Modelling and predicting wetland rice production using support vector regression

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Modelling and predicting wetland rice production using support vector regression

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Abstract

Food security is still one of the main issues faced by Indonesia due to its large population. Rice as a staple food in Indonesia has experienced a decline in production caused by unpredictable climate change. In dealing with climate change, adaptation to fluctuating rice productivity must be made. This study aims to build a prediction model of wetland rice production on climate change in South Kalimantan Province which is one of the national rice granary province and the number one rice producer in Kalimantan Island. This study uses monthly climatic data from Syamsudin Noor Meteorological Station and quarterly wetland rice production data from Central Bureau of Statistics of South Kalimantan. In this research, Support Vector Regression (SVR) method is used to model the effect of climate change on wetland rice production in South Kalimantan. The model is then used to predict the amount of wetland rice production in South Kalimantan. The results showed that the prediction model with the RBF kernel with the parameter of C=1.0, epsilon=0.002 and gamma=0.2 produces good results with the RMSE value of 0.1392.

Keywords: *Indonesia, prediction, support vector regression, wetland rice*

1. Introduction

Food security is a situation where there is food available at all times for everyone, and everyone can get healthy food to live their lives [1]. To achieve food security, we must face various challenges, one of which is global climate change. Climate change is a natural phenomenon that can trigger the existence of extreme weather conditions due to rain patterns that are difficult to predict. In the agricultural sector, there is a close relationship between climate change and farming products [2]. Changes in rainfall patterns, rising sea levels, and temperatures, as well as an increase in extreme climate events such as floods and drought, are some of the severe impacts of climate change. Climate change resulted in an uncertain period of the rainy and dry season so that the estimation of agricultural production and food supplies become difficult. There has been a lot of investigation concerning the effect of climate change to food security around the world [3–6]. Indonesia as one of the countries most affected by climate change also needs to address this problem as soon as possible.

Climate change occurring in Indonesia dramatically affects the agricultural sector, rice that is known as a seasonal crop is relatively sensitive to the state of abundance and shortage of water [7]. On the other hand, rice is the staple food for most people in Indonesia, so the effect of climate change on rice production would affect most of the Indonesian people. In Indonesia, rice commonly divided into two types namely wetland rice and upland rice. The different between the two of them is where they cultivated. For Indonesia, the cultivation of rice greatly depends on the geographic feature of the area. In South Kalimantan (one of the largest rice producers in Indonesia) with the most area covered by wetland, wetland rice is mostly cultivated by households compared to upland rice, approximately 87.69 percent grew wetland rice, while upland rice is only produced by about 11.10 percent [8].

Action has been done by the Indonesian government to address this food security issue. Central Bureau of Statistics has done data collection and calculation of food crop production prediction every year by using a regression analysis method for forecasting of harvested area and exponential smoothing for forecasting food crop productivity [9]. A lot of research also has been done concerning the effect of climate change on agricultural products in Indonesia although the research is mostly done in Java and Sumatera as most of Indonesia rice production comes from those islands [10]. Most research on this area put their emphasized on

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how to mitigate the effect of climate change to agricultural sector in Indonesia [11-14]. However, there has been limited research focused on estimating food crop production whereas these kind of study would help the Indonesian government to determine the best strategies to deal with climate change that is affecting food crop production.

Studies on forecasting of food crop production have conducted in several areas. In India, Fuzzy Time Series model used to forecast rice production in India by using historical time series data of rice production with Mean Square Error (MSE) and Average Forecasting Error Rate(AFER) of 9917.16 and 0.34% respectively [15]. In Indonesia, Supriyanto, et, al. [16] aim to predict the area of harvest and rice productivity using Adaptive Neuro-Fuzzy Inference System (ANFIS) with the accuracy of forecasting produced mean absolute percentage error (MAPE) of 3.122. However, in these studies, climatic factors were not counted as one of the factors influencing agricultural productivity, even though, agriculture is arguably the most affected by climate change [17].

Research on the prediction of food crop production in Indonesia by involving climatic factors has been done using multiple linear regression methods using monthly climate data with accuracy results up to 70% [18]. Another study modeled the relationship of daily climate data and rice production to forecast rice production using Generalized Regression Neural Networks (GRNN), result shows that this method produces a Root Mean Square Error (RMSE) value of 0.296 [19].

In this study, we used Support Vector Regression (SVR) method to model the relationship of monthly climate data to predict wetland rice production in South Kalimantan. South Kalimantan was chosen because it is one of the biggest producers of wetland rice in Indonesia. SVR is an extension of the Support Vector Machine to solve non-linear regression estimation problem [20]. The computational complexity of SVR that is independent of the dimensions of the input space has proven to be useful in the function of estimating the real value. Another advantage of SVR is that is always convergent to a unique and optimal global solution as a result of the convex optimization problem especially compared to the artificial neural network [21, 22]. SVR has extensively applied to various cases of prediction such as earthquake [23], global solar radiation [24], and even to predict the quality of banana [25].

