Relationship Model Anomaly Harvested Rice with a Weighted Rainfall Index in Buru Maluku Using Bootstrap Aggregating MARS Methods to Predict the Forecast Error Rates Harvested Area and Rice Production

Kondo Lembang F[1], Loupatty G[2], Talakua M.W[3]

[1,3] Lecturer of Mathematic Department, Faculty of Mathematics and Natural Sciences, Pattimura University

[2] Lecturer of Physics Department, Faculty of Mathematics and Natural Sciences, Pattimura University

Abstract— Seasonal climate variations is one of the main causes of the diversity of crop production in Indonesia. Long drought and drought causing crop failures and food shortages that could affect agricultural production and food security. The indicator is a decline in acreage , harvested area and production declined sharply when climate irregularities. The magnitude of the impact caused by climatic irregularities cause we need a model that connects the harvested area with indicators of climate anomalies that can do the proper planning and anticipation measures early in order to avoid the risk of crop failure. Buru as the largest rice -producing areas in the provinces of Maluku course is expected to avoid the risk of crop failure in order not to disrupt the supply of rice. Data Collection and forecast rice production annually conducted by the Central Statistics Agency (BPS). BPS forecast model but has not entered a climatic factor, while the climate affect rice production. This research used the bootstrap aggregating MARS method to model anomaly rice harvested area with a weighted rainfall index to predict the error rate forecast harvested area and rice production. From the analysis using the best models of replication bagging MARS 150 times in the first period (January-April) and 200 times in second period (May-August) and third period (September-December) obtained an error rate forecast harvested area and rice production respectively by 5.72% and 6.81%.

Keywords— Anomaly Area harvested, weighted rainfall index, MARS, Boostrap Aggregating, rice production.

1 INTRODUCTION

Rice is the main food for the people of Indonesia, which provides seasonal income and employment for rural communities. Rice production has increased since 1970, but the harvest is particularly vulnerable to climate variability of extreme events: El-Nino and La-Nina. In the event of the El-Nino, rice production has decreased quite dramatically, as in 1991, 1994, and 1997. Similarly, in the La-Nina (1995) also decreased rice production [6]. When the national rice supply is insufficient and a decline in production, the import policy is often done. The problem is the need to forecast future production decline (extreme weather events), so the anticipation can be done. That requires models that accurately forecast rice production in order to support national food security. Data Collection and forecast national rice production every year conducted by the Central Statistics Agency and the Ministry of Agriculture. Forecasts made by the province were calculated based on time series data and the provinces are not based on the sum of the forecast distric/city level. Production per province is obtained by multiplying the harvested area clean with a yield per hectare per unit of harvested area clean for every subround (4 monthly: subround 1 (January-April), subround 2 (May-August), and subround 3 (September-December) [5]. production and harvested area in a year (January to December) is obtained from the sum of production and harvested area for three subround. Yield to each hectare is the yield each hectare in the form of tile results each unit of harvested area.

2 REVIEW OF LITERATURE

2.1 MARS

MARS is an implementation technique popularized by Friedman [4] for solving regression problems with the aim of predicting the response variable values of a number of predictor variables. MARS is an approach to the development of Recursive Partitioning Regression (RPR) which still has the drawback that the resulting model is not continuous at the knots. MARS model is used to overcome weaknesses in the model generate the RPR is continuous at knots. In spline modeling, the first step is to determine the points of data or a change in the pattern of behavior is called the point knots. The selection of knots in MARS using forward and backward algorithms. The selection of the model using a forward step taken to get the maximum number of base functions with base selection criteria function is to minimize Average Sum Of Square Residual. To parsimony concept (simple model) performed a backward step is selecting base functions of forward stage by minimizing the value of the Generalized Cross-Validation or GCV [4].

