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Study of Developing Models of Crop Failure Risk Information

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Abstract: Climate is one factor that can influence plant growth. The risk of crop failure due to climate variability can be in the form of reduced water sources, which impact water needs in the land and the emergence of pests and diseases in plants. The risk of planting failure can impact product quality, which has the potential to decrease, higher plant handling costs, and various things that cause losses to farming businesses. The availability of climate forecast information, such as rainfall and other parameters, encourages writers to apply it to information that is easier for users to understand. One of the machine learning algorithms, Decision Tree, is used as a model in determining the risk of planting failure based on each attribute/parameter, including monthly rain, ENSO and IOD phenomena, drought, groundwater availability, and Oldeman climate type. This study aims to make a model prediction of crop failure risk potential, and the calculation is based on climate prediction data. The results of this study show differences in climatic conditions for each commodity when there is an increased potential risk of planting failure. Monthly rainfall is the most dominant factor influencing rice, maize, and soybean planting failure. Validation of the decision tree model shows that this model is quite good in determining the potential risk of crop failure in all commodities studied, with the proportion of correct proportion of more than 65%. However, the Heidke Skill Score (HSS) shows that this model is good for Paddy and Soybean; Maize shows an HSS of less than zero.

Keywords: Climate; Crop Failure; Decision Tree; Risk.

Introduction

Agriculture is one of the most important sectors in the world, including Indonesia. This is because the main job of Indonesian people is farming. Based on data from Statistics Indonesia [1], the number of people working in agriculture, forestry and fisheries has reached 37 million. This sector (one of which is agriculture) is still very popular among Indonesians because, through the activity, they can supply food that must be fulfilled, such as rice, maize, soybeans, or other staple foods. To ensure food security, a global issue, the Indonesian government has made various ways, one of which is the food self-sufficiency program [2]. Apart from that, the government also issued regulations to 16 Ministers and Heads of Agencies as well as all Governors throughout Indonesia in the form of The President of the Republic of Indonesia Instruction Number 5 of 2011 concerning Securing National Rice Production in the Face of Extreme Climates [3].

West Nusa Tenggara Province is one of the food production centers in Indonesia, which has a high harvest area and production of food crops such as rice, maize, and soybeans [4]. Therefore, West Nusa Tenggara province and several other provinces have been designated rice self-sufficient areas and have become contributor areas to national food crops that are quite high in quantity. Agricultural activities are the leading sector in the West Nusa Tenggara region, making this province part of the rural region in Indonesia. However, the climate conditions in West Nusa Tenggara are one of the challenges that farmers must face. The existence of the presidential instructions mentioned previously makes the Meteorological, Climatological, and Geophysics Agency for Indonesia (BMKG) obligated to make extreme climate analyses and forecasts. It has to disseminate climate early warning information to related agencies (such as the Ministry of Agriculture) [5].

Agricultural activities are greatly influenced by various factors, one of them being weather and climate (extreme climate conditions or climate change). Climate change can affect the planting period, increase plant pest attacks, increase the risk of crop failure, and decrease crop yields and farmer incomes [6]. One indicator of climate change is the increasing intensity and frequency of extreme rainfall. High rainfall intensity can cause puddles or possibly flooding, which can then damage crops and result in crop failure and crop failure [7]. Apart from flooding, another problem that is a challenge for agriculture is drought conditions. Drought can be described as a period that occurs in reduced rainfall until it is below normal in an area. Extreme climate will worsen drought conditions in a region. Agriculture is one of the sectors most vulnerable to drought disasters. Apart from flooding, another problem that challenges agriculture is drought conditions. Drought is a period of reduced rainfall below normal in an area. Extreme climate will worsen drought conditions in a region. Agriculture is one of the sectors that are most vulnerable to drought disasters.

The frequency of long dry seasons or droughts in Indonesia in 1844 and 1960 was only one time in 4 years;

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from 1961-2006, the frequency increased to 1 time in 2-3 years [8]. According to the Directorate of Plant Protection [9], drought will have an impact on decreasing surface and groundwater supplies, disrupting cropping patterns, and potentially increasing crop failure; the first rainy season after the drought, based on experience, can increase attacks by the main pests (rats, leafhoppers, stem borers and grasshoppers) and land fires agriculture and forests have the potential to increase.

