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Random Forest Model for Food Security Index Prediction Using Climate and Socioeconomic Panel Data in North Sumatra

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Abstract−This study develops and evaluates a Random Forest Regression model for predicting the Food Security Index (IKP) using climate and socioeconomic panel data from 33 regencies/cities in North Sumatra, with Deli Serdang Regency as the principal case discussed. The predictors comprise poverty rate, gross regional domestic product (GRDP) per capita, annual rainfall, and annual rainy days. The common modeling period was 2020–2021. Of 66 potential regency-year observations, eight lacked IKP values in 2021, leaving 58 complete observations. To account for the panel structure, model performance was evaluated using nested group-aware cross-validation, with regency/city as the grouping variable. Across five outer folds, Random Forest achieved RMSE 8.450 ± 2.703, MAE 6.289 ± 2.018, and R^2 −0.501 ± 1.500. Linear regression obtained RMSE 8.282 ± 2.431, MAE 6.401 ± 2.262, and R^2 −0.363 ± 1.192, while a single decision tree obtained RMSE 9.821 ± 3.482, MAE 8.030 ± 2.849, and R^2 −0.972 ± 1.871. Thus, no model demonstrated strong or stable out-of-group generalization. Repeated group-aware permutation analysis identified poverty rate as the most consistent predictor. The results are predictive and associational, not causal, and the present model should be regarded as an exploratory proof of concept requiring larger, spatially resolved data for robust regional forecasting.
Keywords: Food Security Index; Random Forest Regression; Panel Data; Feature Importance; Machine Learning

1. INTRODUCTION

Food security is a strategic issue that directly affects the social stability, economic performance, and sustainable development of a region. As one of the food-producing buffer areas in North Sumatra Province, Deli Serdang Regency plays an important role in meeting regional food needs, particularly for rice and horticultural commodities. In recent years, however, food security in this region has faced increasingly complex challenges driven by climate change, land-use conversion, population growth, and the socioeconomic dynamics of rural communities [1]. Shifting rainfall patterns, rising average temperatures, and extreme climatic events such as droughts and floods have directly affected agricultural productivity, while uncertainty in the planting season makes it difficult for farmers to determine the optimal planting time, ultimately reducing crop yields [2]. Meanwhile, socioeconomic factors such as household income, the proportion of the poor population, access to agricultural infrastructure, farmers' educational attainment, and the number of active farmers also influence a community's capacity to withstand food crises [3].

At present, the mapping and prediction of food security conditions in Deli Serdang are still predominantly carried out using conventional statistical methods and periodic evaluations based on simple historical data. This approach has not been able to capture the complex, non-linear relationships between climatic variables and socioeconomic indicators in shaping the regional food security index [4], so that early warning of potential food vulnerability remains suboptimal. Machine learning offers an alternative that can model such non-linear relationships without requiring strict distributional assumptions, and has been applied increasingly to agricultural and food-related prediction problems.

Prior studies provide useful but partial grounding for this problem. Reviews of machine learning and deep learning in precision agriculture emphasize models such as LSTM and CNN for complex agricultural data [5], [6], while Random Forest has been applied to crop-yield prediction using climate and biophysical variables [7]. Machine-learning approaches have also been used to estimate socioeconomic indicators such as poverty from multi-source data [8], [9]. A food-security prediction study using SVM and K-Nearest Neighbors reported encouraging performance [10], while other work has examined artificial intelligence for climate-change adaptation and agriculture [11]. Cross-national research further demonstrates the importance of economic and social indicators in food-security outcomes [12], [13], and recent work has explored machine-learning-based short-term food-security forecasting [14]. Within the literature reviewed in this study, relatively limited attention has been given to combining climate and socioeconomic variables in a regency/city-level panel-data framework while using the regional Food Security Index as the prediction target. This reviewed scope, rather than an exhaustive systematic review, motivates the present study.