The minimum GCV as a criterion for determining knots are as follows:

$$GCV(M) = \frac{\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(y_i - \hat{f}_M(x_i)\right)^2}{\left(1 - \frac{C(M)}{N}\right)^2}$$

where

M	: The number of base functions
$C(M)$	: The number of parameters in the model = trace (B(BTB)-1BT)+1
B	: Matrix of base function
N	: The number of data
y_i	: Value of the response variable
$\hat{f}_M(x_i)$	: Estimated value of the response variable on M base functions.

From forward and backward, MARS models obtained as follows:

$$\hat{f}(x) = a_0 + \sum_{m=1}^{M} a_m \prod_{k=1}^{K_m}\left[s_{km}\left(x_{v(k,m)} - t_{km}\right)\right]_+$$

where

a_0	: main of base function
a_m	: coefficients of m-base functions
M	: maximum of base function
K_m	: degree of interaction
s_{km}	: ± 1
$x_{v(k,m)}$	: independent variables
t_{km}	: Point knots of independent variables $x_{v(k,m)}$

Algorithms for MARS models are as follows:

1. Starting with a simple model involving only constant base functions.
2. Finding space of base functions, for each variable and for all knots are possible, and add it to minimize the prediction error.
3. Repeat steps 2 to obtain a model that has maximum complexity.

Finally, in the last stage, the trimming procedure is applied in which the base functions are not significantly removed to obtain the minimum GCV.

2.2 Bagging MARS

Bagging method was first used by Breiman [1]. Bagging is used as a tool to form a more stable classifier. Bagging predictors is a method to generate multiple versions of a predictor and use it to aggregate predictors. Multiple versions of the bootstrap replication is formed by a set of data.

Defined a set data £ consists of $(y_n, x_n), n = 1, \ldots, N$ where y a numerical response or a class label. If x the input is then y predicted by ϕ (x ,£), where ϕ (x ,£) is a predictor. To gain a better predictor performed bootstrap replication {$£_k$} is then called { ϕ (x,$£_k$) }. Performed totally B-times of bootstrap replication so that {$£^{(B)}$} from £ where {$£^{(B)}$} resampling with replacement and established predictors of { ϕ (x,$£^{(B)}$}.

Bagging MARS algorithm is as follows.

1. Taking bootstrap n samples of set data £ with n-repetitions to each aggregate variables in each observation.
2. MARS modeling sets data £B bootstrap sample results.
3. Test the model generated in step 2.
4. Repeating steps 1-3 as much as B-times (bootstrap replication).
5. Obtain the best model.
6. Forming bagging MARS models of the average of each parameter at each sampling to B-times.

To obtain better results then the bootstrap replication is done as much as possible.

2.2.1 Weighted rainfall index and anomalies Harvested Rice

Weighted rainfall index (weighted rainfall index: WRI) is compiled based on monthly rainfall data is weighted. WRI which can be used in the modeling is that the WRI weighted system has been modified by Sutikno (2008). The modification is written as follows.

$$WRI_{t,D} = R^*_{t,D} \frac{LT_t}{L_{standard}}$$

where,

$$R^*_{t,D} = \sum_{j=1}^{m} \frac{A_j}{A} R_j \ , \ A = \sum_{j=1}^{m} A_j$$

Description:

$R^*_{t,D}$: Area weighted rainfall Regional weather forecast region (DPM) / DPM revision in the region/ district/ city

m : a large area of DPM

A_j : Total area of j-DPM

LT_t : Plant area at t-month

$L_{standard}$: standard area for rice crops in the regional

j : DPM regional (1, 2, 3, ..., m)

t : Months (1, 2, ..., 12)

D : Regional

Model anomalies rice harvested area to each period ($AnLP_p$) with a weighted rainfall index (WRI) is as follows.

$$AnLP_{pi} = WRI_{1i} + WRI_{2i} + WRI_{3i} + WRI_{4i}$$

From the equation above three equations obtained for each of the following.

