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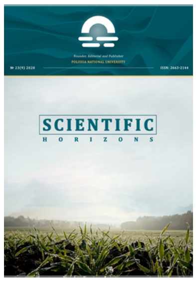

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Rice yield prediction using Bayesian analysis on rainfed lands in the Sumbing-Sindoro Toposequence, Indonesia

Abdul Aziz*
Postgraduate Student
Universitas Sebelas Maret
57126, 36 Ir. Sutami, Surakarta, Central Java, Indonesia
http://orcid.org/0000-0002-9688-3180

Komariah
Doctor of Applied Science, Soil Science, and Pydrometeorology
Universitas Sebelas Maret
57126, 36 Ir. Sutami, Surakarta, Central Java, Indonesia
https://orcid.org/0000-0001-7704-0754

Dwi Priyo Ariyanto
Doctor of Soil and Water Conservation
Universitas Sebelas Maret
57126, 36 Ir. Sutami, Surakarta, Central Java, Indonesia
https://orcid.org/0000-0001-6605-9599

Sumani
Doctor of Agroclimatology
Universitas Sebelas Maret
57126, 36 Ir. Sutami, Surakarta, Central Java, Indonesia

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Abstract. Since rainfed rice fields typically lack nutrients, frequently experience drought, and require more fund to support farming operations, the production results become erratic and unpredictable. This research aims to construct location-specific rice yield predictions in the rainfed rice fields among the Sumbing-Sindoro Toposequence, Central Java, using a Bayesian method. This study is a survey with an exploratory descriptive methodology based on data from both field and laboratory research. Prediction model analysis using the Bayesian Neural Network (BNN) method on 12 geographical units, sampling spots were selected with intention. The following variables were measured: soil (pH level, Organic-C, Total-N, Available-P, Available-K, soil types, elevation, slope) and climate (rainfall, evapotranspiration). According to the statistical analysis used, the BNN model's performance has the highest accuracy, with an RMSE value of 0.448 t/ha, which compares to the MLR and SR models, indicating the lowest error deviation. To obtain the ideal parameter sampling design, parameter distribution is directly and simultaneously optimised using an optimisation technique based on Pareto optimality.

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**Corresponding author*

The top 7 data sets (slope, available-P, evapotranspiration, soil type, rainfall, organic-C, and pH) yielded the highest accuracy based on the test results for the three-parameter groups. The coefficient of determination has the highest value, 0.855, while the RMSE test for the model using the top 7 data set has the lowest error value at 0.354 t/ha and 18.71%, respectively. By developing location-specific rice yield predictions using a Bayesian method, farmers and agricultural practitioners can benefit from more accurate and reliable estimates of crop productivity

Keywords: Agricultural sustainability; Bayesian Neural Network (BNN); food security; rainfed rice field; yield prediction

INTRODUCTION

While just 26.91 million tonnes of rice were produced nationally in Indonesia in 2020, the country's overall rice consumption topped 30 million tonnes (Lotulung, 2020; Ministry of Agriculture, 2020). In order to meet the country's food needs, rainfed lowland areas are anticipated to provide for Indonesians who eat rice as their primary source of nutrition (Wihardjaka *et al.,* 2020). In Central Java, there are 77,532 hectares of rainfed paddy fields, and 342,777 tonnes of Milled Dry Grain (MDG) are produced annually, according to BPS Central Java Province, (2018). As a result, following irrigated lowland rice, rice produced from rainfed lowland rice now contributes the most to national rice production. The Indonesian government is still working on expanding the nation's rice production in several ways, one of which is by growing rice on drylands, such as rainfed lowland rice.

Difficulties in increasing rice yield in Indonesia include using inefficient farming techniques and parts of its rainfed rice fields, which are highly vulnerable to climate change (Ruminta *et al*., 2017). According to Rahayu (2014) the productivity of irrigated lowland rice fields is more significant due to more frequent planting than rainfed rice fields, which can only yield 1-2 times a year. In order to boost rice output, rainfed rice fields can be a valuable resource that needs to be adequately managed (Sinaga *et al.*, 2014).

As rainfed rice fields are typically nutrient deficient, often suffer from drought, and require more financing to sustain farming activities, production outcomes are unstable and unpredictable (Novia & Satriani, 2020). As noted by Murniati *et al.* (2017), in order to grow rainfed rice, farmers must be able to adapt to the environment and available resources. To maximise the yield of rainfed rice fields, farmers need to be aware of climate change, crop types, cropping patterns, irrigation management, and the right sowing period. Therefore, a yield prediction model is needed as a guide for adaptation during cultivation to facilitate effective management of rainfed rice fields.

Estiningtyas & Syakir (2018) argue that in crop production, the level of production is determined by three main factors: climate, soil, and plants. These three factors need to interact together with proper management to produce optimal yields. The lack of any one factor will affect production results. Site-specific cropping practices are a way of adapting cultivation to the local agro-ecosystem. According to Anupama & Lakshmi (2021), farmers need advice on the right planting time and cultivation methods with the best yield prediction model that is expected to yield the highest profit with little investment.

One of the most complex issues in precision agriculture is yield prediction. Since crop yields rely on various factors, including climate, soil, fertiliser use, and seed variety, yield prediction requires numerous data sets (Van Klompenburg *et al.,* 2020). The machine learning model is a methodology that can forecast yields since it can ascertain how plants react to elements that have an impact on crop output, such as the soil, the environment, cultivation methods, and seed kinds used (Pant *et al.,* 2021). Machine learning algorithms attempt to forecast crop yields based on empirical correlations between yield-driving elements and historical yield records rather than modelling biophysical processes in crop agriculture (Wang *et al.,* 2020). The Bayesian model is the machine learning model used in this research. According to *Drury et al.* (2017), Bayesian is appropriate for agriculture because it can represent interdependent causal elements or factors, give a general overview of partial or uncertain information, combine new information, and draw new conclusions using new information. Liu *et al.* (2017) pointed out that machine learning algorithms play a role in data-driven models to improve forecasting accuracy.