This study addresses this gap by developing a Random Forest Regression model using panel observations from 33 regencies/cities across North Sumatra Province, with Deli Serdang Regency serving as the principal case discussed. The predictors are rainfall, number of rainy days, poverty rate, and GRDP per capita. The contribution lies in integrating the available climate and socioeconomic panel data, comparing Random Forest with linear-regression and single-tree baselines, and examining feature importance under group-aware validation. The analysis is predictive and associational and is not designed to establish causal effects.

2. RESEARCH METHODOLOGY

2.1 Research Design and Data Sources

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This study employs a quantitative-computational approach using panel observations from 33 regencies/cities in North Sumatra. Food Security Index (IKP) data were obtained from the National Food Agency Open Data portal at the regency/city level (accessed June 1, 2026). Poverty-rate and GRDP-per-capita data were obtained from official Statistics Indonesia (BPS) datasets, accessed through the SISADA Kota Pematangsiantar portal on June 1, 2026. GRDP per capita at constant 2010 prices was used as a proxy for regional income. Annual rainfall and rainy-day observations were obtained from BMKG Region I and represent the Medan/Deli Serdang observation area rather than individual regencies/cities. Consequently, all regencies/cities within the same year receive the same climate values. This limitation is explicitly considered when interpreting the climate variables.

Table 1. *Data Sources Used in This Study*

Data Source	Data Type	Description
National Food Agency Open Data	Food Security Index (IKP)	Regency/city-level IKP; 2020–2021 used; accessed June 1, 2026
BPS North Sumatra via SISADA Kota Pematangsiantar	Poverty rate; GRDP per capita	Official BPS data; GRDP at constant 2010 prices; accessed June 1, 2026
BMKG Region I	Annual rainfall; annual rainy days	Medan/Deli Serdang representative observation; same annual values across regencies/cities

2.2 Data Preprocessing

The datasets were merged by regency/city and year. The common modeling period was 2020–2021, producing 66 potential observations (33 regencies/cities × 2 years). Eight regency/city observations lacked IKP values in 2021; these rows were not imputed and were excluded through complete-case selection, leaving 58 complete observations. No target-value interpolation was performed. Data-dependent preprocessing, when required, is fitted only within training folds to avoid information leakage. Because Random Forest does not require feature scaling, unnecessary normalization was not applied to the final pipeline.

2.3 Model Development

Because the observations form a regency/city-by-year panel, evaluation uses five GroupKFold folds, ensuring that all observations from a regency/city are held entirely in either training or validation data within a fold. Hyperparameter selection is performed only within the corresponding outer-training data using inner GroupKFold cross-validation. Random Forest hyperparameters were searched over n_estimators = {100, 200, 300}, max_depth = {4, 6, 8, unlimited}, and min_samples_split = {2, 4, 6}. Multiple linear regression and a single decision tree were retained as benchmark models.

2.4 Model Evaluation

Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2), defined as follows:

$$\mathrm{RMSE} = \sqrt{\left[\left(\frac{1}{n}\right) \Sigma_{\mathrm{i}}{}^{=1\mathrm{n}}\ (y_{\mathrm{i}} - \hat{y}_{\mathrm{i}})^2\right]} \tag{1}$$

$$\mathrm{MAE} = \left(\frac{1}{n}\right) \Sigma_{\mathrm{i}}{}^{=1\mathrm{n}}\ |y_{\mathrm{i}} - \hat{y}_{\mathrm{i}}| \tag{2}$$

$$R^2 = 1 - \left[\frac{\Sigma_{\mathrm{i}}{}^{=1\mathrm{n}}(y_{\mathrm{i}} - \hat{y}_{\mathrm{i}})^2}{\Sigma_{\mathrm{i}}{}^{=1\mathrm{n}}(y_{\mathrm{i}} - \bar{y})^2}\right], \tag{3}$$

where y_i is the observed IKP, $\hat{y}_i$ is the predicted IKP, $\bar{y}$ is the mean observed IKP, and n is the number of validation observations. Performance is summarized across five outer group-aware folds as mean ± standard deviation. Permutation importance was additionally assessed using 100 repeated group-aware train-test splits.