$$AnLP_{1i} = WRI_{1i} + WRI_{2i} + WRI_{3i} + WRI_{4i}$$
$$AnLP_{2i} = WRI_{5i} + WRI_{6i} + WRI_{7i} + WRI_{8i}$$
$$AnLP_{3i} = WRI_{9i} + WRI_{10i} + WRI_{11i} + WRI_{12i}$$

where

i = 1, 2, 3,..., n (n is the number of observations)
p = 1, 2, 3 (Period)

$AnLP_1$ = harvested area Anomaly in first period (January to April)

$AnLP_2$ = harvested area Anomaly in second period (May to August)

$AnLP_3$ = harvested area Anomaly in third period (September to December)

WRI_1, ..., WRI_4 indicates a weighted rainfall index first until the fourth month in a first period (WRI_1 = in January, WRI_2 = in February, WRI_3 = in March, WRI_4 = in April).

WRI_5, ..., WRI_8 indicates a weighted rainfall index first to fourth month in a second period (WRI_5 = in May, WRI_6 = in June, WRI_7 = in July, WRI_8 = in August).

WRI_9, ..., WRI_{12} indicates a weighted rainfall index first to fourth month in a third period (WRI_9 = in September, WRI_{10} = in October, WRI_{11} = in November, WRI_{12} = in December).

3 METHOD OF ANALYSIS

Methods of data analysis performed in this study can be explained as follows .

1. Identification of data includes the identification and the relationship between WRI and $AnLP_p$ that can be shown on the scatter plot.
2. To model based anomaly harvested area weighted rainfall index for the data in- sample using the bagging MARS method with the following stages.
   - In MARS models for the first sets data
     - Determine the maximum base functions
     - Determine the maximum number of interactions
     - Determine the minimum number of observations between knots
     - Determine the number of degrees of freedom
   - Getting the best MARS models for the initial set of data based on the value of the smallest MSE and GCV.
   - Getting the significant variables of the best MARS models for the initial set of data.
   - Perform bagging of the pair response variable and the predictor variables were significant from the best MARS models for data sets beginning with 50, 100, 200, and 250 bootstrap replication.
   - Perform MARS modeling on each sample-B bootstrap replication with the maximum number of base functions, the maximum amount of interaction and the minimum number of observations between knots is equal to the maximum number of base functions, the maximum amount of interaction and the minimum number of observations between knots at best MARS models for data sets beginning.
   - Getting MSE at each sampling B bootstrap replication.
   - Getting MSE bagging of the average MSE at each sampling to B
   - Bagging MARS model obtained is the best MARS models for the initial data sets. This is because

the value of changing each knots for each replication so that the estimated parameters cannot be averaged.

3. Counting rice production forecast for the year to out -sample of data as follows.
   - Calculating forecast rice harvested area forecast results by adding the anomalous area harvested to each period results of MARS best modeling with an average area harvested during a certain period (2002 to 2008).
   - Suspect productivity to each period using the average productivity of the last five years (2007 to 2011).
   - Calculating forecast rice production to each period.

     $P_p = Pro_p \times LP_p$ with $p = 1,2,3$

     P_p : forecast of production in the p-period

     Pro_p : forecast of productivity in the p-period

     LP_p : forecast of harvested area in the p-period
   - Getting forecast of rice production for the year, which is the sum of the third period of the forecast.
   - Comparing rice production forecast results have been obtained with the MARS method with the actual value of rice production from BPS issued last three years (2009 to 2011).

4 Discussion

4.1 Identification Data

To model the relationship between the anomalous area harvested and predictor variables weighted rainfall index first identified patterns of relationship between the two. Identification of relationship pattern is very necessary to know the exact model in modeling the relationship between the two variables.

Figure 1 shows that the pattern of relationships between AnLP and WRI appears no linierity clear pattern not even have a specific pattern. Likewise, the direction of the relationship is positive or negative. This suggests that AnLP in first period (January to April), second period (May to August), and third period (September to December) are not affected by these two variables are linearly so necessary to find the possibility of non-linear statistical models.