The West Nusa Tenggara region is vulnerable to drought disasters. In 2020, the drought disaster also hit the West Nusa Tenggara region, covering 6,730 hectares of rice fields experiencing drought and 459 hectares of rice fields (threatened by crop failure) [10]. Drought events have also occurred in other areas; for example, drought in Indramayu Regency [11] is the main cause (79.8%) of crop failure apart from OPT (15.6%) and flooding (5.6%). Droughts generally last for 1-8 months. Farmers experienced drought most often for six months (32%). Farmers most often experience drought in June (32.2%). The peak of drought events generally occurs in the Gadu season, namely June-August.

Increasingly uncertain climate conditions and the absence of impact-based climate information, especially in the agricultural sector, make it necessary to carry out and develop this study. The limitations of climate information users in interpreting information issued by BMKG make this climate-based crop failure information system a solution for the public, especially farmers, to understand the climate better. Apart from that, people can be more aware of the importance of climate so that the benefits of this information become more pronounced. Based on this, the specific purpose of this study is to develop a model for calculating the value of the risk of failure of agricultural commodity crops.

Research Methods

In this research, the data that will be used to build the model is divided into two, namely climate data (local and global) and agricultural data, which are described as follows:

Local climate data are divided into rainfall data and air temperature data. Monthly rainfall data was obtained from 12 collaborative rain posts in the Central Lombok Regency from January 2018 to March 2023. Meanwhile, the air temperature data came from West Nusa Tenggara's Climatology Station and Zainudin Abdul Majid's Meteorology Station. Locations for observing rainfall and air temperature are in Table 1.

Global climate data consists of ENSO index data and Dipole Mode index, which comes from the JMA (Japan Meteorological Agency) with the same period as local climate data.

Agricultural data consist of the planting area and harvest area data in each category, namely Rice, Maize, and Soybeans, obtained from the Central Lombok Regency Agricultural Service.

The methods consist of several calculations; then, the model development will use the Decision Tree method. Initial calculations in the study to determine the amount of risk were obtained based on six variables, namely Monthly Rainfall, ENSO Index, Dipole Mode Index, Ground Water Availability, Oldeman Climate Type, and Drought Index using the categorized Standardized Precipitation Index (SPI). The weight of each variable is determined sequentially based on the correlation value between the variables used and crop production results. The agricultural data used are the planting area and harvest area data in each category for Central Lombok rice, maize, and soybean commodities.

Table 1. Location of data collection

No	Location (Rainfall Stations/ BMKG Stations)	Latitude	Longitude
1	Batukliang	116.30	-8.57
2	Central of Praya	116.31	-8.73
3	Southwest of Praya	116.20	-8.73
4	Janapria	116.4	-8.69
5	Kopang	116.38	-8.63
6	Mantang	116.31	-8.62
7	East of Praya	116.36	-8.78
8	Praya	116.28	-8.65
9	West of Praya	116.23	-8.77
10	Pringgarata	116.25	-8.62
11	Pujut	116.3	-8.82
12	Puyung	116.23	-8.69
13	Climatology Station of West Nusa Tenggara	116.17	-8.63
14	Meterology Station of Zainudin Abdul Majid	116.28	-8.76

Groundwater availability can be calculated by the land water balance formula, which uses Evapotranspiration and Rainfall to obtain APWL (Accumulation of Potential Water Lost), groundwater availability, deviation of groundwater availability, actual evapotranspiration, and water availability. Calculating each parameter requires some values, such as the coefficient of the plant, permanent wilting point, and field capacity for a particular crop area. Those values are different for each type of plant.

Climate Type. Oldeman and Frere [12] have made a climate classification related to agriculture using the rainy climate parameter. The criteria proposed by Oldeman are based on the number of Wet Months and Dry Months. Oldeman [13] also defines wet months as months with more than 200mm/month and dry months as months with less than100mm/month, while months with rainfall between 100mm –200mm are called humid months.

Standardized Precipitation Index (SPI) is an index that can describe drought by calculating the amount of reduction in rainfall over a certain time scale. McKee et al. [14] divide the SPI calculation time scale into five categories: SPI of 3 months, SPI of 6 months, SPI of 12 months, SPI of 24 months and SPI of 48 months. For the measurement of drought, it can use the SPI calculation on a 3-month scale [15]. A positive SPI value can indicate wet conditions, whereas a negative SPI index indicates dry conditions. SPI classification [16] is explained in table 2.