3. RESULT AND DISCUSSION

3.1 Data Description and Characteristics

The final complete-case dataset contains 58 regency-year observations from 33 regencies/cities for 2020–2021. Poverty rate has the strongest bivariate relationship with IKP (r = −0.543), indicating a moderate negative association. GRDP per capita has a weak positive correlation (r = 0.136), while rainfall and rainy days each show weak negative correlations with IKP (r ≈ −0.096). The climate correlations should be interpreted cautiously because the annual climate values are identical across regencies/cities within a given year and therefore contain no within-year spatial variation.

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Table 2. Descriptive Overview of the Modeling Dataset (N = 58)

Variable	Mean	Std. Dev.	Minimum	Maximum	Unit
IKP	72.54	8.53	49.53	85.66	Index
Poverty rate	10.85	5.08	0.13	26.42	%
GRDP per capita	29766932.54	13076044.30	11832505.03	63321299.44	Rp (constant 2010 prices)
Annual rainfall	3503.14	261.76	3205.00	3729.00	mm/year
Annual rainy days	217.05	18.48	196.00	233.00	days/year

Deli Serdang remains the principal case discussed, but the predictive model is a North Sumatra panel model rather than a model trained only on Deli Serdang observations.

3.2 Correlation Analysis Among Variables

Pearson correlation was used only to describe the direction and strength of bivariate linear associations. Poverty rate showed a moderate negative association with IKP ($r = -0.543$), GRDP per capita showed a weak positive association ($r = 0.136$), and rainfall and rainy days each showed weak negative associations ($r \approx -0.096$). These correlations do not establish causal relationships and are interpreted separately from Random Forest feature importance.

3.3 Hyperparameter Optimization and Overfitting Control

Hyperparameter optimization was conducted exclusively within the training portion of each outer group-aware fold. The selected Random Forest parameters varied across the five outer folds: (1) 100 trees, max_depth = 8, min_samples_split = 6; (2) 300 trees, max_depth = 8, min_samples_split = 6; (3) 100 trees, max_depth = 6, min_samples_split = 4; (4) 300 trees, max_depth = 8, min_samples_split = 2; and (5) 100 trees, max_depth = 4, min_samples_split = 6. The variation in selected hyperparameters across folds indicates sensitivity of model selection to the training subsets, which is expected given the limited sample size.

Table 3. Random Forest Hyperparameters Selected Within the Five Outer Group-Aware Folds

Outer Fold	n_estimators	max_depth	min_samples_split	Selection
1	100	8	6	Inner grouped CV
2	300	8	6	Inner grouped CV
3	100	6	4	Inner grouped CV
4	300	8	2	Inner grouped CV
5	100	4	6	Inner grouped CV

Hyperparameter selection was conducted exclusively within the inner cross-validation folds. Each outer fold was subsequently evaluated using the hyperparameters selected from its corresponding inner training-validation procedure, thereby preventing information from the outer validation data from influencing model selection.

3.4 Model Performance and Comparison with Benchmark Models

Across five outer group-aware validation folds, Random Forest obtained RMSE 8.450 ± 2.703, MAE 6.289 ± 2.018, and R^2 −0.501 ± 1.500. Multiple linear regression obtained RMSE 8.282 ± 2.431, MAE 6.401 ± 2.262, and R^2 −0.363 ± 1.192. The single decision tree obtained RMSE 9.821 ± 3.482, MAE 8.030 ± 2.849, and R^2 −0.972 ± 1.871. Random Forest therefore achieved the lowest average MAE but did not outperform linear regression on average RMSE or R^2. The negative and highly variable R^2 values show that none of the models provides strong or stable generalization to regencies/cities excluded from training.