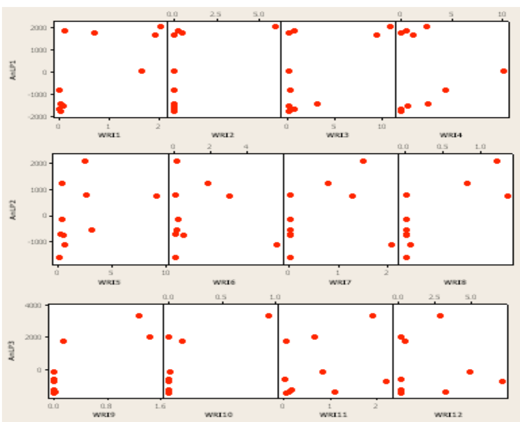

Figure 1. Scatterplot AnLP and WRI in Buru

4.2 Relationship between the model anomaly rice harvested to each Period ($AnLP_p$) and weighted rainfall index (WRI) using Bagging MARS method.

In this study bagging MARS method is applied in modeling the anomalous area harvested per period as the response variable and weighted rainfall index as a predictor variable. The data used for modeling can be quite small, namely 10 years since year 2002 to year 2011, so it needs to be done in preparing the model resampling methods. Resampling method used is that a bagging sampling with replacement for a data set consisting of the response variable and the predictor variables (significant base functions).

4.2.1 Relationship between the model anomaly rice harvested area (AnLP) and the weighted rainfall index (WRI) in first period using bagging MARS method.

4.2.1.1 MARS Model

Initial step of MARS modeling done by trial and error on the maximum base function (BF), maximum interaction (MI), minimum number of observations between knots or minimum observation (MO), and the number of degrees of freedom (DB) until an optimal model is obtained with the MSE and GCV minimum. Friedman [4] suggests a maximum number of basis functions of two to fourth times the number of predictor variables. Maximum interaction one, two, or three with a consideration if more than three will result in a very complex model. As well as, the minimum distance between knots or knots as the minimum observation between 0, 10, 20, 50, and 100.

TABLE 1. TRIAL AND ERROR MODEL MARS A FIRST PERIOD IN BURU

BF	MI	MO	DB	R^2	MSE	GCV
8	**1**	**0**	**1**	**0.507**	**544216.122**	**1523805.55**
8	2	0	1	0.204	1240372.80	3088471.75
8	3	0	1	0.204	1240372.80	3088471.75
12	1	0	1	0.507	544216.122	1523805.55
12	2	0	1	0.204	1240372.80	3088471.75
12	3	0	1	0.204	1240372.80	3088471.75
16	1	0	1	0.507	544216.122	1523805.55
16	2	0	1	0.204	1240372.80	3088471.75
16	3	0	1	0.204	1240372.80	3088471.75

Table 1 shows the value of R^2, MSE, and GCV in combination BF, MI, MO, and DB based on the criteria of goodness of the model, selected models with minimum MSE and GCV. From the above results it can be concluded the model with a combination of BF = 8, MI = 1, MO = 0, and DB = 1 is the best model. The best MARS model is as shown below.

$$\hat{f}(x) = 1031.325 + 985.757BF_1 - 9439.66BF_4$$

where

$$BF_1 = \max(0, WRI_1 - 0.088) = \begin{cases} 0, & \text{if } WRI_1 \le 0.088 \\ (WRI_1 - 0.088), & \text{if } WRI_1 > 0.088 \end{cases}$$

$$BF_4 = \max(0, 0.251 - WRI_2) = \begin{cases} 0, & \text{if } WRI_2 \ge 0.251 \\ (0.251 - WRI_2), & \text{if } WRI_2 < 0.251 \end{cases}$$

From the best MARS models can be interpreted that each increase of one unit of the base functions 1 (BF_1) can increase rice yields broad anomalies in the period 1 at 985.757 if weighted rainfall index in January (WRI_1) more than 0,088 mm, with a base of other functions that go assumed to be constant in the model. Meanwhile, for each increase of one unit of the base function 4 (BF_4) can reduce anomalies rice harvested area of 9,439.66 a first period if the weighted rainfall index in February (WRI_2) of less than 0.251 mm with base other functions are included in the model held constant. The next best model obtained from two predictor variables were entered into the model, which is a weighted index of rainfall in February (WRI_2) and weighted rainfall index in January (WRI_1) based on the relative variable importance table. Percentage of contribution weighted rainfall index in February (WRI_2) and weighted rainfall index in January (WRI_1) are shown in Table 2 below.