Table 2. SPI Classification

Value	Classification
> 2.0	Extremely Wet
1.5 – 1.99	Very Wet
1.0 – 1.49	Moderately Wet
-0.99 – 0.99	Near Normal
-1.0 – (-1.49)	Moderately Dry
-1.5 – (-1.99)	Very Dry
< 2.0	Extremely Dry

After each of the variables' input of the model has been obtained (Ground Water Availability, Oldeman Climate Type, SPI, Monthly Rainfall, ENSO Index, Dipole Mode Index), the model will be built using the Decision Tree method. A decision tree is a hierarchical model consisting of a discriminant function, or decision rule, that is applied recursively to partition the feature space of a dataset into pure subspaces with a single class [17]. The main components of a decision tree include decision nodes, branches, and leaf nodes. In a decision tree structure, each decision node represents a feature variable, and each branch represents one of the states of these feature variables based on a decision rule. Leaf nodes determine the expected value of the target variable.

Decision trees are built recursively by partitioning the complete dataset (marked by the root node) into several small subsets using a splitting criterion. The goal is to find a set of decision rules that naturally partition the feature space to provide an informative and robust hierarchical classification model. One of the most famous separation criteria is the Gini index. The Gini index is calculated using the following formulation [18]:

$$Gini\ (Y) = 1 - \sum_{i} [p\ (Y = i)]^2$$

The node splitting criterion based on the Gini index aims to obtain the maximum reduction in the impurity of the node Y dataset by finding the best partition x* of the observations and then dividing the node Y dataset into two child node subsets, Yl and Yr, as follows:

$$\max_{x \in X} \Delta Gini(Y, x)$$

$$\Delta Gini(Y, x) = Gini\ (Y) - p(Y_l)Gini(Y_l) - p(Y_r)Gini(Y_r)$$

Where Δgini (Y, x) represents the decrease in impurity, x ∈ X refers to the set of divisions generated by all features, Yl and Yr are the left and right child nodes of the node dataset Y, respectively; and p(Yl) and p(Yr) are the proportions of observations in the node Y dataset that belong to the left and right child nodes, respectively.

After the model is formed, it will be divided into two subsets: training and testing data. The training data is used to build the tree, and the testing data is used to test the tree's performance. Apart from that, the model needs to be validated to see the performance of the model being built. A contingency table is one method for calculating multi-category parameter model validation. Generally, the contingency table is carried out on a binary parameter model (figure 1), so the contingency table for multi-category parameters will still be converted like the contingency table for binary parameters (figure 2). Off-diagonal cells provide information about the error prediction. The bias (b) is some category under or over-predicted, while POD (Probability of Detection) measures the success in detecting events of different categories. Proportion Correct (P.C.) is calculated to determine the number of correct predictions or the level of model accuracy, as depicted in Table 3.

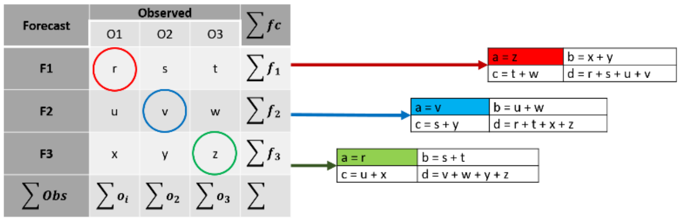

Figure 1. The contingency table of the binary parameter model [19].

Event Forcast	Event Observed: Yes	Event Observed: No	Marginal Total
Yes	Hit	False Alarm	Fc Yes
No	Miss	Correct Rejection	Fc No
Marginal Total	Obs Yes	Obs No	Sum Total

Event Forcast	Event Observed: Yes	Event Observed: No	Marginal Total
Yes	a	b	a + b
No	c	d	c + d
Marginal Total	a + c	b + d	a + b + c + d = n

Figure 2. The contingency table of the multi-category parameter model [19].

Table 3. Contingency Table Verification Attribute [19]

Verification Attribute	Formula
Bias(B)	(a+b)/(a+c)
Probability Of Detection (POD)	a/(a+c)
FAR (False Alarm Ratio)	b/(a+b)
F (False Alarm Rate)	b/(b+d)
T.S. (Treat Score)	a/(a+b+c)

Another verification attribute is calculating the skill model by calculating the Heidke Skill Score (HSS) value. HSS is a score that measures the extent of predictability of an event by distinguishing between correct cases (actual events) and incorrect cases (events that did not occur). This helps to measure the extent of predictability better than just randomly guessing conditions. HSS scores can be generalized to multi-category cases [19]:

$$\mathrm{HSS} = \frac{\{\sum \mathrm{p}(\mathrm{f_i}, \mathrm{o_i}) - \sum \mathrm{p}(\mathrm{f_i})\mathrm{p}(\mathrm{o_i})\}}{1 - \sum \mathrm{p}(\mathrm{f_i})\mathrm{p}(\mathrm{o_i})}$$

Where p(fi. oi) is the number of correct prediction events in all categories compared to the total amount of data, p(fi) is the number of predictions in a particular category compared to the amount of data, and p(oi) is the number of observation events in a particular category compared to the amount of data.