2. Research Method

We used monthly climate data obtained from the Meteorological Agency Climatology and Geophysics Station Climatology Kelas I Banjarbaru from 2004-2016. The data includes six (6) climate indicator that is rainfall, minimum temperature, maximum temperature, average temperature, average humidity, and solar radiation. We obtained climate data from 2 stations, namely Syamsudin Noor Meteorology Station in Banjarbaru City and Stagen Meteorology Station in Kotabaru Regency. We also used wetland rice production data from Department of Food Crops and Horticulture of South Kalimantan. This data has a four-monthly format that is, January-April, May-August, and September-December. We used 6 (six) climate indicator as an input to model wetland rice production using Support Vector Regression (SVR). Overview of the architecture of the SVR model that we build could be seen as in Figure 1.

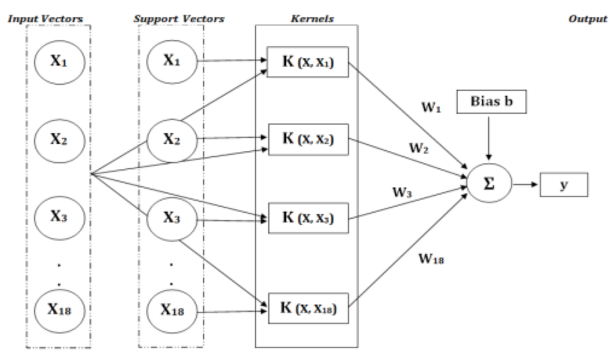


Figure 1. The architecture of the model

Before we do the mapping process, the data must be normalized first. In the training process, the data were conducted using 108 monthly climate data from 2004 to 2015, where the climate data grouped into data per 3 (three) months, i.e. January-March, May-July, and September-November. For every three months, the monthly climate data denoted by X uses 18 climate data as inputs to mapped to output targets in the form of wetland rice production data per 4 (four) months. This process is done to build a prediction model of wetland rice production for the forthcoming month.

The process starts with the data from the year 2004 to 2016, where the climate data used as input and wetland rice production data as the output.All of the data normalizedin range 0 and 1, the data is then divided into training data and test data. The training data used are monthly climate data and wetland rice production from the year 2004 until 2015. As for test data, monthly climate and wetland rice production data of 2016 will be used.This data used to test the model that produced by using data that has never been seen in the training process.

After the data is divided, the input and output will be mapped from low-dimensional space to the feature space through the training process, i.e., data input in the form of monthly climate data of 2004-2015 against the output target of wetland rice production data of 2004-2015. Subsequently, the model generated from the training process validated by using the data from the year of 2015 to measure the performance the model by looking at the value of the Root Mean Square Error (RMSE) and R Square (R2) that is obtained.

Furthermore, we tested the results of the model that validated before using test data, which is the monthly data of 2016 as input. The performance of the model tested by inserting the data that has never been seen by the model to let it predict the output that is wetland rice production of the upcoming month. The value that the model predicted is still in normalized form i.e. (in range of 0 to 1). Therefore, thedenormalization process is done to restore the data to the actual value.In this study, we will also compare the monthly climate data from Syamsudin Noor Meteorological Station and Stagen Meteorological Station. Research method that is used in this study can be seen in Figure 2.

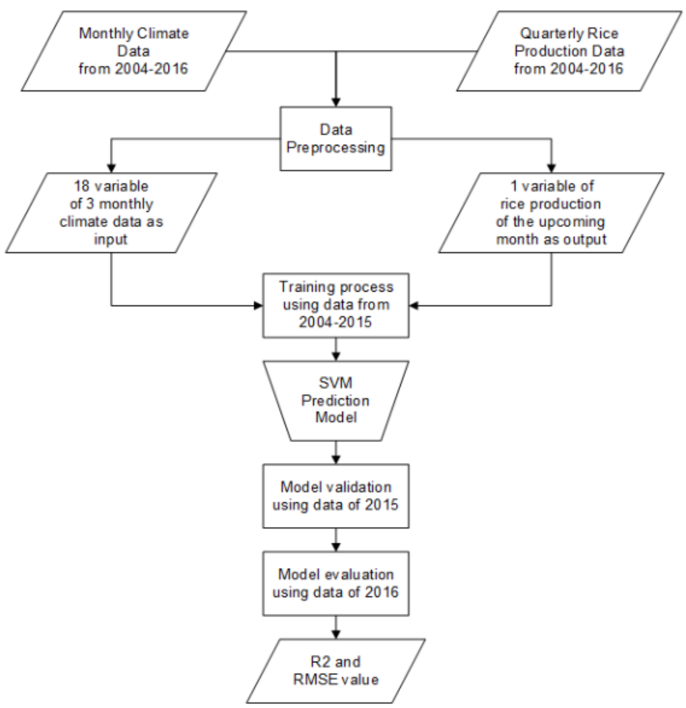


Figure 2. Research method

3. Results and Discussion

Based on the results of previous experiments using monthly climate data from Syamsudin Noor Meteorological Station, different accuracy results obtained in the prediction model using various parameters.This experiment is done to get an appropriate SVR prediction model using the right combination of parameters that can be seen as in Table 1.