This research was conducted to identify yields in rainfed rice fields with a harvest prediction model based on specific soil and climate characteristics to provide recommendations regarding cultivation management efforts and planting time to reduce the risk of crop failure, especially in the Sumbing-Sindoro toposequences. Soil and climate characteristics variables were used in this study as a prediction basis for estimating crop yields. This prediction model is expected to help farmers determine the inputs and adaptations to obtain optimal results.

MATERIALS AND METHODS

Study area. The research was carried out on two mountain toposequences in Central Java, Indonesia, specifically on the southern slopes of Mount Sumbing and the southwest of Mount Sindoro (Fig. 1). To assess the nutrient level, soil samples were collected for the survey.

The study site's rainfed rice crops produced an average of 1.87 t/ha in harvest. This research used 21 site locations as research samples. These location points were made up of elevation, which were created at specific research locations based on the variety of environmental variables present there.

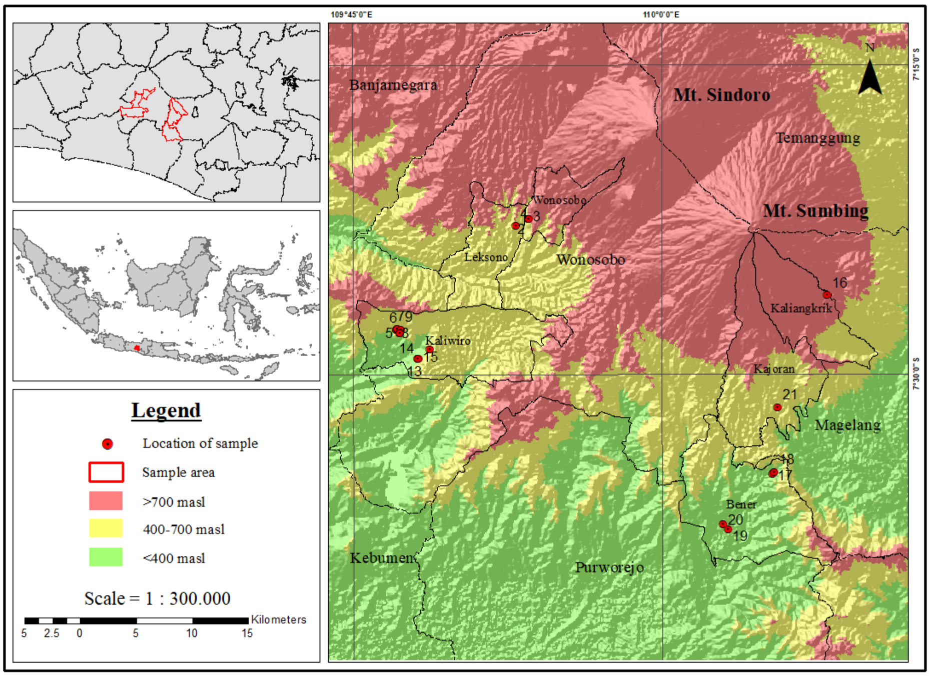


Figure 1. *Location of research toposequence (the southern slopes of Mount Sumbing and the southwest of Mount Sindoro)*

Research parameter. Characteristics of the soil and plant yield data recap. According on field observations and the outcomes of laboratory analyses of soil properties, this study employed data on soil characteristics in the field.

Table 1. *Research parameter about soil charactestics and yield on location-specific toposequence*

Soil and plant characteristics (unit)	Toposequences	
	Mount Sumbing	Mount Sindoro
Soil Characteristics		
pH	6	5-6
Organic-C (%)	1.45-5.27	1.18-5.98
Total-N (%)	0.54-1.40	0.64-1.01
Available-P (ppm)	2.39-9.55	0.29-7.65
Available-K (me/100g)	0.33-0.55	0.29-0.47
Type of soil	Inceptisols and Alfisols	Entisols, Inceptisols and Ultisols
Slope (%)	0-25	0-25
Plant yield data recap		
Yield (t/ha)	1.24-3.72	0.62-3.87

Note: *Analysis of soil characteristics based on Indonesian Soil Research Institute procedures (2009) and data on plant yield recap based on social survey carried out by researchers immediately at the research site*
Source: *compiled by the authors*

Characteristics of the climate. Climate is used in the model to assume the amount of water available and usable by plants. In the yield prediction model, climate factors affect crop productivity, and rainfall and air temperature are the main factors determining crop yields (M & B, 2021)which is a difficult task because of the climatic factors, soil fertility, nutrients and so on. Precise crop forecast requires fundamental understanding of the functional association between crop and input parameters and to predict the crop yield in advance we developed an Adaptive Lemuria algorithm. Our proposed model comprises of Deep Belief Network for feature learning and pre-training, Decision tree & K-Means clustering (HDTKM. Two factors are used in this prediction model: rainfall and evapotranspiration. This analysis used rainfall and air temperature data as a database. The data were taken from climatology stations at the research site (2012-2021). The evapotranspiration calculation process uses the Thornthwaite method.