Agricultural data obtained is then converted into Risk categories. The agricultural data used is Planted Area and Harvested Area, which are available monthly. The planting area is the land that will be planted with a particular commodity. In contrast, the harvested area is the land from which a commodity is ready to be harvested [20].

Results and Discussion

The risk category for planting failure is determined based on the percentage difference between the Planted Area and the Harvested Area during the lifetime of each commodity. Table 6. Describes an explanation of each category of risk of planting failure.

Table 6. Explanation of Risk Category

Risk Category	Explanation
Safe / No-Risk / N.R.	Historical data on commodity planting shows that there are no reports of planting failures or the percentage difference between Planted Area and Harvested Area <=0%
Low Risk / L.R.	Historical data on commodity planting shows that there are low reports of planting failure or the percentage difference between Planted Area and Harvested Area <=33%
Medium Risk / M.R.	Historical data on commodity planting shows that there are reports of moderate planting failures or a percentage difference between Planted Area and Harvested Area of 33 – 67%
High Risk / H.R.	Historical data on commodity planting shows that there are high reports of planting failures or the percentage difference between Planted Area and Harvested Area >=67%
Not the Right Commodity / NRC	Historical data on commodity planting shows that there was no planting then.

Information is obtained based on the agricultural data used, as shown in Table 7. Soybeans are the commodity rarely planted, with a percentage during the calculation period in 12 regions of about 88.4%, followed by maize at 65.5%. Paddy is the main commodity grown but has the greatest risk compared to maize and soybeans. Approximately 15% of the paddy data samples used are at risk of crop failure, of which 8% are at high risk. Meanwhile, maize is 4.4%, and soybeans are 7%, which has a risk of crop failure. The total paddy crop is generally safe or no-risk, as with maize commodities. Meanwhile, the percentage of Safe and Risky categories for soybean commodities shows a similar value, around 7%. Table 7. Shows the distribution of the risk of crop failure for each commodity in each category of parameters/attributes used in building a climate-based calculation of the potential risk of crop failure.

Table 7. Percentage (%) of risk categories for each commodity

Commodity	N.R.	L.R.	MR	HR	NRC
Paddy	50.7	4.8	2.1	7.9	34.5
Maize	32.9	1.4	0.8	2,2	65.5
Soya bean	7.6	1.0	0.8	5.2	88.4

Figure 1. Shows the weight of the climate parameters used in calculating the risk of crop failure using the decision tree model. The result shows that monthly rainfall greatly determines crop failure risk for paddy, maize, and soybean commodities. For paddy commodities, the weight of monthly rainfall is almost 0.5 compared to other climate parameters. This shows that the diversity or variation of monthly rainfall will greatly influence the crop success of paddy plants. The lowest weights are generally seen in the Oldeman and SPI parameters.

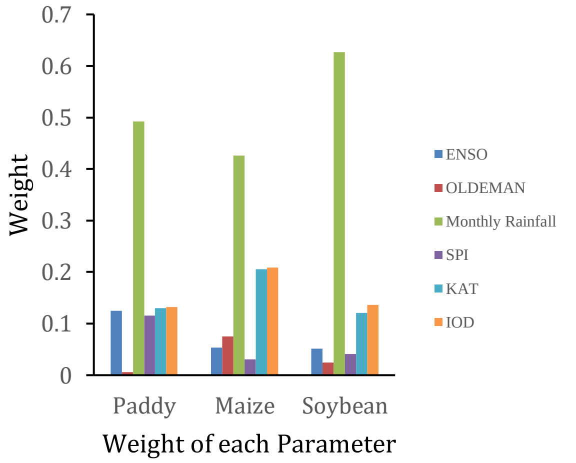

Figure 1. Weight of each Parameter

Monthly Rainfall

The risk of crop failure due to variations in monthly rainfall for each commodity generally shows different criteria. There is a risk of crop failure in paddy plants in as much as 15% of all the data used; another 35% are not in the right conditions for the crop, and 50% are in safe conditions. Generally, paddy crops begin when the rainfall is>50 mm in 10 days or >150 mm in a month [20] [21]. This study consistently found that crop failure risk generally occurs when rainfall conditions are less than 150 mm/month. This is determined based on the percentage of data at risk of crop failure in the <150 mm/month category, greater than the percentage of total data in the safe category.