Table 4. Group-Aware Cross-Validation Performance (Mean ± SD Across Five Outer Folds)

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Model	RMSE (mean ± SD)	MAE (mean ± SD)	R^2 (mean ± SD)	Interpretation
Multiple Linear Regression	8.282 ± 2.431	6.401 ± 2.262	−0.363 ± 1.192	Lowest mean RMSE / highest mean R^2
Single Decision Tree	9.821 ± 3.482	8.030 ± 2.849	−0.972 ± 1.871	Weakest average performance
Random Forest	8.450 ± 2.703	6.289 ± 2.018	−0.501 ± 1.500	Lowest mean MAE

Table 4 presents the predictive performance of the three models under group-aware cross-validation. Random Forest achieved an average RMSE of 8.450 ± 2.703, MAE of 6.289 ± 2.018, and R^2 of −0.501 ± 1.500. Compared with the single Decision Tree, Random Forest produced lower RMSE and MAE values and a higher R^2, indicating better average predictive performance under the applied validation scheme. However, Random Forest did not consistently outperform Multiple Linear Regression across all evaluation metrics. Multiple Linear Regression achieved a slightly lower RMSE (8.282 ± 2.431) and a higher R^2 (−0.363 ± 1.192), whereas Random Forest achieved the lowest MAE (6.289 ± 2.018). Therefore, the results do not indicate a single model that is consistently superior across all performance measures. The negative mean R^2 values and relatively large standard deviations across validation folds further indicate substantial variability in predictive performance. This suggests that the available dataset provides limited information for generalizing IKP predictions to regencies/cities that were not represented during model training.

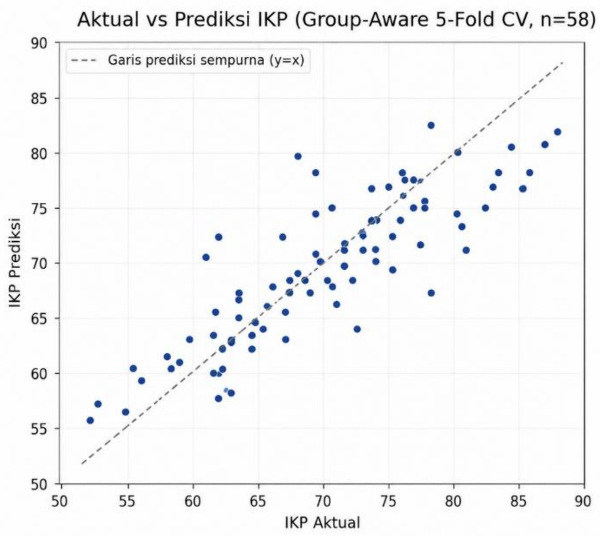

Fig. 1. Actual versus Predicted Food Security Index (IKP) Using Group-Aware 5-Fold Cross-Validation

Figure 1 presents the relationship between the actual and predicted Food Security Index (IKP) values obtained using group-aware 5-fold cross-validation. Each point represents an out-of-fold prediction, where observations from the same regency/city were kept within the same fold to prevent geographic information leakage between training and validation data. The dashed diagonal line represents perfect prediction, where the predicted IKP is equal to the actual IKP. The dispersion of several observations away from the diagonal line indicates variability in the model's predictive performance across regencies/cities. This pattern is consistent with the cross-validation results, where Random Forest achieved an average RMSE of 8.450 ± 2.703, MAE of 6.289 ± 2.018, and R^2 of −0.501 ± 1.500. These results indicate that although the model captures some patterns in the data, its ability to generalize IKP predictions to geographically unseen regencies/cities remains limited under the available dataset.

3.5 Feature Importance Analysis

Permutation importance was estimated using 100 repeated group-aware splits to assess the stability of each predictor's contribution to model performance. In each split, regency/city was used as the grouping variable, ensuring that observations from the same geographic unit were not simultaneously included in the training and validation sets. Feature importance was quantified as the change in validation RMSE (ΔRMSE) after randomly permuting each predictor while keeping the remaining predictors unchanged. A positive ΔRMSE indicates an increase in prediction error after permutation, suggesting that the corresponding predictor provides useful predictive information to the model. Conversely,

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values close to zero indicate limited predictive contribution, while negative values suggest that the predictor does not consistently improve out-of-group predictive performance.