Table 2. *Research parameter about climate characteristics on location-specific toposequence*

Climate (unit)	Toposequences	
	Mount Sumbing	Mount Sindoro
Rainfall (mm/year)	3.954-4.874	3.024-3.445
Evapotranspiration (mm/day)	1.47-2.93	5.27-5.81

Note: *Analysis of climate characteristics based on climatology stations at the research site (2012-2021)*
Source: *compiled by the authors*

Particularly in rainfed rice fields, which require almost no input and rely on rainwater for irrigation, the specifics of a location's soil and climate significantly impact agricultural production. Soil and climate characteristics are used in this study as the primary predictor parameters in the model. Using the information on the physical properties of the land and the actual climate in the field, it will be conceivable to describe the land's potential for crop production (Abdalla *et al.*, 2019).

Bayesian Neural Network (BNN). The Bayes' theorem was developed into the BNN method, which utilises the posterior probability value of the input data to offer information through particular parameters. Machine learning research yields BNN, a tool for examining decision-making under ambivalent circumstances. Using probabilities that define the relationship between variables, Bayes' theorem can be used to reflect the impact on existing data in practice (Batta, 2020). The Bayes' theorem can be expressed as:

$$P(Y) = \frac{P(X)P(X)}{P(Y)} \tag{1}$$

In this study, the BNN method was used because, precisely, BNN can estimate the distribution of predictions through the interpretation of the uncertainty of the input parameters. The BNN analysis results used 21 data samples, with 10 input parameters consisting of 2 indicators: soil and climate. The data is running and tested using different numbers of neurons to get the most effective results and close to the actual results. A trial and error method is used to get the optimal number of neurons in a prediction model (Liu *et al.,* 2001). The framework of the analysis carried out in this study is shown in Figure 2.

This research uses BNN to produce accurate yield predictions through various input parameters. The concept is expected to explain the relationship between variables and produce a predicted crop yield that is close to the actual crop yield. The prediction model for rainfed rice yields was developed using regional and field data to obtain an accurate model through 2 mountain toposequences. In particular, the model developed based on the input parameters can be seen in Figure 2. By incorporating factors of land characteristics in the form of climate and actual soil characteristics in the field as supporting parameters to increase the accuracy of the prediction model, this research was conducted to obtain: machine learning model prediction of rainfed rice fields with actual and location-specific parameters.

Figure 2. *Framework of prediction yield using BNN*

Model accuracy analysis. The predictive model's capacity and reliability are evaluated using accuracy analysis, which is also used to rate the model. The coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percent error were all calculated during the analysis (MAPE). The following equation is used:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y)^2}{n}} \tag{2}$$

$$MAPE = \sum_{i=1}^{n}\left|\frac{y_i - y}{y_i}\right| \times 100\% \tag{3}$$

Note: *yi = prediction result; y = average actual yield; n = amount of data sample*

The research's reliance on the RMSE accuracy model aims to standardise the measurement of a model's inaccuracy in forecasting quantitative data, demonstrating how dispersed the data are around the most appropriate line (Ali *et al.,* 2023). The RMSE is calculated by dividing the error (yi-y) by the number of data points (n). Unlike the MAPE accuracy model, which is used to estimate a model's relative error magnitude, the MAPE approach is helpful when determining the forecast's accuracy depending on the size or magnitude of the forecast variable; in other words, MAPE tells how significant the prediction mistake is (Son *et al.,* 2022).

RESULTS AND DISCUSSION

Examining BNN neurons. Using the BNN methods, predictions of the rice crop in rice fields that receive rainwater were analysed. To find a model with the highest coefficient of determination (R^2) and the lowest RMSE value, prediction analysis using BNN starts by trial and error testing the data and the number of neurons.

Table 3. *Comparison of model accuracy and the number of neurons employed*

Model accuracy	Number of neurons employed									
	1	2	3	4	5	6	7	8	9	10
R^2	0.793*	0.741	0.716	0.695	0.683	0.677	0.669	0.694	0.655	0.656
RMSE (t/ha)	0.448*	0.505	0.530	0.549	0.560	0.564	0.572	0.550	0.583	0.582

Note: *R^2 = higher is better; RMSE = lower is better; * = better*
Source: *compiled by the authors*

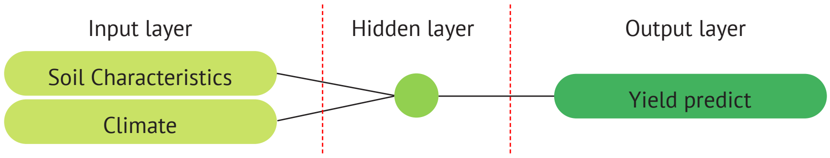


Figure 3. *Neuron of prediction yield using BNN*

The analysis was repeated ten times. Each checked the value of the neurons from 1 to 10, so that this analysis of BNN predictions was completed. According to the Table 3 above, neurons 1 through 10 have different R^2 and RMSE values. According to Table 3, the forecast of the rice harvest in fields that get rainwater is most suited for the criterion since it has an R^2 value of 0.793 and an RMSE of 0.448 t/ha. As the number of neurons used rises, performance in neuron testing declines.

BNN model performance. This research assessed the accuracy of two approaches for forecasting rainfed lowland rice yields. Stepwise Regression (SR) and Multiple Linear Regression (MLR) were the techniques utilised to compare the BNN model (SR). Multiple linear regressions, or MLR, is a statistical technique for predicting a value by integrating multiple parameters. While SR constructs the regression function based on the chosen parameters that have a strong relationship with the dependent variable, SR is a statistical development method from the regression method. Model evaluation criteria include RMSE, Pearson correlation, and R^2.