Table 1. Prediction Model from Syamsudin Noor Meteorological Station

i	Kernel	Parameter C	ε	γ	Validation RMSE	Validation R^2	Prediction RMSE
1	RBF	1.0	0.001	0.3	0.0073	0.9992	0.1457
2	RBF	1.5	0.001	0.3	0.0008	0.9999	0.1544
3	RBF	2.0	0.001	0.3	0.0009	0.9999	0.1551
4	RBF	2.5	0.001	0.3	0.0011	0.9999	0.1577
5	RBF	1.0	0.002	0.1	0.0562	0.9558	0.1564
6	RBF	1.0	0.012	0.1	0.0628	0.9449	0.1582
7	RBF	1.0	0.022	0.1	0.0713	0.9289	0.1567
8	RBF	1.0	0.032	0.1	0.0756	0.9201	0.1582
9	RBF	1.0	0.002	0.2	0.0279	0.9890	0.1392
10	RBF	1.0	0.002	0.45	0.0018	0.9999	0.1485
11	RBF	1.0	0.002	0.7	0.0020	0.9999	0.1473
12	RBF	1.0	0.002	0.95	0.0018	0.9999	0.1550

From the experimental results that have been done in Table 1, the appropriate prediction model using the data in the experiment to-9 with RMSE validation 0,0279, R2 0,9890 and has the smallest prediction RMSE value 0.1392 that is achieved with the combination of parameters kernel: RBF, C: 1.0, ε: 0.002 and γ: 0.2.

Based on previous experiments using data from Syamsudin Noor Meteorological Station, in comparison, there will also be experiments on monthly climate data using Stagen Station data.This experiment is conducted to see if the prediction model will be better than the previous data.The results of the experiment can be seen as in Table 2.

Tabel 2. Prediction Model from Stagen Meteorological Station

i	Kernel	Parameter C	ε	γ	Validation RMSE	Validation R^2	Prediction RMSE
1	RBF	1.0	0.001	0.3	0.0868	0.8947	0.1942
2	RBF	1.5	0.001	0.3	0.0803	0.9098	0.2023
3	RBF	2.0	0.001	0.3	0.0719	0.9279	0.2166
4	RBF	2.5	0.001	0.3	0.0556	0.9567	0.2303
5	RBF	1.0	0.002	0.1	0.1109	0.8283	0.1819
6	RBF	1.0	0.012	0.1	0.1075	0.8388	0.1846
7	RBF	1.0	0.022	0.1	0.1031	0.8516	0.1867
8	RBF	1.0	0.032	0.1	0.1028	0.8524	0.1820
9	RBF	1.0	0.002	0.2	0.0956	0.8723	0.1882
10	RBF	1.0	0.002	0.45	0.0630	0.9445	0.2093
11	RBF	1.0	0.002	0.7	0.0019	0.9999	0.2275
12	RBF	1.0	0.002	0.95	0.0020	0.9999	0.2247

The results of the experiments that have been done in Table 2, obtained the corresponding prediction model in the 5th experiment with RMSE validation 0.1109, R2 0.8283 and has the smallest predicted RMSE value 0.1819 that achieved with the combination of kernel parameters: RBF, C: 1.0, ε: 0.002 and γ: 0.1.Furthermore, from the previous experimental results by combining different settings to obtain an appropriate prediction model for wetland rice prediction, a comparison of validation of the prediction model results from the two different station data as can be seen in Table 3.

From Table 3 can be seen that the prediction model obtained from the training data process using monthly climate data from Syamsudin Noor Meteorological Stationis an appropriate model for the prediction of wetland rice production compared to the model that is using the monthly climate data of Stagen Meteorological Station.This is shown by the result of R^2 of Syamsudin Noor Meteorological Station is more prominent, that is 0.9890 where the result is close to 1 which means the model is considered fit.

Table 3. Comparison of Validation Results of the Model

Data	Parameter				RMSE	R^2	Prediction	Target
	Kernel	C	E	γ				
Syamsudin Noor	RBF	1.0	0.002	0.2	0.0279	0.9890	392900	390888
							888025	927611
							649674	651586
Stagen	RBF	1.0	0.002	0.1	0.1109	0.8283	539435	390888
							877407	927611
							639614	651586

Furthermore, the predicted data validation results from 3 (three) outputs obtained are close to the actual target, and the resulting RMSE value is also smaller that is 0.0279. Subsequently, the model that validated with the data of 2015 is then used to predict test data of 2016, where it is to confirm whether the model can predict accurately by using data that it has never seen in the training process. The experimental results of the prediction model seen as in Table 4.

