSSION

### 3.1.Comparison Of Changes In Rice Field

Polewali Mandar Regency experienced quite significant changes in land cover, especially changes in agricultural land cover to non- agricultural land cover. Initial finding of the research show that in 10 years period from 2010 to 2020 there was a change in agricultural land use (reduction in rice field area) of 1,073 ha. This is in accordance with previous research findings [33] which show that agricultural land is often converted into non-agricultural land, especially residential areas, to meet the needs of the increasing population. The results of the inventory of agricultural land (rice fields) as a result of the comparison of land use data series for 2010 and 2020 are presented in table 2.

**Table 2.** Comparative results of rice fields change in 2010 and 2020

| Landuse 2010 | Landuse 2020 | Breadth of change (ha) |
|---|---|---|
| Swamp | | 16 |
| | Rice field | 16 |
| Rice Field | | 15.967 |
| | Uncultivated area | 12 |
| | Settlement | 174 |
| | Rice Field | 14.894 |

| Landuse 2010 | Landuse 2020 | Breadth of change (ha) |
|---|---|---|
| | Bush | 157 |
| | Plantation | 729 |
| Plantation | | 408 |
| | Rice field | 408 |
| **Grand Total** | | **16.391** |

(Source: Data analysis,2025)

The table above focuses on the conversion of agricultural land use (rice fields). Changes in rice fields can be seen in both years. The incidence of changes in rice fields does not only show the conversion of rice fields to other land uses, based on this data there are also other land uses that were converted to rice fields. The conclusion is that changes in the use of vulnerable rice fields over a period of 10 years show a reduction in the area of rice fields by 1,073 hectares. The event of conversion of rice fields is used as the dependent variable in calculating the frequency ratio of each parameter.

## 3.2.Calculation of Frequency Ratio (FR) values

Frequency ratio as part of statistical analysis combined with spatial approach using geographic information system has proven to be effective to predict changes in various spatial parameters in time dimension. Previous studies have shown that this method can be used to predict development and growth of urban area [26] [27] [28], but its application in predicting changes in land cover is still quite limited. Statistical analysis allows for frequency discrimination of the magnitude of the incidence of rice field conversion for each causal factor adopted. The ratio in Table 3 shows the influence of causative factors in the class on the incidence of rice field conversion, a value > 1 indicates a high chance of paddy land conversion occurring, and a ratio < 1 indicates the opposite opportunity.

**Table 3.** Frequency ratio value for each parameter

| Independent variable | Classification | Class Output | % Output | Class Input | % Input | Frequency Ratio |
|---|---|---|---|---|---|---|
| Topography | 0 - 25 asl | 741.77 | 0.69 | 15243.84 | 0.93 | 0.74 |
| | 25 - 100 asl | 73.97 | 0.07 | 615.57 | 0.04 | 1.84 |
| | 100 - 500 asl | 73.55 | 0.07 | 297.36 | 0.02 | 3.78 |
| | 500 - 1000 asl | 183.45 | 0.17 | 234.31 | 0.01 | 11.96 |
| Slope | 0 - 2 % | 650.78 | 0.61 | 15135.19 | 0.92 | 0.66 |
| | 2 - 8 % | 290.97 | 0.27 | 916.23 | 0.06 | 4.85 |
| | 8 - 15 % | 11.12 | 0.01 | 22.56 | 0.00 | 7.53 |
| | 15 - 25 % | 5.05 | 0.00 | 8.98 | 0.00 | 8.59 |
| | 25 - 40 % | 84.38 | 0.08 | 188.62 | 0.01 | 6.84 |
| | > 40 % | 30.45 | 0.03 | 119.50 | 0.01 | 3.89 |
| Geomorphology | Sulawesi Fluvial Plain | 595.05 | 0.55 | 14654.24 | 0.89 | 0.62 |
| | Sulawesi Structural Mountains | 342.64 | 0.32 | 1309.14 | 0.08 | 4.00 |
| | Sulawesi Structural Hills | 135.04 | 0.13 | 427.71 | 0.03 | 4.82 |
| Soil Types | Alluvial | 441.93 | 0.41 | 12554.41 | 0.77 | 0.54 |
| | Brown Forest Soil | 155.22 | 0.14 | 1328.59 | 0.08 | 1.79 |
| | Grumusol | 184.63 | 0.17 | 2000.45 | 0.12 | 1.41 |
| | Mediterranean | 183.45 | 0.17 | 234.31 | 0.01 | 11.96 |
| | Podzolic | 20.87 | 0.02 | 74.86 | 0.00 | 4.26 |
| | Rendzina | 86.63 | 0.08 | 198.48 | 0.01 | 6.67 |
| Rainfall intensity | 1500-2500 mm/year | 103.48 | 0.10 | 589.30 | 0.04 | 2.68 |
| | 2501-3500 mm/year | 894.27 | 0.83 | 15416.23 | 0.94 | 0.89 |
| | 3501-4000 mm/year | 74.99 | 0.07 | 385.56 | 0.02 | 2.97 |
| Distance from river | 0 – 750 m | 382.82 | 0.36 | 6115.70 | 0.37 | 0.96 |