TABLE 2. PERCENTAGE OF CONTRIBUTIONS OF EACH VARIABLE IN THE FIRST PERIOD

Variable	Contribution
WRI_2	100 %
WRI_1	57.711 %

4.2.1.2 MSE calculations on models of bagging MARS

MARS modeling of the data sets obtained MSE Value in the first period is 544,216.122. To minimize the error variance performed on the data resampling. Table 3 below shows the results for the first period bagging MARS in Buru.

TABLE 3. RESULTS OF BAGGING MARS IN FIRST PERIOD

Bootstrap replication	Average value of MSE	Decrease in the value of MSE
25 times	19511.60	524704.522
50 times	3566.25	540649.872
100 times	3993.14	540222.982
150 times	**1538.90**	**542677.222**
200 times	2413.91	541802.212

Table 3 gives the smallest MSE value of the information obtained during the boostrap replicate as much as 150 times. thus it can be concluded that the best results obtained in the replication boostrap bagging as many as 150 times. Bagging models can lower the MSE value of the data model that is equal to the initial set of 544,216.122 be 1,538.90 or in other words bagging can reduce the value of MSE of 542,677.222 of the initial data sets.

4.2.2 Relationship between the model anomaly rice harvested area (AnLP) and the weighted rainfall index (WRI) in second period using bagging MARS method.

4.2.2.1 MARS Model

Trial and error to BF, MI, MO, and DB MARS modeling in second period are shown in Table 4.

TABLE 4. TRIAL AND ERROR MODEL MARS A SECOND PERIOD IN BURU

BF	MI	MO	DB	R^2	MSE	GCV
8	**1**	**0**	**1**	**0.261**	**637497.059**	**1147494.92**
8	1	0	2	0.088	637497.059	1416660.57
8	1	0	3	0.088	637497.059	1416660.57
12	1	0	1	0.261	637497.059	1147494.92
12	1	0	2	0.088	637497.059	1416660.57
12	1	0	3	0.088	637497.059	1416660.57
16	1	0	1	0.261	637497.059	1147494.92
16	1	0	2	0.088	637497.059	1416660.57
16	1	0	3	0.088	637497.059	1416660.57

From Table 4 it is seen that the best MARS model is a combination of BF = 8, MI = 1, MO = 0, and DB = 1. It can be seen from the MSE and the smallest GCV among others, are respectively 637,497.059 and 1,147,494.92 so the best MARS model is as shown below.

$$\hat{f}(x) = -566.237 + 1654.87BF_1$$

where

$$BF_1 = \max\left(0, WRI_8 - 0.22\times10^{-7}\right) = \begin{cases} 0, & \text{if } WRI_8 \le 0.22\times10^{-7} \\ \left(WRI_8 - 0.22\times10^{-7}\right), & \text{if } WRI_8 > 0.22\times10^{-7} \end{cases}$$

This model can be interpreted that each increase of one unit of the base functions 1 (BF1) can increase rice yields broad anomaly in second period for 1,654.87 if weighted rainfall index in August (WRI_8) more than 0.22×10^{-7} mm, on the base of other functions in the model are held constant. Furthermore, Table 5 looks only variable weighted rainfall index in August (WRI_8) are included in the model. So important variable scores for weighted rainfall index in August (WRI_8) worth 100%, which means the variable weighted rainfall index in August has a dominant influence on anomalous rice harvested area in second period (May-August).