Table 5. Permutation Importance Across 100 Repeated Group-Aware Validation Splits

Variable	Repeated group-aware permutation importance (ΔRMSE)	Interpretation
Poverty rate	1.685 ± 1.399 (95% CI: 1.408–1.963)	Strongest; positive in 91% of splits
GRDP per capita	−0.371 ± 0.711	Unstable / no consistent added value
Rainy days	≈ +0.008	Negligible under current data structure
Rainfall	≈ +0.008	Negligible under current data structure

Across 100 repeated group-aware validation splits, poverty rate showed the strongest and most consistent predictive contribution (mean ΔRMSE = 1.685 ± 1.399; 95% CI: 1.408–1.963), with positive importance in 91% of splits. GRDP per capita did not show stable additional predictive value (mean ΔRMSE = −0.371 ± 0.711). Rainfall and rainy days produced only very small changes in validation RMSE (approximately +0.008 on average). These values measure predictive importance, not percentages of causal influence. The near-zero climate importance should not be interpreted as evidence that climate is substantively irrelevant because the available climate measurements lack regency/city-level spatial variation within each year.

3.6 Prediction Results for Deli Serdang Regency

Deli Serdang serves as the principal case of interest within the North Sumatra panel. Model evaluation focuses on generalization to geographic groups excluded from training; therefore, Deli Serdang-specific fitted values are not used as evidence of out-of-sample predictive accuracy.

3.7 Discussion and Study Limitations

The results identify poverty rate as the most consistent predictor of IKP in the available panel dataset. Its moderate negative Pearson correlation ($r = -0.543$) describes the direction of the observed association, while repeated group-aware permutation importance demonstrates useful predictive information. These findings do not establish causality. The observational design cannot determine whether reducing poverty would itself cause IKP to increase, because both variables may also be influenced by unobserved socioeconomic, institutional, infrastructural, and policy factors. GRDP per capita showed only a weak positive bivariate correlation and did not provide stable additional predictive information under repeated grouped validation. The small predictive contribution of rainfall and rainy days is constrained by the regional climate-data design.

For Deli Serdang, the observed combination of relatively low poverty and high IKP is consistent with the broader negative association found in the panel, but it should not be treated as evidence of a causal mechanism. The predictive relevance of poverty suggests that household economic vulnerability warrants further policy investigation rather than proving that a particular poverty-reduction intervention will directly increase IKP.

4. CONCLUSION

This study evaluated the prediction of the Food Security Index (IKP) using climate and socioeconomic panel data from 33 regencies/cities in North Sumatra, with Deli Serdang as the principal case discussed. A total of 58 complete observations from 2020–2021 were analyzed using a group-aware validation framework that accounted for the geographic structure of the panel data. Random Forest achieved an average RMSE of 8.450 ± 2.703, MAE of 6.289 ± 2.018, and R^2 of −0.501 ± 1.500. Although Random Forest produced the lowest average MAE and performed better than the single Decision Tree across the evaluated metrics, Multiple Linear Regression achieved a slightly lower RMSE and higher R^2. These results indicate that no single model consistently dominated across all evaluation metrics and that predictive performance varied considerably across geographically separated validation folds.

Among the examined predictors, poverty rate showed the strongest and most consistent relationship with IKP. It exhibited a moderate negative correlation with IKP ($r = -0.543$) and the highest repeated group-aware permutation importance (mean ΔRMSE = 1.685 ± 1.399), indicating that poverty rate provides comparatively consistent predictive information for regional IKP variation. However, these findings represent predictive associations rather than causal effects. The limited predictive contribution of rainfall and rainy days should also be interpreted cautiously because the available climate data lacked regency/city-level spatial variation.

Overall, the findings demonstrate both the potential and limitations of applying machine-learning methods to regional food-security prediction using a small panel dataset. The current model is more appropriately considered an

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exploratory predictive framework than a definitive forecasting model. Future research should incorporate longer temporal coverage, regency/city-specific climate observations, additional socioeconomic and food-security determinants, and external validation to improve predictive robustness and generalizability.

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