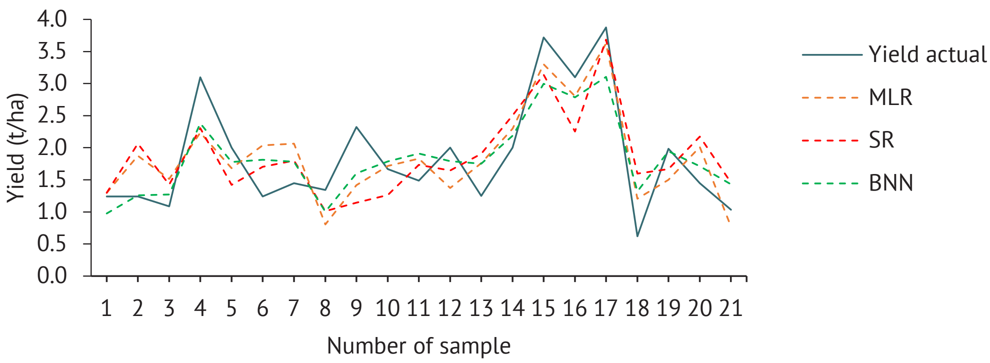


Figure 4. *BNN model performance compared to MLR and SR*

Figure 4 demonstrates that the results from the three prediction models are consistent with the actual yields. However, according to the statistical analysis used, the BNN model's performance has the highest accuracy, with an RMSE value of 0.448 t/ha, which compares to the MLR and SR models, indicating the lowest error deviation. These findings are further supported by the BNN model's Pearson correlation coefficient and coefficient of determination, which have the highest values at 0.890 for Pearson and 0.793 for R^2. The accuracy of the SR approach, on the other hand, is the lowest, with a Pearson value of 0.729 and an R^2 of 0.532. This demonstrates that the sensitivity of the BNN model outperforms that of the MLR and SR prediction techniques.

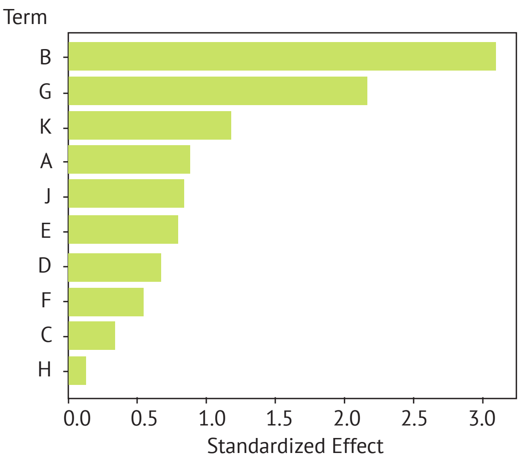
Table 4. *Comparison of an RMSE value to the MLR, SR, and BNN models*

Model accuracy	MLR	SR	BNN
R^2	0.643	0.532	0.793*
Pearson correlation	0.802	0.729	0.890*
RMSE (t/ha)	0.522	0.597	0.448*

Note: *R^2 = higher is better; RMSE = lower is better; * = better*
Source: *compiled by the authors*

According to (Abbaszadeh *et al.*, 2022), yield prediction is essential for agricultural planning and management and production and food security on a national and international level (Khaki & Wang, 2019) environment, and their interactions. Accurate yield prediction requires fundamental understanding of the functional relationship between yield and these interactive factors, and to reveal such relationship requires both comprehensive datasets and powerful algorithms. In the 2018 Syngenta Crop Challenge, Syngenta released several large datasets that recorded the genotype and yield performances of 2,267 maize hybrids planted in 2,247 locations between 2008 and 2016 and asked participants to predict the yield performance in 2017. As one of the winning teams, we designed a deep neural network (DNN. The Bayesian Neural Network is one of the models utilised in this study. Harvest prediction has now been widely established (BNN) (Semenova *et al.,* 2020). The two key input parameters for the model created in this study are soil and the actual field climate (Tables 1 and 2). Figure 3 findings demonstrate that when compared to the MLR and SR approaches, the prediction of rice harvest using BNN analysis yields results nearly identical to the actual and expected harvest values, with an R^2 coefficient of determination of 0.793. The research results of Singh Boori *et al.* (2022) showed that machine learning-based harvest prediction models produce higher sensitivity and accuracy with the regression method. Yield prediction using machine learning is a complex development influenced by soil parameters and environmental conditions (Velmurugan *et al.*, 2021).

Features importance analysis. The Pareto chart of standardised effects approach, which can display a parameter's impact on crop yields from largest to smallest, is then used in this research to examine the significance of parameters in the BNN model. To obtain the ideal parameter sampling design, parameter distribution is directly and simultaneously optimised using an optimisation technique based on Pareto optimality. A set of parameters with the maximum accuracy is produced using Pareto-measured importance features and the values of R^2, RMSE, and MAPE. The authors suggest the top 3, top 5, and top 7 parameters as three crucial ones. The effectiveness of these three parameter sets concerning the entire set of parameters is then evaluated.



Predictor	Name
A	Type of soil
B	Slope
C	Elevation
D	pH
E	Organic-C
F	Total-N
G	Available-P
H	Available-K
J	Rainfall
K	Evapotranspiration

Figure 5. *Pareto chart of standardised effects*

The top 7 data sets yielded the highest accuracy based on the test results for the three-parameter groups (Fig. 6). According to parameter set testing, accuracy rises when more parameters are added but falls when the entire data set is used. The coefficient of determination has the highest value, 0.855, while the RMSE test for the model using the top 7 data set has the lowest error value at 0.354 t/ha and 18.71%, respectively. It is preferable to use the top 7 data sets, including slope, available-P, evapotranspiration, soil type, rainfall, organic-C, and pH.

Although irrigated rice fields are Indonesia's largest source of rice (Indonesia Ministry of Agriculture, 2020), rainfed rice fields still produce comparatively little rice compared to irrigated rice fields. Rainfall affects whether the rice harvest in fields nourished by the rain is successful or unsuccessful. According to Chakraborty & Newton (2011), irregular rainfall patterns and decreasing rainfall, which result in water stress throughout the plant growth stage, are to blame for the productivity of rainfed lowland rice fields.