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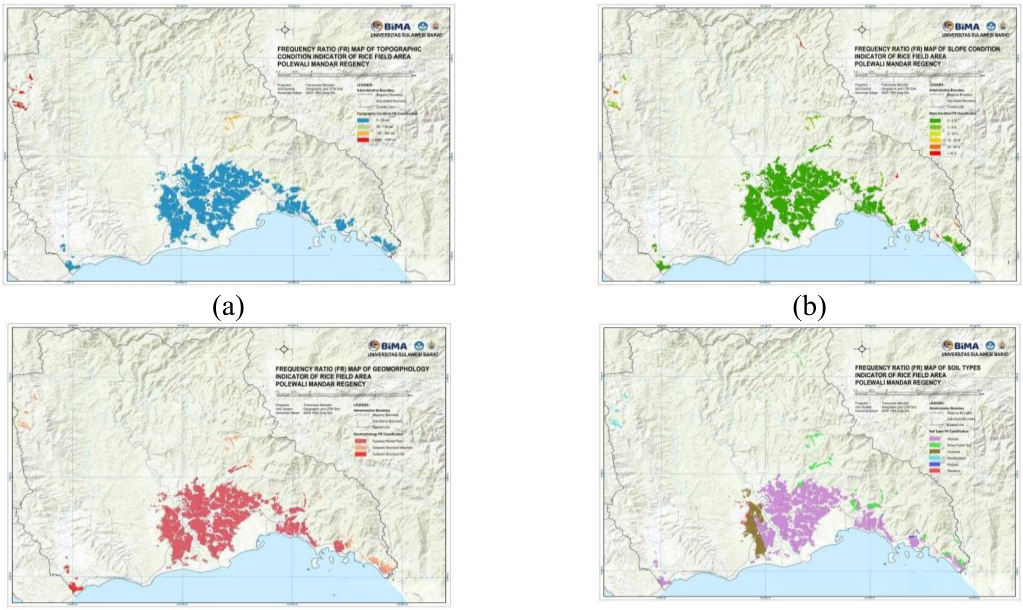
| Independent variable | Classification | Class Output | % Output | Class Input | % Input | Frequency Ratio |
|---|---|---|---|---|---|---|
| | 750 – 1750 m | 471.35 | 0.44 | 6605.74 | 0.40 | 1.09 |
| | >1750 m | 218.57 | 0.20 | 3669.65 | 0.22 | 0.91 |
| Distance from road | 0 – 500 m | 995.47 | 0.93 | 14179.74 | 0.87 | 1.07 |
| | 500 – 1000 m | 72.74 | 0.07 | 2087.94 | 0.13 | 0.53 |
| | 1000 – 1500 m | 4.53 | 0.00 | 122.75 | 0.01 | 0.56 |
| | >1500 | 0.00 | 0.00 | 0.66 | 0.00 | 0.00 |
| Distance from settlement | 0-500 | 879.21 | 0.82 | 13147.13 | 0.80 | 1.02 |
| | >500 | 193.53 | 0.18 | 3243.96 | 0.20 | 0.91 |
| Settlement density | Low | 419.13 | 0.39 | 5749.35 | 0.35 | 1.11 |
| | Medium | 379.75 | 0.35 | 6710.53 | 0.41 | 0.86 |
| | High | 273.85 | 0.26 | 3931.21 | 0.24 | 1.06 |
| Spatial pattern (as in spatial plan document) | Forest | 62.90 | 0.06 | 169.27 | 0.01 | 5.68 |
| | Mangrove | 0.00 | 0.00 | 0.57 | 0.00 | 0.07 |
| | Fisheries | 0.99 | 0.00 | 68.88 | 0.00 | 0.22 |
| | Plantation | 171.39 | 0.16 | 229.57 | 0.01 | 11.41 |
| | Settlement | 266.30 | 0.25 | 2032.16 | 0.12 | 2.00 |
| | Agriculture | 483.68 | 0.45 | 504.75 | 0.03 | 14.64 |
| | Riparian | 0.00 | 0.00 | 2.14 | 0.00 | 0.00 |
| | Rverbank | 11.67 | 0.01 | 256.43 | 0.02 | 0.70 |