In maize plants, there is a risk of crop failure of 5%, 65% of which are not planted, and 30% are safe. The risk of crop failure is generally indicated when rainfall is <50 mm/month and rain is >150 mm/month. Likewise, for soybean plants, the risk of crop failure is 7%; 88% are not planted and 5% are safe. This condition shows that crop failures in soybean commodities were greater during the study period than those that were not at risk / safe. The risk of crop failure is generally indicated when rainfall is <50 mm/month and rain is >150 mm/month.

Table 8. Distribution of prediction parameters (%) in each paddy risk class category

Parameter	Category	Paddy (%)					Soya bean (%)					Maize (%)				
		N.R.	L.R.	MR	HR	NRC	NR	LR	MR	HR	NRC	NR	LR	MR	HR	NRC
GWA	Enough	20.2	2,2	0.2	0.5	8.3	2,4	0.5	0.3	1.3	50.2	9.7	0.3	0.2	1.6	35.5
	Currently	15.7	1.9	0.8	2.5	5.9	4.1	0.5	0.3	2.5	24.5	13.7	0.8	0.2	0.5	14.9
	Not enough	14.8	0.6	1.1	4.9	20.3	1.1	0.0	0.2	1.4	13.7	9.5	0.3	0.5	0.2	15.1
Oldeman Climate Types	A	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	B	2,2	1.0	0.0	0.6	4.6	0.3	0.0	0.2	1.3	6,7	2.7	0.5	0.3	0.3	4.6
	C	25.8	1.4	1.3	3.3	9.9	2,2	0.3	0.3	1.4	37.4	9.2	0.2	0.0	0.5	31.8
	D	15.9	2,2	0.6	3.0	19.9	4.8	0.6	0.3	2.5	33.4	14.8	0.8	0.5	1.3	24.3
	E	6,8	0.2	0.2	1.0	0.2	0.3	0.0	0.0	0.0	7.9	5.1	0.0	0.0	0.2	3.0
SPI	Very Dry	1.1	0.0	0.0	0.0	1.4	0.2	0.0	0.0	0.0	2,4	0.8	0.0	0.0	0.0	1.7
	Dry	2.1	0.0	0.2	0.3	0.6	0.2	0.0	0.0	0.2	2.9	1.0	0.2	0.0	0.0	2.1
	A bit crunchy	3.5	0.5	0.0	0.3	2.5	1.9	0.2	0.2	0.2	4.5	0.3	0.0	0.3	0.6	5,6
	Normal	35.6	3.7	1.3	7.0	25.9	5.4	0.6	0.6	4.1	64.5	23.5	1.0	0.5	1.7	48.5
	A bit wet	4.3	0.5	0.6	0.2	2.7	0.6	0.2	0.2	0.5	7.9	3,2	0.2	0.2	0.3	5,6
	Wet	3.0	0.2	0.0	0.0	0.6	0.2	0.0	0.0	0.2	3.5	1.7	0.0	0.0	0.0	2.1
	Very wet	1.1	0.0	0.0	0.2	0.6	0.0	0.0	0.0	0.2	1.7	0.5	0.0	0.0	0.0	1.4
Monthly rainfall	<20	6.2	0.0	1.0	4.5	11.8	3.3	0.3	0.2	1.9	17.6	10.5	0.6	0.5	0.2	11.4
	21 – 50	3.8	0.3	0.5	1.7	5,6	1.3	0.0	0.2	1.6	8.9	6,8	0.2	0.2	0.2	4.6
	51 – 100	4.5	0.5	0.2	0.3	2.9	0.6	0.2	0.2	0.3	7.0	2.7	0.3	0.0	0.3	4.9
	101 – 150	3.7	0.3	0.2	0.5	2.9	0.0	0.0	0.0	0.3	7.2	2.1	0.2	0.2	0.0	5.1
	151 - 200	7.2	1.4	0.2	0.6	2.9	1.0	0.3	0.2	0.2	10.8	3.7	0.2	0.0	0.3	8.3
	201 – 300	12.4	1.4	0.0	0.2	4.8	1.0	0.2	0.2	0.3	17.8	4.1	0.0	0.0	0.5	14.8
	301 – 400	8.3	0.5	0.2	0.0	2.5	0.5	0.0	0.0	0.5	11.4	2.1	0.0	0.0	0.5	9.9
	401 – 500	2.9	0.3	0.0	0.2	1.1	0.0	0.0	0.0	0.2	4.8	0.8	0.0	0.0	0.0	4.1
	>500	1.9	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	2.9	0.2	0.0	0.0	0.3	2.4
ENSO Index	La-Nina Strong	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Moderate La Nina	9.9	0.5	0.0	0.2	2.9	1.0	0.3	0.0	0.0	12.1	3,2	0.2	0.0	0.5	9.5
	Weak La-Nina	16.2	1.9	0.6	1.9	13.7	1.7	0.2	0.5	1.9	30.0	11.0	0.5	0.2	0.3	22.4
	Normal	11.8	1.1	1.1	4.5	11.0	3.5	0.3	0.2	3.0	25.4	11.9	0.8	0.6	1.3	17.8
	Weak El Nino	12.9	1.3	0.3	1.4	7.0	1.4	0.2	0.2	0.3	20.8	6,8	0.0	0.0	0.2	15.7
	Moderate El-Nino	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Strong El Nino	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
IOD Index	Negative	22.9	2.7	0.5	2.1	16.5	2.7	0.5	0.5	2.9	41.2	11.4	0.6	0.2	2.1	33.4
	Neutral	12.9	0.2	0.8	1.6	11.3	1.9	0.2	0.0	1.3	23.4	9.9	0.3	0.2	0.0	16.2
	Positive	14.9	1.9	0.8	4.3	6,7	3.0	0.3	0.3	1.1	23.8	11.6	0.5	0.5	0.2	15.9