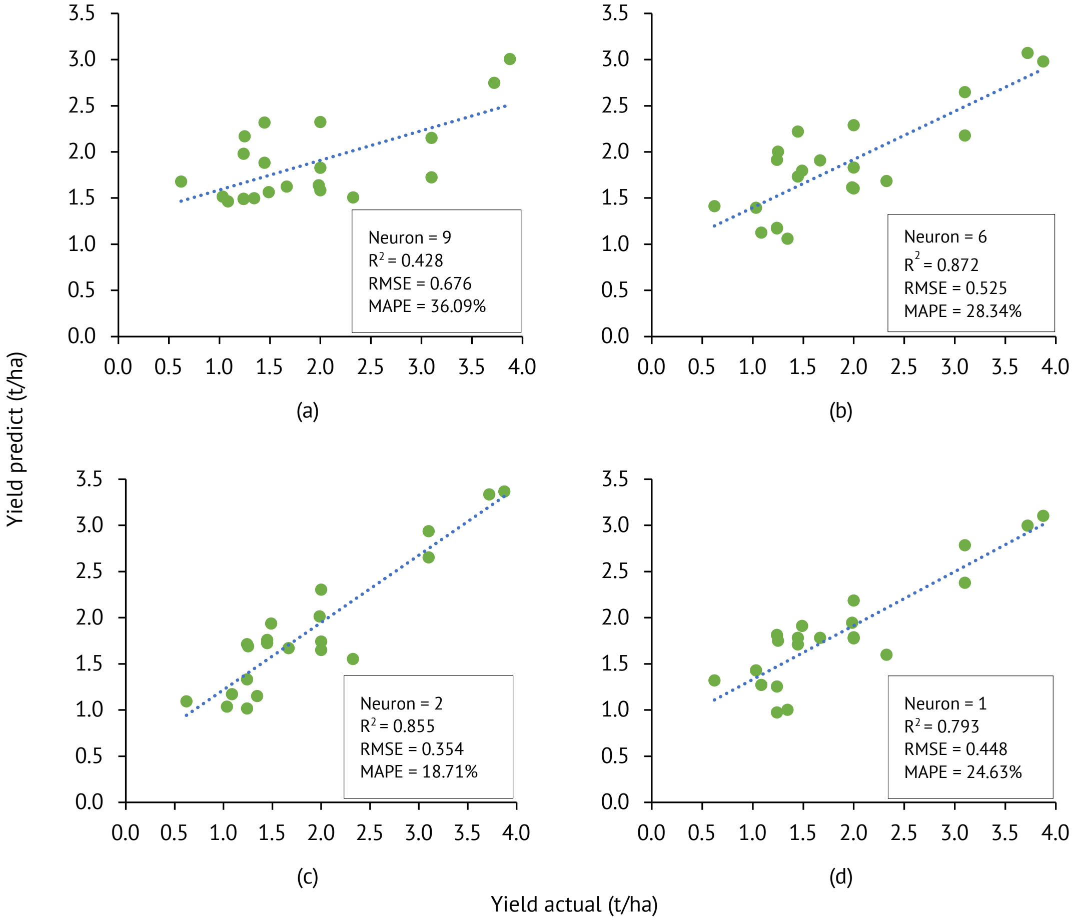


Figure 6. *BNN model by different feature sets; (a) top 3; (b) top 5; (c) top 7; (d) full set*

Using the Pareto approach, an experiment was conducted to improve performance and identify parameters that significantly impact yield prediction (Vojnov *et al.*, 2022) along with wheat, the most important staple crop in the Republic of Serbia, which is of great significance for ensuring national food security. With the increasing demand for food and forage, intensive agricultural practices have been adopted in the maize production systems. In this direction, considerable research efforts have been made to examine the effects of different types of cover crops as a green manure on maize productivity; however, no consistent conclusions have been reached so far. Therefore, the objective of the present study is to examine the possibility of predicting the effects of winter cover crops (CC. Following the tests, it was discovered that, as shown in Figure 6c, the model containing the top 7 data set parameters had the best accuracy. The accuracy of the yield from the prediction model and the actual outcomes are strongly correlated. An accuracy test can be used to verify this. The MAPE value obtained from this study is 18.71% and is within a reasonably practicable forecasting model capacity (0-20%), according to the BNN model accuracy test findings with the top 7 data sets (Maricar, 2019) a company can be running. The income in a company can be said is uncertain every few. So the required a calculation to predict the income of a company every few. In this case the applied calculation analyze methods of moving average with exponential smoothing with the value of the alpha 0.1, 0.5, 0.9, to calculate earnings forecasts on the XYZ Company. Both methods compared to get a better method that have the highest accuracy value (the value of the smallest error. The results of the RMSE analysis, which measures the magnitude of the prediction results' error rate, likewise indicated good results with a value of 0.354 t/ha. The RMSE value measures a forecast's accuracy; the smaller (near 0) it is, the better. While Babaee *et al*. (2021) used input data on rainfall, permeability, soil texture, soil type, evapotranspiration, as well as inflow and outflow of water into paddy fields using the artificial neural networks (ANN) method, the study by Ma *et al*. (2021)the United States supplies more than 30% of the global corn production. Accurate and timely estimation of corn yield is therefore essential for commodity trading and global food security. Recently, several deep learning models have been explored for corn yield forecasting. Despite success, most existing models only provide yield estimations without quantifying the uncertainty associated with the predictions. Also, the traditional deep learning approaches typically require a large training set and are easily prone to overfitting when the number of samples in the training set is relatively small. To address these limitations, in this study, we developed a county-level corn yield prediction model based on Bayesian Neural Network (BNN regarding the prediction of corn harvest using satellite, climate, and soil data using the BNN method shows an RMSE value of 1.03 t/ha.