(Source: Data analysis,2025)

Based on the frequency ratio calculation as displayed in table 3, the highest ratio can be found in the spatial pattern parameter, which is agricultural land with ratio 14.64. This finding is evidence that further strengthens the theory that there has been a significant change in the function of rice fields in Polewali Mandar Regency. The other highest ratios were in the topographic parameters of the altitude class 500-100 meters above sea level (11.96), the soil type parameters in the Mediterranean class (11.96) and the spatial pattern parameters of the plantation class (11.41). Spatial distribution of frequency ratio calculation result for each indicator for the area of rice field can be displayed in figure 2 and figure 3.



(a) (b)

(c) (d)

**Figure 2**. Map of frequency ratio (FR) for indicator: (a) Topography, (b) Slope, (c) Geomorphology, (d) Soil Types.

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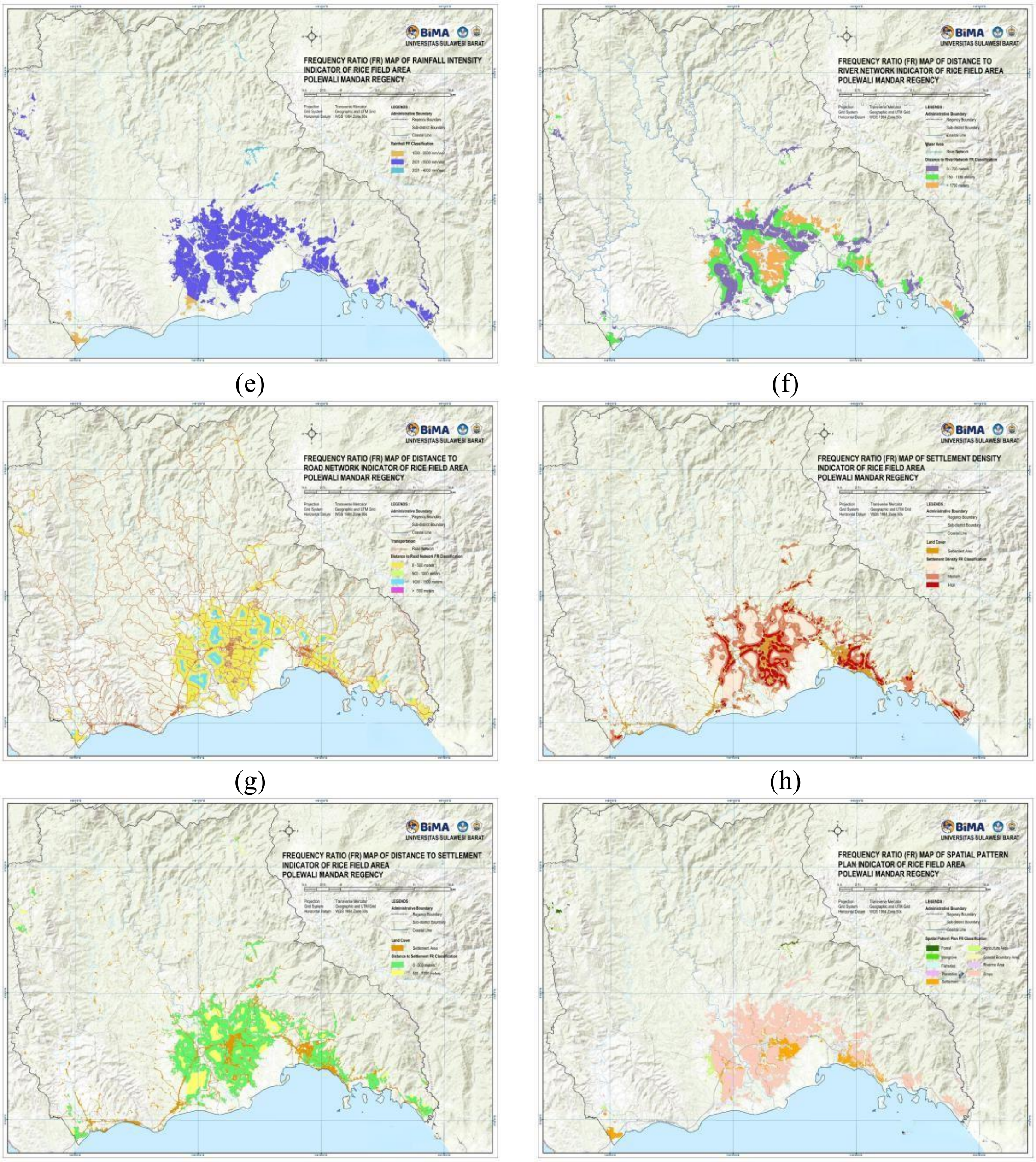