Ground Water Availability / GWA

Groundwater is vital for communities and ecosystems in the semi-arid agro-climatic zone [23]. Crops are one of the most impacted creatures by the lack of groundwater. The risk of crop failure due to monthly groundwater availability for each commodity generally shows different criteria. There is a risk of crop failure in paddy plants in as much as 14.7% of all the data used; another 34.3% are not in the right conditions for a crop, and 50% are in safe conditions. The risk of crop failure generally occurs when the GWA condition is in the deficient category. The risk of crop failure in maize plants is 4.6%; 65.5% are not planted, and 32.9% are safe. Likewise, for soybeans, the percentage risk of crop failure is 7%, 88.4% is not planted, and 7.6% is safe. This condition shows that the occurrence of crop failures in soybean commodities during the study period was lesser than that which was not at risk / safe. The risk of crop failure is generally indicated when GWA is low to moderate [24].

ENSO

During the data analysis period, ENSO conditions only occurred in Moderate La-Nina, Weak La-Nina, Normal, and Weak El-Nino. Strong El-Nino results in reduced paddy production [25]. The risk of crop failure due to the ENSO phenomenon in each commodity generally shows different criteria. There is a risk of crop failure in paddy plants in as much as 14.8% of all the data used; another 34.6% are not in the right conditions for a crop, and 50.8% are in safe conditions. Both La-Nina and El-Nino have the potential to cause paddy crop failure. La Nina can trigger extreme rainfall that can cause too much runoff; the worst is a flood. El-Nino conditions will increase the potential for crop failure because they cause the rainfall to decrease significantly. Still, in this study, only 3% of the data was found to have a risk of paddy crop failure. The risk of crop failure in maize plants is 4.6%; 65.5% are not planted, and 32.9% are safe. The risk of crop failure is generally indicated when ENSO is in the Weak to Moderate La-Nina category. The percentage risk of crop failure in soybean plants is 7.1%; 88.3% are not planted, and 7.6% are safe. The risk of crop failure is generally indicated when ENSO is in the Weak La-Nina category.

IOD

The IOD phenomenon has an impact on climate variability in Indonesia. The IOD phenomenon is divided into three categories: Negative IOD, Positive IOD, and Neutral IOD. Negative IOD has an impact on increasing rainfall, while positive IOD has an impact on reducing rainfall in Indonesia. Neutral IOD indicates no influence of IOD on climate conditions in Indonesia. The risk of paddy crop failure will increase when the IOD is in the positive category. As much as 7% of the paddy data used has a risk of crop failure. On the other hand, in soybean plants, the risk of crop failure will increase when the IOD is in the negative category, namely 4% of the total data. Likewise, the risk of crop failure in maize plants tends to occur when the IOD is in the Negative IOD category.