TABLE 5. PERCENTAGE OF CONTRIBUTIONS OF EACH VARIABLE IN THE SECOND PERIOD

Variable	Contribution
WRI_8	100 %

4.2.2.2 MSE calculations on models of bagging MARS

The best MARS models between anomalous rice harvested area weighted rainfall index in second period provide information that model has a MSE is 637,497.059, with a significant predictor variables are weighted rainfall index in August (WRI_8). Table 6 below shows the average MSE in second period.

Table 6 provides information that bootstrap replication earned 200 times average value of the smallest MSE is 3,017.05, So based on the above results it can be concluded that the results obtained by bagging the best with an average value of the smallest MSE is a bootstrap replicate as much as 200 times. With replication as much as 200 times, bagging can reduce MSE of the initial set of data models is 637,497.059 be 3,017.05 or in other words bagging can reduce the value of MSE of 634,480.009 from the initial set of data models.

TABLE 6. RESULTS OF BAGGING MARS IN SECOND PERIOD

Bootstrap replication	Average value of MSE	Decrease in the value of MSE
25 times	13521.9	623975.159
50 times	15068.9	622428.159
100 times	7378.2	630118.539
150 times	4284.14	633212.919
200 times	**3017.05**	**634480.009**

4.2.3 Relationship between the model anomaly rice harvested area (AnLP) and the weighted rainfall index (WRI) in third period using bagging MARS method.

4.2.3.1 MARS Model

Table 7 gives information based on that value the smallest MSE and GCV is combination of BF=8, MI=1, MO=0, and DB=1. So that model with the combination is the best model. This model is shown below.

$$\hat{f}(x) = 2355.804 - 24391.732BF_2$$

where

$$BF_2 = \max\left(0, 0.141 - WRI_9\right) = \begin{cases} 0, & \text{if } WRI_9 \ge 0.141 \\ \left(0.141 - WRI_9\right), & \text{if } WRI_9 < 0.141 \end{cases}$$

TABLE 7. TRIAL AND ERROR MODEL MARS A THIRD PERIOD IN BURU

BF	MI	MO	DB	R^2	MSE	GCV
8	**1**	**0**	**1**	**0.761**	**453362.558**	**816052.711**
8	2	0	1	0.749	453362.558	858437.928
8	3	0	1	0.749	453362.558	858437.928
12	1	0	1	0.761	453362.558	816052.711
12	2	0	1	0.749	453362.558	858437.928
12	3	0	1	0.749	453362.558	858437.928
16	1	0	1	0.761	453362.558	816052.711
16	2	0	1	0.749	453362.558	858437.928
16	3	0	1	0.749	453362.558	858437.928

From the best model can be interpreted that each increase of one unit of the base function 2 (BF_2) can reduce anomalies rice harvested area in the period 3 of 24,391.732 if weighted rainfall index in September (WRI_9) of less than 0.141 mm, with bases other functions assumed to be constant in the model. Later in the third period, based on table 8 weighted rainfall index in September (WRI_9) contributes 100%, which means the variable weighted rainfall index in September to have a dominant influence on anomalous rice harvested area in the third period.

TABLE 8. PERCENTAGE OF CONTRIBUTIONS OF EACH VARIABLE IN THE THIRD PERIOD

Variable	Contribution
WRI_9	100 %

4.2.3.2 MSE calculations on models of bagging MARS

The best MARS models between anomalous rice harvested area weighted rainfall index for the third period provides information that the model has a MSE is 453,362.558 significant predictor variables are weighted rainfall index in September (WRI_9). Table 9 below shows the average MSE results of bagging MARS in third period.

TABLE 9. RESULTS OF BAGGING MARS IN THIRD PERIOD

Bootstrap replication	Average value of MSE	Decrease in the value of MSE
25 times	11418.200	441944.358
50 times	9452.840	443909.718
100 times	3224.570	450137.988
150 times	1213.380	452149.178
200 times	**961.970**	**452400.588**

Table 9 provides information that the bootstrap replication earned 200 times the average of the smallest MSE value is 961.970, so it can be concluded that the results obtained by bagging the best with an average value of the smallest MSE is a bootstrap replicate as much as 200 times. With replication as much as 200 times, bagging can reduce MSE of the initial set of data models for 453,362.558 be 961.970, or in other words, bagging can reduce the value of MSE is 452,400.588 from the initial set of data models.