Smaller inputs will not reveal much about the algorithm's pattern throughout the BNN model's development, leading to a narrower stretch model (Baldos *et al.,* 2019). Typically, the input layer gathers various data from the outside world, and the neural network uses this data to process it for learning, recognition, or other purposes. Pareto analysis can improve the accuracy of the final prediction model and help with input efficiency in machine learning applications. In order to lower the danger of outliers when the BNN learns patterns from this algorithm, it is possible to delete factors from the Pareto process that are irrelevant to crop yields. By lowering the size of the stress-strain curve, Pareto makes the neural network less complex and increases the neural network's capacity for learning (He *et al.,* 2022).

Since BNN prediction analysis has been shown to have high accuracy and sensitivity, it has become a fascinating issue to explore in this era, particularly for diverse plant commodities (Hafezi *et al.,* 2021) a novel Learning Scenario Development Model (LSDM. The accuracy of the model with location and treatment-specific parameters has been demonstrated to enhance with the addition of more parameter components, particularly off-farm, in future research. Based on the results of this investigation, it was discovered that the BNN model predicts rainfed lowland rice yields with reasonable accuracy using input characteristics related to the soil and climate. The decrease of parameters while developing a model with superior performance proves that the outcomes of constructing the BNN model with Pareto are also satisfactory.

Crop yield predictions is crucially important in agricultural planning and management. It is also crucial to food production and security on a regional to global scale (Chhogyel *et al.,* 2020). Crop yield prediction that is reliable and timely allows for timely import and export decisions to promote and reinforce national food security (Basso & Liu, 2019). This is becoming increasingly essential as global warming and population growth continue. In agriculture, empirical connections have been routinely employed for crop production prediction. These approaches primarily rely on the assumption of linearity between crop output and other parameters such as canopy reflectance and meteorological data. The yield projections are particularly prone to overfitting due to severe non-linearity and a high degree of autocorrelation among these variables. To address this issue, many studies have effectively used Machine Learning (ML) models to estimate crop productivity.

CONCLUSIONS

By applying the Bayesian Neural Network (BNN) method to analyse prediction models across 12 geographical units, the study achieved the highest accuracy in yield predictions compared to the MLR and SR models. The BNN model demonstrated an RMSE value of 0.448 t/ha, indicating a low level of error deviation.

To optimise the parameter sampling design, an optimization technique based on Pareto optimality was employed, resulting in the selection of the top 7 variables (slope, available-P, evapotranspiration, soil type, rainfall, organic-C, and pH) that yielded the highest accuracy for the three-parameter groups. The coefficient of determination reached a value of 0.855, indicating a strong relationship between the variables. Additionally, the RMSE test for the model utilising the top 7 data set achieved the lowest error value at 0.354 t/ha and 18.71%, respectively.

The findings of this study contribute to the field of rainfed rice cultivation by providing location-specific predictions of rice yield, which can assist farmers and agricultural practitioners in making informed decisions and optimising resource allocation. By considering soil and climate variables, the developed model offers valuable insights into improving agricultural productivity and mitigating the risks associated with nutrient deficiency and drought in rainfed rice fields. Future research in the field of rainfed rice cultivation and yield prediction should focus on refining prediction models, expanding to other regions and crops, incorporating additional variables, conducting long-term monitoring and validation, integrating remote sensing and satellite data, and assessing the socio-economic implications for sustainable agricultural practices.

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CONFLICT OF INTEREST

None.

REFERENCES

[1] Abbaszadeh, P., Gavahi, K., Alipour, A., Deb, P., & Moradkhani, H. (2022). Bayesian multi-modeling of deep neural nets for probabilistic crop yield prediction. *Agricultural and Forest Meteorology,* 314, article number 108773. doi: 10.1016/j.agrformet.2021.108773.

[2] Abdalla, M., Hastings, A., Cheng, K., Yue, Q., Chadwick, D., Espenberg, M., Truu, J., Rees, R. M., & Smith, P. (2019). A critical review of the impacts of cover crops on nitrogen leaching, net greenhouse gas balance and crop productivity. *Global Change Biology*, 25(8), 2530-2543. doi: 10.1111/gcb.14644.

[3] Ali, F., Sarwar, A., Ilahi Bakhsh, F., Ahmad, S., Ali Shah, A., & Ahmed, H. (2023). Parameter extraction of photovoltaic models using atomic orbital search algorithm on a decent basis for novel accurate RMSE calculation. *Energy Conversion and Management*, 277, article number 116613. doi: 10.1016/j.enconman.2022.116613.

[4] Anupama, C.G., & Lakshmi, C. (2021). A comprehensive review on the crop prediction algorithms. *Materials Today: Proceedings*, 86. doi: 10.1016/j.matpr.2021.01.549.

[5] Babaee, M., Maroufpoor, S., Jalali, M., Zarei, M., & Elbeltagi, A. (2021). Artificial intelligence approach to estimating rice yield. *Irrigation and Drainage*, 70(4), 732-742. doi: 10.1002/ird.2566.

[6] Baldos, U.L.C., Viens, F.G., Hertel, T.W., & Fuglie, K.O. (2019). R&D spending, knowledge capital, and agricultural productivity growth: A Bayesian approach. *American Journal of Agricultural Economics,* 101(1), 291-310. doi: 10.1093/ajae/aay039.

[7] Basso, B., & Liu, L. (2019). Seasonal crop yield forecast: Methods, applications, and accuracies. *Advances in Agronomy,* 154, 201-255. doi: 10.1016/bs.agron.2018.11.002.