(e) (f)
(g) (h)
(i) (j)

**Figure 3**. Map of frequency ratio (FR) for indicator: (e) Rainfall intensity, (f) Distance from river, (g) Distance from road, (h) Distance from settlement, (i) Settlement density, and (j) Spatial pattern

The FR value of each causative factor will then be analyzed using a GIS approach with an overlay method and adding the Sustainable Food Farming Area (or KP2B in Indonesian) as a boundary to get a value that represents the spatial modeling prediction of rice field conversion for the next 10 years with the 2020 database as the base year for the prediction.

### 3.3. Validation of modeling results

Determining the Validation of modeling results was carried out using a statistical approach depicted through the Receiver Operating Characteristic (ROC) curve. Validation of the ROC curve in Table 4 uses pixel sampling of rice fields with a total of 214,510 pixels. AUC Success validation uses 70% (150,157 pixels) of landslide event pixels, 30% (64,353 pixels) is used in AUC Predictive validation.

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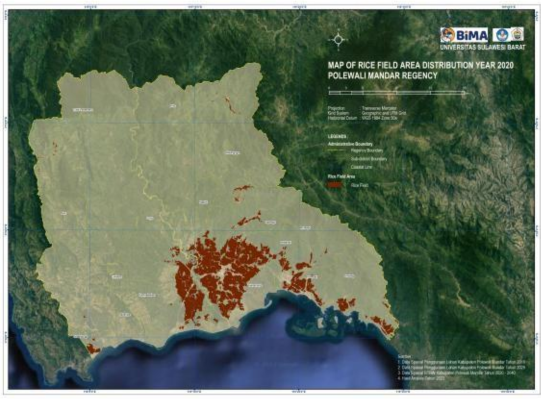
The process of validating the model prediction results was carried out 10 times with random sampling of a predetermined number of points.

**Table 4.** AUC curve value resulting from ROC validation of rice field conversion modeling with 10 repetitions

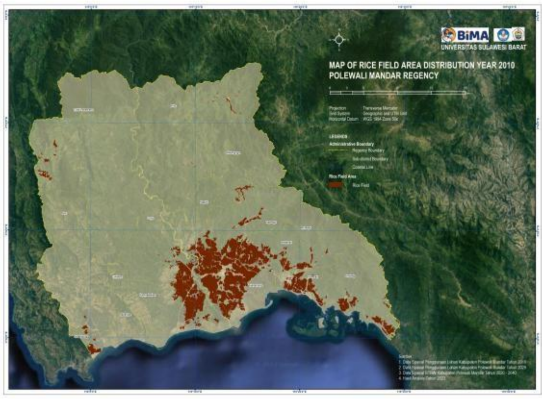
| Methods | Iteration | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | 10 |
| AUC *Succes* | 0,83 | 0,83 | 0,83 | 0,83 | 0,83 | 0,83 | 0,83 | 0,83 | 0,83 | 0,83 |
| AUC *Predictive* | 0,75 | 0,75 | 0,75 | 0,75 | 0,75 | 0,75 | 0,75 | 0,75 | 0,75 | 0,75 |