Table 4. Comparison of Evalution Resultsof the Model

Data	Parameter				Prediction RMSE	Prediction	Target
	Kernel	C	ε	γ			
Syamsudin Noor	RBF	1.0	0.002	0.2	0.1392	534139	498811
						830105	807025
						585493	778366
Stagen	RBF	1.0	0.002	0.1	0.1819	548984	498811
						754990	807025
						530779	778366

In Table 4 the results for the accuracy of the model when the model is used to predict the test data which is the actual data of rice field production in 2016, using monthly climate data Syamsudin Noor Meteorological Station yield a smaller RMSE value compared to using climate data from Stagen Meteorological Station with RMSE value of 0.1392. Although the RMSE results generated in the predictions increased compared when using the validation data of year 2015, the value of the predicted outputs produced is good enough. Since the model can recognize data that is not in the training process and the predicted results are quite close to the actual target data.The result of the validation output of the prediction model also visualized in the form of Figures 3 and 4.

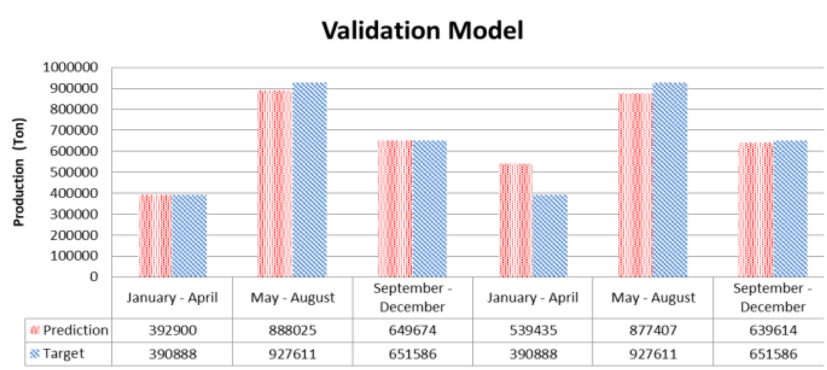
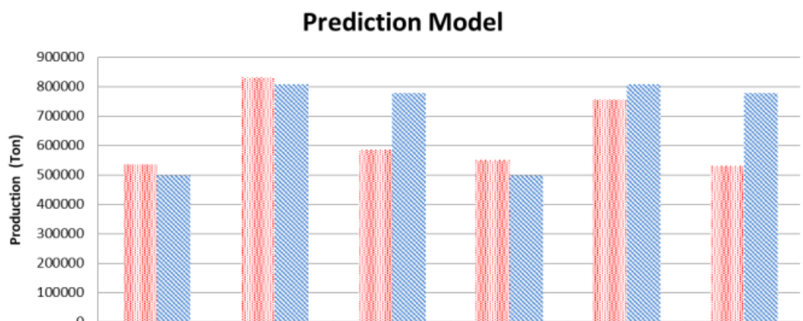


Figure 3. Prediction results on validation data

From Figure 3 we can see the prediction model prediction using monthly climate data from Syamsudin Noor Meteorological Station obtained the difference in the prediction of wetland rice production with the target in January-April amounted to 2,058 ton, May-August amounted to 1,912 ton.By using Stagen Station climate data, the difference between the production of wetland rice with the target in January-April is 148,547 ton, May-August of 50,204 ton and September - December of 11,972 ton and the output of the model when used for the prediction of the testing data also visualized in Figure 3.



	January - April	May - August	September - December	January - April	May - August	September - December
Prediction	534139	830105	585493	548984	754990	530779
Target	498811	807025	778366	498811	807025	778366

Figure 4. Prediction results on test data

4. Conclusion

Based on observations during the process of validation and testing process the model. We concluded that the model that produced has been able to predict wetland rice production in South Kalimantan for the next month using three monthly climate data from Syamsudin Noor Meteorological Station. The model produces an RMSE value of 0.1392 by using RBF kernel with parameter of C=1.0, epsilon=0.002 and gamma=0.2. From these results, it said that to obtain an appropriate model; it is necessary to combine optimal parameters and suitability of data with parameters to obtain better results. Also, the amount of data used may also affect the performance of the model. As more data used in the training process, more variations of the data will be learned by the model to get better predictive results.

Further studies should be carried out to select features from climate variables that influence the value of rice production the most so it would simplify the model that generated. The Support Vector Regression (SVR) method could be applied to predict rice production using climate factor variables by producing predictive values that are close to the actual value. However, further experiments need to be conducted to combine other factors that could also influence rice productivity.

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