[8] Batta, M. (2020). Machine Learning Algorithms - A review. *International Journal of Science and Research IJSR*, 9(1), 381-386. doi: 10.21275/ART20203995.

[9] BPS Provinsi Jawa Tengah. (2018). *Luas Panen, Produksi, dan Produktivitas Padi Ladang Menurut Kabupaten/ Kota di Provinsi Jawa Tengah* (Kuintal/Hektar). Retrieved from https://jateng.bps.go.id/indicator/53/55/1/padi-ladang.html.

[10] Chakraborty, S., & Newton, A.C. (2011). Climate change, plant diseases and food security: An overview. *Plant Pathology*, 60(1), 2-14. doi: 10.1111/j.1365-3059.2010.02411.x.

[11] Chhogyel, N., Kumar, L., Bajgai, Y., & Hasan, M.K. (2020). Perception of farmers on climate change and its impacts on agriculture across various altitudinal zones of Bhutan Himalayas. *International Journal of Environmental Science and Technology*, 17, 3607-3620. doi: 10.1007/s13762-020-02662-8.

[12] Drury, B., Valverde-Rebaza, J., Moura, M.F., & de Andrade Lopes, A. (2017). A survey of the applications of Bayesian networks in agriculture. *Engineering Applications of Artificial Intelligence,* 65, 29-42. doi: 10.1016/j.engappai.2017.07.003.

[13] Estiningtyas, W., & Syakir, M. (2018). Pengaruh perubahan iklim terhadap produksi padi di lahan tadah Hujan. *Jurnal Meteorologi Dan Geofisika*, 18(2), 83-93. doi: 10.31172/jmg.v18i2.406.

[14] Hafezi, R., Akhavan, A.N., Pakseresht, S., & Wood, D.A. (2021). Global natural gas demand to 2025: A learning scenario development model. *Energy,* 224, article number 120167. doi: 10.1016/j.energy.2021.120167.

[15] He, Z.C., Huo, S.L., Li, E., Cheng, H.T., & Zhang, L.M. (2022). Data-driven approach to characterize and optimize properties of carbon fiber non-woven composite materials. *Composite Structures,* 297, article number 115961. doi: 10.1016/j.compstruct.2022.115961.

[16] Khaki, S., & Wang, L. (2019). Crop yield prediction using deep neural networks. *Frontiers in Plant Science*, 10, article number 621. doi: 10.3389/fpls.2019.00621.

[17] Liu, J., Goering, C.E., & Tian, L. (2001). A neural network for setting target corn yields. *Transactions of the ASAE*, 44(3), 705-713. doi: 10.13031/2013.6097.

[18] Liu, S., Wang, X., Liu, M., & Zhu, J. (2017). Towards better analysis of machine learning models: A visual analytics perspective. *Visual Informatics*, 1(1), 48-56. doi: 10.1016/j.visinf.2017.01.006.

[19] Lotulung, A. (2020). *Kementan prediksi nilai konsumsi pangan naik di 2020*. Retrieved from https://money.kompas.com/read/2019/12/31/181626826/kementan-prediksi-nilai-konsumsi-pangan-naik-di-2020.

[20] M, T.S., & B, J. (2021). Adaptive lemuria: A progressive future crop prediction algorithm using data mining. *Sustainable Computing: Informatics and Systems,* 31, article number 100577. doi: 10.1016/j.suscom.2021.100577.

[21] Ma, Y., Zhang, Z., Kang, Y., & Özdoğan, M. (2021). Corn yield prediction and uncertainty analysis based on remotely sensed variables using a Bayesian neural network approach. *Remote Sensing of Environment,* 259, article number 112408. doi: 10.1016/j.rse.2021.112408.

[22] Maricar, M.A. (2019). Analisa perbandingan nilai akurasi moving average dan exponential smoothing untuk sistem peramalan pendapatan pada Perusahaan XYZ. *Jurnal Sistem Dan Informatika,* 13(2), 36-45.