(Source : Data analysis, 2025)

The validation of the rice field conversion prediction model was conducted using the Receiver Operating Characteristic (ROC) approach with the Area Under Curve (AUC) indicator. The test results through 10 iterations showed that the AUC Success value ranged from 0.829–0.830, while the AUC Predictive value was in the range of 0.751–0.752. The AUC Success value, which is in the good category (0.8–0.9), indicates that the model is able to explain historical rice field conversion patterns with a high level of accuracy. This means that the combination of causative variables used including biophysical factors and accessibility significantly contributes to distinguishing converted and unconverted areas. Meanwhile, the AUC Predictive value, which is in the sufficient category (0.7–0.8), indicates that the model has adequate predictive ability against independent test data. The difference between the AUC Success and Predictive values is relatively small (<0.1), so it can be concluded that the model does not experience significant overfitting and has a fairly good level of generalization. The stability of the AUC value across all iterations also indicates that the model is robust to sampling variations. Thus, the integration of the Frequency Ratio (FR) approach as the basis for statistical weighting and Spatial Multi-Criteria Analysis (SMCA) using an overlay technique has been proven to produce a model with moderate to good performance. Overall, these validation results indicate that the model is suitable for use in predicting medium-term rice field conversion simulations and supporting further analysis related to production estimation and food self-sufficiency evaluation.



(a)



(b)

**Figure 4.** Map of the distribution of rice fields in Polewali Mandar Regency year 2010 (a) and year 2020 (b)

### 3.4. Prediction Modeling Results of The Distribution of Rice Field Conversion

The results obtained were classified into 10 classes using a geometrical interval approach to determine predictions of the spatial distribution of rice field conversion every year for 10 years.

**Table 5.** Classification Of Area Of Converted Rice Fields For 10 Years

| Classification | Interval | Prediction (year) | Converted Land Area (ha) |
|---|---|---|---|
| 1 | 28,24 – 52,65 | Year – 1 (2021) | 64.86 |
| 2 | 17,05 – 28,24 | Year – 2 (2022) | 117.43 |

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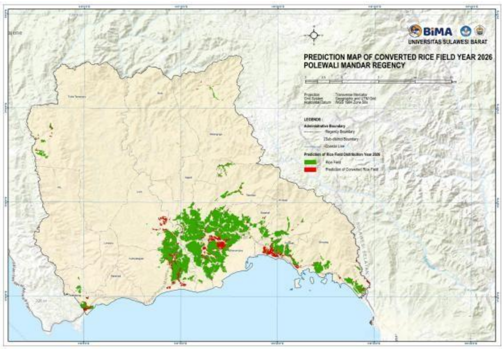
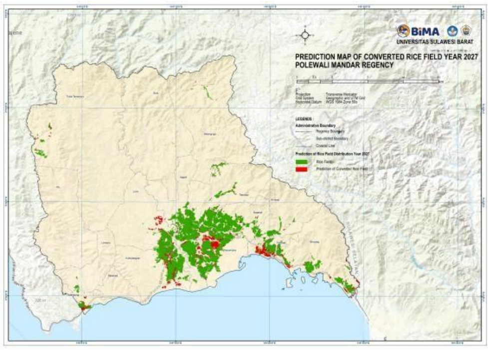
| Classification | Interval | Prediction (year) | Converted Land Area (ha) |
|---|---|---|---|
| 3 | 11,91 – 17,05 | Year – 3 (2023) | 221.52 |
| 4 | 9,56 – 11,91 | Year – 4 (2024) | 965.56 |
| 5 | 8,48 – 9,56 | Year – 5 (2025) | 450.53 |
| 6 | 7,98 – 8,48 | Year – 6 (2026) | 105.11 |
| 7 | 7,76 – 7,98 | Year – 7 (2027) | 167.86 |
| 8 | 7,65 – 7,76 | Year – 8 (2028) | 365.00 |
| 9 | 7,42 – 7,65 | Year – 9 (2029) | 337.05 |
| 10 | 6,93 – 7,42 | Year – 10 (2030) | 10.66 |