SPI and Oldeman

SPI is an index that describes drought conditions in a region. Drought generally has an impact on agricultural yields, which tend to decrease. During the analysis period, the percentage of data in the dry category was 12%. The increase in the risk of crop failure when there is a drought, is generally shown to be greatest in maize commodities, 30% of which have a risk of crop failure when the SPI Index shows Slightly Dry to Very Dry conditions. Meanwhile, paddy and soybean commodities only account for around 8%. SPI and Oldeman climate types have the smallest weight values in determining the risk of crop failure.

Decision Tree Model Validation

Multi-category validation is applied in assessing the performance of the decision tree model, which is used to calculate the potential risk of crop failure using a multi-category contingency table. The contingency table for each commodity used can be seen in Tables 9 to 11. The graph 2 shows the P.C. and HSS values for each commodity used. The greater the P.C. value, the higher the model's accuracy, and vice versa. HSS shows how well a prediction model is in predicting events. Validated data results from split data (75% for training and 25% for testing) to build and evaluate the model.

Table 9. Contingency Risks of Failure to Paddy Plants

	O. NRC	O. L.R.	O. N.R.	O. H.R.	O. MR	Precision
f. NRC	47	1	18	9	1	61.84%
f. L.R.	0	1	1	0	0	50.00%
f. N.R.	5	5	61	0	2	83.56%
f. H.R.	2	0	0	3	0	60.00%
f. MR	0	0	0	0	0	0.00%
Precision	87.04%	14.29%	76.25%	25.00%	0.00%	

Table 10. Contingency Risk of Failure to Maize Crops

	O. NRC	O. N.R.	O. MR	O. L.R.	O. H.R.	Precision
f. NRC	83	27	1	2	2	72.17%
f. N.R.	20	25	0	0	1	54.35%
f. MR	0	0	0	0	0	0.00%
f. L.R.	0	0	0	0	0	0.00%
f. H.R.	0	0	0	0	0	0.00%
Precision	80.58%	48.08%	0.00%	0.00%	0.00%	

Table 11. Contingency Risks of Failure to Soybean Plants

	O. NRC	O. N.R.	O. H.R.	O. MR	O. L.R.	Precision
f. NRC	132	11	6	1	1	87.41%
f. N.R.	5	1	0	0	0	16.67%
f. H.R.	2	0	2	0	0	20.00%
f. MR	0	0	0	0	0	0.00%
f. L.R.	0	0	0	0	0	0.00%
Precision	94.96%	8.33%	25.00%	0.00%	0.00%	

The accuracy of the soybean commodity shows the highest P.C. value, namely around 81.99%, with an HSS of 0.192797. Meanwhile, the P.C. value of paddy and maize commodities is 71.79% and 74.53%, with HSS of 0.57857 and -0.0763, respectively. A comparison of each commodity's P.C. and HSS values can be seen in graphs 2 and 3.

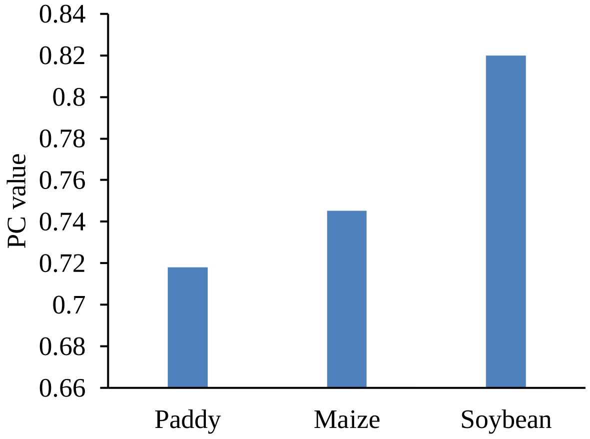

Figure 2. Proportion of Correct (P.C.)