[23] Murniati, K., Mulyo, J.H., Irham, I., & Hartono, S. (2017). Efisiensi teknis usaha tani padi organik lahan sawah tadah hujan di kabupaten tanggamus provinsi Lampung. *Jurnal Penelitian Pertanian Terapan,* 14(1), 31-38. doi: 10.25181/jppt.v14i1.139.
[24] Novia, R.A., & Satriani, R. (2020). Analisis efisinesi teknis usahatani padi sawah tadah hujan di kabupaten Banyumas. *Mediagroediagro,* 16(1), 48-59. doi: 10.31942/mediagro.v16i1.3389.
[25] Pant, J., Pant, R.P., Singh, M.K., Singh, P., & Pant, H. (2021). Analysis of agricultural crop yield prediction using statistical techniques of machine learning. *Materials Today: Proceedings*, 46(20), 10922-10926. doi: 10.1016/j.matpr.2021.01.948.
[26] Rahayu, W. (2014). Ketersediaan pangan pokok pada rumah tangga petani padi sawah irigasi dan tadah hujan di kabupaten Karanganyar. *Jurnal Sosial Ekonomi Pertanian*, 7(1), 45-51.
[27] Ruminta, R., Wahyudin, A., & Sakinah, S. (2017). Respon pertumbuhan dan hasil tanaman padi terhadap jarak tanam pada lahan tadah hujan dengan menggunakan pengairan intermittent. *Agrin,* 21(1), 46-58. doi: 10.20884/1.agrin.2017.21.1.338.
[28] Semenova, E., Williams, D.P., Afzal, A.M., & Lazic, S.E. (2020). A Bayesian neural network for toxicity prediction. *Computational Toxicology,* 16, article number 100133. doi: 10.1016/j.comtox.2020.100133.
[29] Sinaga, Y.P.A., Razali, R., & Sembiring, M. (2014). Evaluasi kesesuaian lahan untuk padi sawah tadah hujan (*Oryza Sativa* L.) di kecamatan muara kabupaten tapanuli utara. *Jurnal Agroekoteknologi Universitas Sumatera Utara*, 2(3), 1042-1048.
[30] Singh Boori, M., Choudhary, K., Paringer, R., & Kupriyanov, A. (2022). Machine learning for yield prediction in Fergana valley, Central Asia. *Journal of the Saudi Society of Agricultural Sciences,* 22(2), 107-120. doi: 10.1016/j.jssas.2022.07.006.
[31] Son, N.T., Chen, C.F., Cheng, Y.S., Toscano, P., Chen, C.R., Chen, S.L., Tseng, K.H., Syu, C.H., Guo, H.Y., & Zhang, Y.T. (2022). Field-scale rice yield prediction from Sentinel-2 monthly image composites using machine learning algorithms. *Ecological Informatics,* 69, article number 101618. doi: 10.1016/j.ecoinf.2022.101618.
[32] Van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture*, 177, article number 105709. doi: 10.1016/j.compag.2020.105709.
[33] Velmurugan, P., Kannagi, A., & Varsha, M. (2021). Superior fuzzy enumeration crop prediction algorithm for big data agriculture applications. *Materials Today: Proceedings,* 81(2), 112-117. doi: 10.1016/j.matpr.2021.02.578.
[34] Vojnov, B., Ja´cimovi´c, G., Ja´cimovi´c, J., Dan, S̄, Šeremeši´c, Š., Pezo, L., Lončar, B., De Krsti´ckrsti´c, Đ, Vuji´c, S.V., & Cupina, B. (2022). The effects of winter cover crops on maize yield and crop performance in semiarid conditions — Artificial neural network approach. *Agronomy,* 12(11), article number 2670. doi: 10.3390/agronomy12112670.
[35] Wang, Y., Satake, A., Sano, S., & Furutani, S. (2020). Stable adaptive estimation for speed-sensorless induction motor drives: A geometric approach. In *Proceedings – 2020 International Conference on Electrical Machines, ICEM 2020* (pp. 1232-1238). doi: 10.1109/ICEM49940.2020.9270926.
[36] Wihardjaka, A., Pramono, A., & Sutriadi, M.T. (2020). Peningkatan produktivitas padi sawah tadah hujan melalui penerapan teknologi adaptif dampak perubahan iklim. *Jurnal Sumberdaya Lahan,* 14(1), article number 25.

Прогнозування врожайності рису з використанням байєсівського аналізу на богарних землях у топосекції Сумбінг-Сіндоро, Індонезія

Абдул Азіз

Аспірант
Університет Себелас Марет
57126, вул. Сутамі, 36, Суракарта, Центральна Ява, Індонезія
http://orcid.org/0000-0002-9688-3180

Комарія

Доктор прикладних наук, ґрунтознавства та гідрометеорології
Університет Себелас Марет
57126, вул. Сутамі, 36, Суракарта, Центральна Ява, Індонезія
https://orcid.org/0000-0001-7704-0754

Дві Прійо Аріянто

Доктор ґрунтознавства та охорони водних ресурсів
Університет Себелас Марет
57126, вул. Сутамі, 36, Суракарта, Центральна Ява, Індонезія
https://orcid.org/0000-0001-6605-9599

Сумані

Доктор агрокліматології
Університет Себелас Марет
57126, вул. Сутамі, 36, Суракарта, Центральна Ява, Індонезія

Анотація. Оскільки на богарних рисових полях зазвичай бракує поживних речовин, вони часто страждають від посухи і потребують більше коштів для підтримки сільськогосподарських операцій, результати виробництва стають нестабільними і непередбачуваними. Це дослідження має на меті побудувати прогнози врожайності рису на богарних рисових полях у топосистемі Сумбінґ-Сіндоро, Центральна Ява, з використанням байєсівського методу для конкретної місцевості. Це дослідження є опитуванням з дослідницькою описовою методологією, що ґрунтується на даних польових і лабораторних досліджень. Аналіз моделі прогнозування з використанням методу нейронних мереж Байєса (BNN) на 12 географічних одиницях, точки вибірки були обрані навмисно. Були виміряні наступні змінні: ґрунт (рівень pH, органічний вуглець, загальний азот, доступний фосфор, доступний калій, типи ґрунтів, висота, схил) та клімат (кількість опадів, випаровування). Відповідно до використаного статистичного аналізу, модель BNN має найвищу точність із середньоквадратичним відхиленням (RMSE) 0,448 т/га, що порівняно з моделями MLR та SR вказує на найнижче відхилення помилки. Для отримання ідеального дизайну вибірки параметрів, розподіл параметрів було оптимізовано безпосередньо і одночасно за допомогою методу оптимізації, заснованого на оптимальності за Парето. За результатами тестування для груп з трьома параметрами найвищу точність показали 7 найкращих наборів даних (нахил, доступний P, випаровування, тип ґрунту, кількість опадів, органічний вуглець та pH). Коефіцієнт детермінації має найвище значення – 0,855, в той час як тест RMSE для моделі, що використовує 7 найкращих наборів даних, має найнижче значення похибки – 0,354 т/га та 18,71 % відповідно. Розробляючи прогнози врожайності рису для конкретної місцевості за допомогою байєсівського методу, фермери та аграрні практики можуть отримати вигоду від більш точних і надійних оцінок продуктивності культури

Ключові слова: сільськогосподарська стійкість; нейронна мережа Байєса (BNN); продовольча безпека; богарне рисове поле; прогнозування врожайності