(Source: Data analysis,2025)

From analysis result displayed in table 5, the prediction of rice field conversion in Polewali Mandar Regency is fluctuative with the highest conversion occurred in year 2024, followed by year 2025. Then, from the prediction result above, prediction map of rice field conversion in Polewali Mandar Regency for year 2026 to 2030 made and presented in figure 5.




(a)

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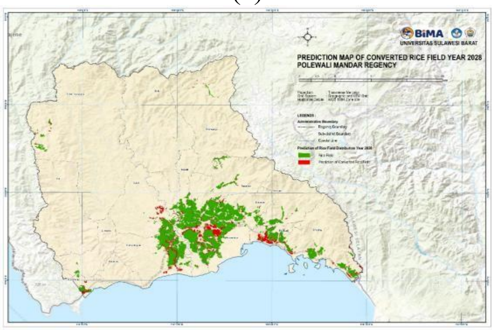
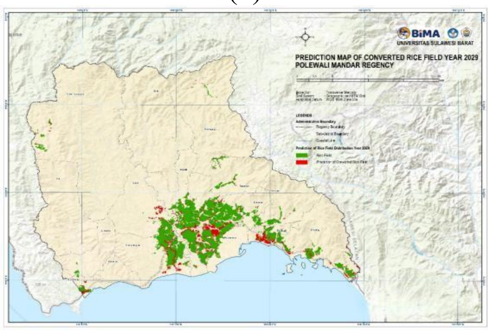
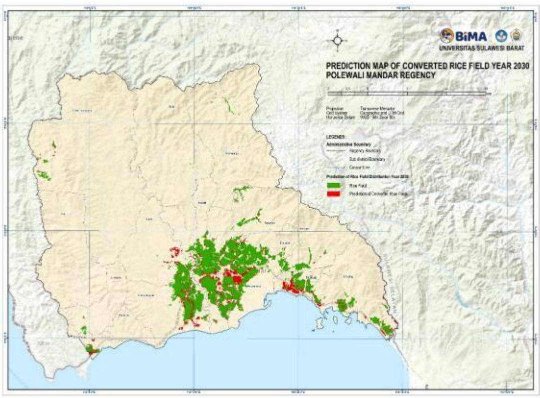



(c)




(d)




(e)

**Figure 5.** Prediction map of the converted rice fields distribution in Polewali Mandar Regency year 2026 (a), 2027 (b), 2028 (c), 2029 (d) and 2030 (e)

## 4. CONCLUSION

This study demonstrates that the integration of Frequency Ratio (FR) and Spatial Multi-Criteria Analysis (SMCA) within a GIS framework provides a robust and replicable approach for predicting spatial patterns of rice field conversion. Historical analysis confirms a substantial reduction in rice field area between 2010 and 2020, reflecting increasing development pressure and demographic growth. The modeling results indicate that conversion is spatially associated with biophysical suitability, accessibility to infrastructure, settlement proximity, and the direction of regional spatial planning policies. Validation results (AUC success = 0.83; predictive = 0.75) confirm that the model achieves good explanatory power and adequate predictive capability, with stable performance across iterations. The projected distribution for 2026–2030 highlights areas that are potentially vulnerable to continued agricultural land loss, particularly outside designated sustainable food agricultural zones. Beyond quantifying land conversion, this study contributes a spatially explicit decision-support framework that can assist local governments in balancing urban development and agricultural preservation. The findings emphasize the importance of strengthening spatial control mechanisms, optimizing land-use zoning enforcement, and integrating predictive modeling into regional planning processes. By anticipating future conversion patterns, policymakers can design targeted interventions to maintain productive rice fields and enhance long-term regional food security resilience.

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