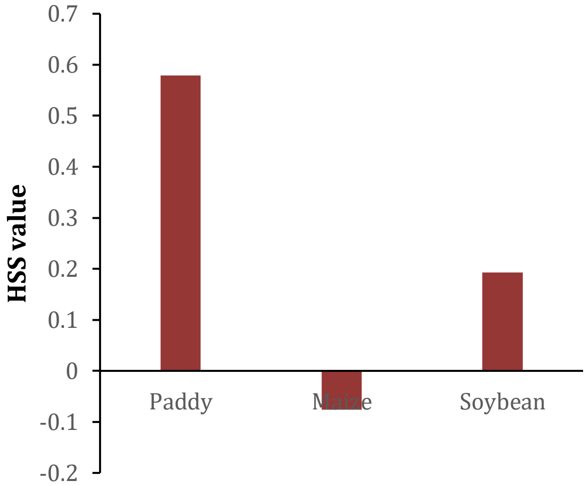

Figure 3. Heidke Skill Score (HSS)

Table 12. Validation of the Risk of Failure to Plant Paddy

NRC			LR			NR			HR			MR		
BIAS	=	1.407	BIAS	=	0.286	BIAS	=	0.913	BIAS	=	0.417	BIAS	=	0.000
POD	=	0.870	POD	=	0.143	POD	=	0.763	POD	=	0.250	POD	=	0.000
FAR	=	0.382	FAR	=	0.500	FAR	=	0.164	FAR	=	0.400	FAR	=	1
F	=	0.284	F	=	0.007	F	=	0.158	F	=	0.014	F	=	0.000
T.S	=	0.566	T.S	=	0.125	T.S	=	0.663	T.S	=	0.214	T.S	=	0.000
PC	=	0.769	PC	=	0.955	PC	=	0.801	PC	=	0.929	PC	=	0.981

Table 13. Validation of the Risk of Failed Maize Crop

NRC			LR			NR			HR			MR		
BIAS	=	1.117	BIAS	=	0.000	BIAS	=	0.885	BIAS	=	0.000	BIAS	=	0.000
POD	=	0.806	POD	=	0.000	POD	=	0.481	POD	=	0.000	POD	=	0.000
FAR	=	0.278	FAR	=	1	FAR	=	0.457	FAR	=	1	FAR	=	1
F	=	0.552	F	=	0.000	F	=	0.202	F	=	0.000	F	=	0.000
T.S	=	0.615	T.S	=	0.000	T.S	=	0.342	T.S	=	0.000	T.S	=	0.000

Table 14. Validation of the Risk of Failure to Plant Soybeans

NRC			LR			NR			HR			MR		
BIAS	=	1.022	BIAS	=	0.000	BIAS	=	0.250	BIAS	=	2.000	BIAS	=	0.000
POD	=	0.914	POD	=	0.000	POD	=	0.167	POD	=	0.375	POD	=	0.000
FAR	=	0.106	FAR	=	1	FAR	=	0.333	FAR	=	0.813	FAR	=	1
F	=	0.682	F	=	0.000	F	=	0.007	F	=	0.088	F	=	0.000
T.S	=	0.825	T.S	=	0.000	T.S	=	0.154	T.S	=	0.143	T.S	=	0.000

Validation is also done by looking at the Bias, Probability of Detection (POD), False Alarm (FAR), and Treat Score values. The bias Range is from zero to infinity, with an unbiased score = 1. With B > 1 (< 1), the forecasting system indicates over-forecasting (under-forecasting) of events. Bias is also known as the Frequency Bias Index (FBI). As with continuous variables, bias is not a measure of accuracy. The probability of Detection can measure the proportion of observed events that are predicted correctly. The POD range is zero to one, with a perfect score = 1. The opposite attribute of POD is FAR. FAR ranges from 0-1, perfect value FAR = 0. A performance measure that is widely used for rare events is the Treat Score (T.S.). T.S. scores range from 0 – 1, perfect score = 1, no skill = 0. Tables 12 to 14 show the validation attribute values (BIAS, POD, FAR, T.S.) for Paddy (12), Maize (13), and Soybean (14) commodities in each crop failure risk category.

Conclusion

The risk of crop failure does not only occur in areas with the Oldeman climate type, which has little rain (D, E) but also has the potential to occur in areas with the Oldeman climate type, which is quite wet (B, C). This shows that climate variability significantly influences the occurrence of crop failure in paddy, maize, and soybeans. Monthly rainfallfall variations are the most dominant factor influencing crop success. Monthly rainfallfall variations can be caused by the ENSO and IOD phenomena. Variations in monthly rainfall will impact Plant Water Availability (KAT) and contribute to meteorological drought. The decision tree model is quite good in determining the risk of failure to plant paddy plants. In soybean plants, this model has not been able to properly determine the risk of crop failure, as with maize plants. Even though the accuracy value is quite good, the other validation attributes of the decision tree model are incapable of determining the risk of plant failure in maize and soybean plants.

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