4.3 Rice Production forecast

To evaluate the model and see the level of reliability that is formed, it can be seen from the average forecast error rates for harvested area and production of rice in the year 2009 to the year 2011. Rice production Forecast to each period is the multiplication of the value of the harvested area forecast productivity. Used to estimate the productivity of the average productivity value over the last five years. While the forecast harvest area was obtained from the sum of the forecast anomalies rice harvested area with average area of rice crop. Of the best MARS models which have been obtained from the previous analysis can be calculated models forecast values for harvested area and production of rice to each period as shown in Table 10.

TABLE 10. FORECAST VALUE OF HARVESTED AREA AND RICE PRODUCTION TO EACH PERIOD (USING MODELS MARS)

Period	Year	Harvested Area		Production		(Abs (Δ)/Act) x100%	
		Actually	Forecast	Actually	Forecast	Harvested area	Production
First period	2009	3897	2747.045	148086	104563.5	29.50%	29.39%
	2010	1393	863.342	52934	32862.2	38.02%	37.92%
	2011	2293	2569.570	87134	97808.2	12.06%	12.25%
	average					26.53%	26.52%
Second period	2009	5628	4818.40	242004	203153.5	14.38%	16.05%
	2010	2371	3033.99	101953	127919.4	27.96%	25.46%
	2011	4280	5037.54	184040	212392.8	17.69%	15.40%
	average					20.01%	18.07%
Third period	2009	3320	3806.9	119520	136203.8	14.66%	13.95%
	2010	3569	3830.9	128484	136203.8	7.33%	6.67%
	2011	4901	3830.9	176760	136203.8	21.83%	22.45%
	average					14.61%	14.36%

Δ = actually – forecast

Table 10 provides information based on the results of the forecast error for the harvested area and rice production to each period look distinctly average prediction error rate is at least third periods respectively 14.61% and 14.36%, followed by a period of 2 each by 20.01% and 18.97%, as well as period 1 respectively 26.53% and 26.52%. BPS and the Ministry of Agriculture every year to data collection and forecast rice production in Indonesia is divided into three periods, namely from January to April, May to August, and September to December. Harvested area of each period obtained from the amount of harvested area in the first month until the fourth month in a period. Production and harvested area in one year (January to December) is obtained from the sum of production and harvested area for three periods. So the forecast results for the year and harvested area of rice production MARS models as shown in Table 11 below.

TABLE 11. FORECAST VALUE OF HARVESTED AREA AND RICE PRODUCTION HARVESTED TO EACH YEAR

Year	Harvested area (Ha)		Production (ton)		(Abs (Δ)/Act) x100%	
	Actually	Forecast	Actually	Forecast	Harvested area	Production
2009	12845	11372.36	509610	439746.59	11.46%	13.70%
2010	7333	7728.27	283371	298837.10	5.39%	5.45%
2011	11474	11438.05	447934	442286.77	0.31%	1.26%
average					5.72%	6.81%

Δ = actually – forecast

Based on the results of Table 11 forecasts to each year for harvested area and rice production of MARS models can be calculated the average error rate forecast harvested area of rice by 5.72% while the average error rate for rice production forecast is 6.81%. Average error rate of rice production forecast issued BPS to each province ranged from 5% to 10%.

5 CONCLUSIONS

Results of rice harvested area forecast MARS model in Buru has an error rate forecast is 5.72%. As for rice production forecast results have an error rate of 6.81%. In accordance with an error rate forecast of rice production issued BPS ranging between 5% to 10%, it can be said rice production forecast errors in Buru is in accordance with the rate specified by BPS.

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