Mitigation: Journal of Atmospheric and Earth Sciences
Vol. 01, No. 1, October 2025, pp. 1~14
ISSN: xxxxxx, DOI: xxxxxxxxxx

Ordinal Logistic Regression Analysis on the Nature of Monthly Rainfall Against ENSO, IOD, Monsoon and SST

Andriyas Aryo[1], Zauyik Nana Ruslana[2], M. Y. Matdoan[3]

[1]Badan Meteorologi klimatologi dan Geofisika, Yogyakarta, Indonesia
[2]Badan Meteorologi klimatologi dan Geofisika, Yogyakarta, Indonesia
[3]Department of Statistics, Faculty of Sciences and Tachonolgy,
University of Pattimura, Ambon, Indonesia

Article Info

Article history:

Received month dd, yyyy
Revised month dd, yyyy
Accepted month dd, yyyy

Keywords:

ENSO,
IOP,
The nature of rain,
Monsun,
Regresi logistik ordinal

ABSTRACT

Climate variability is strongly influenced by large-scale phenomena such as El Nino Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD), regional scales such as monsoon and local scales such as Sea Surface Temperature (SST) in waters close to a location. These climate phenomena interact with each other so that climate variability forms so that rainfall conditions can vary above normal, normal or below normal. Ordinal logistic regression is a regression method that can describe the relationship of climate phenomena to the nature of rainfall which is ordinal data. Based on partial tests, it was shown that ENSO, IOD and SST had a significant influence in influencing the nature of rain in the Semarang area. El Nino, Neutral IOD and IOD+ will provide an opportunity for above-normal or normal rainfall of 0.11, 0.20, 0.03 respectively against below-normal rainfall properties compared to their references (La Nina and IOD-). Meanwhile, SST can increase the chance of rain in the upper normal or normal category by 2.44 compared to the below normal conditions. The probability of normal upper (lower) rainfall will increase when La Nina (El Nino) and IOD- (IOD+) occur accompanied by the warming (cooling) of SST in the Java Sea.

.

Corresponding Author:
Andriyas Aryo
Department of Statistics, Faculty of Science and Data Analytics,
Institut Teknologi Sepuluh Nopember (ITS)
60111, Surabaya, Indonesia

1. INTRODUCTION

Climate information is one of the most important information today, as climate has a wide influence on all aspects of human life. Global warming triggers climate change, which has an impact on the frequency of extreme climates or climate stagnation. Indonesia is an archipelagic country located between two large oceans, namely the Indian and Pacific Oceans and flanked by two continents of Asia and Australia. Indonesia's geographical conditions cause the climate in Indonesia to be very complex. In general, the climate in Indonesia is influenced by global scale phenomena such as *El Nino Southern Oscillation* (ENSO) and *Indian Ocean Dipole* (IOD), regional scales such as monsoon and local scales such as *Sea Surface Temperature* (SST) [1,2,3,4]. These three phenomena interact with each other to form different climatic variabilities in Indonesia.

Central Java is one of the number 3 rice barn areas in Indonesia [5]. Rice plants are highly dependent on climatic conditions, where climatic conditions with below-normal rainfall can trigger drought which can cause puso but conversely above-normal rainfall conditions can cause flooding or inundation. It is very important to know the dominant climatic phenomenon in influencing rainfall conditions in the Central Java region. By knowing the dominant phenomenon that affects rainfall conditions in Central Java, it is possible to anticipate adverse adverse impacts and optimize the beneficial impact of possible climate anomalies.

To interpret parameters and obtain a model of the relationship between the nature of rain (ordinal scale) with ENSO, IOD, Monsoon and SST, ordinal logistic regression model was used. Ordinal logistic regression is a regression model used to model the relationship between ordinal-scale polykotom categorical response variables and predictor variables that are categorical or continuous. Studies of ordinal logic regression have been widely carried out in the health [6], socio-economic [7], education [8], transportation [9] and many more sectors. Ordinal logistic regression is considered suitable to determine the relationship between the nature of rain as the response variable on an ordinal scale and the predictor variable is ENSO, IOD which is considered ordinal scale while SST and monsoon index are continuous.

2. METHOD

a. Research Location.

In this study, monthly rainfall data measured at the Central Java Climatology Station was used.

b. Research Data

In this study, the data used was monthly rainfall data during the period 1992-2023 measured at the Central Java Climatology Station, which was then processed into ordinal-scale rain behavior data (response data). The nature of rainfall is a comparison of the amount of rainfall over a set period of time with its normal amount of rainfall (30-year average). The nature of rain is divided into 3 (categories), namely:

- Above Normal (AN): if rainfall is more than 115% of normal
- Normal (N): if rainfall is between 85%-115% of normal
- below Normal (BN): if rainfall is less than 85% of normal

The free variable data includes the ENSO Index, IOD index, SST in the Java Sea, and monsoon index, where the ENSO and IOD indices are ordinal-scale variables while SST and monsoon indexes are continuous-scale variables. The definition of the free variables used in this study includes:

- ENSO
  ENSO is an anomaly in sea surface temperature in the eastern to central Pacific Ocean. If the sea surface temperature in the eastern to central Pacific Ocean warms (>0.5 °C), El Nino *occurs, while it cools (< (-0.5)* °C), then the La Nina phenomenon *occurs* [10].
- IOP
  IOD is a comparison of SST between the western Indian Ocean and the eastern Indian Ocean in the south of Indonesia. If the value is >0.4°C, it is called IOD+, while if it is <-0.4°C, it is called IOD-[11].
- SST
  SST is the heat or cold of sea level. The SST used as a reference in this study is the sea SST in the South of Java Island with an area covering 4.5°S – 6.5°S and 109°E – 112°E. SST data in the Java Sea was obtained from *the National Oceanic and Atmospheric Administration* (NOAA) [12].
- Indek Monsun
  A monsoon wind is a wind that blows throughout the year with a change of direction on a seasonal scale. During the rainy season, the Asian monsoon wind, which is the wind that blows from Asia to Australia, and in the dry season, the Austrian monsoon wind, which blows from Australia to Asia. To determine the strength of the monsoon winds blowing, one of them is the AUSMI monsoon index (*Australian Monsoon Index*) which is defined as the average zonal wind at an altitude of 850 mb in the area of 5°LS-15°LS and 110°W-130°E [3]. To calculate the monsoon index, *reanalysis data* downloaded from NOAA [13] was used.

Table 1. Research Variables

Variabel	Remarks	Kategorial	Scale
And	Nature of Rain	1 : Below Normal 2 : Normal 3 : Normal top	Ordinal
X1	ENSO	1: La Nina 2 : Neutral 3 : The Child	Ordinal
X2	IOD	1 : IOD- 2 : Neutral 3 : IOD	Ordinal

X3	SST	Continuous
X4	Monsoon	Continuous

c. Logistic Regression

Logistic regression is a method that can be used to find the relationship between a *dichotomous* (nominal/ordinal scale with two categories) or *a polychotomous* (nominal or ordinal scale with more than two categories) response variables and one or more categorical or continuous scale predictor variables [14]. The equation of the logistic regression model with p variables with the opportunity function $\pi(x) = E(y|x)$ is expressed in Equation 1.

$$\pi(x) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_p x_p}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_p x_p}} \quad (1)$$

Furthermore, to make it easier to estimate the regression parameters, a logit transformation is carried out from the following:$\pi(x)$,

$$g(x) = ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_0 + \beta_1 x_1 + \beta_{12} x_2 + \cdots + \beta_p x_p + \varepsilon \quad (2)$$

1. Regresi logistik ordinal

Ordinal logistic regression is a regression model used to model the relationship between ordinal-scale polykotom categorical response variables and predictor variables that are categorical or continuous. Cumulative odds are defined as follows:$P(Y \le r|x_i)$.

$$P(Y \le r|x_i) = \pi(x) = \frac{exp\left(\beta_{0r} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}{1 + exp\left(\beta_{0r} + \sum_{k=1}^{p} \beta_k x_{ik}\right)} \quad (3)$$

where is the value of observation i (i = 1, 2, ..., n) of each p predictor variable. The estimation of ordinal logistic regression parameters is carried out by transforming to the logit function of $x_i = (x_{il}, x_{i2}, \dots, x_{ip})P(Y \le r|x_i)$

$$logit\ P(Y \le r|x_i) = ln\left(\frac{P(Y \le r|x_i}{1 - P(Y \le r|x_i}\right) \quad (4)$$

By substituting Equation 3 into Equation 4, it is obtained

$$logit\ P(Y \le r|x_i) = ln\left(\frac{\frac{exp\left(\beta_{0r} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}{1 + exp\left(\beta_{0r} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}}{1 - \frac{exp\left(\beta_{0r} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}{1 + exp\left(\beta_{0r} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}}\right)$$

$$logit\ P(Y \le r|x_i) = \beta_{0r} + \sum_{k=1}^{p} \beta_k x_{ik} \quad (5)$$

With values for each β_k*k=1, 2, ..., p* in each ordinal logistic regression model is the same.
If there are three categories of response variables, namely r = 0, 1, 2, then the cumulative probability of the r response is as follows:

$$P(y \le 1|x_i) = \frac{exp\left(\beta_{01} + \sum_{k=1}^{p} \beta_k\, x_{ik}\right)}{1 + exp\left(\beta_{01} + \sum_{k=1}^{p} \beta_k x_{ik}\right)} \quad (6)$$

$$P(y \le 2|x_i) = \frac{exp\left(\beta_{02} + \sum_{k=1}^{p} \beta_k\, x_{ik}\right)}{1 + exp\left(\beta_{02} + \sum_{k=1}^{p} \beta_k x_{ik}\right)} \quad (7)$$

Based on the two cumulative chances in equations 6 and 7, the chances for each response category are as follows:

$$P(Y = 1) = \pi_1(x) = \frac{exp\left(\beta_{01} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}{1 + exp\left(\beta_{01} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}$$

$$P(Y_r = 2) = \pi_2(x) = \frac{exp\left(\beta_{02} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}{1 + exp\left(\beta_{02} + \sum_{k=1}^{p} \beta_k x_{ik}\right)} - \frac{exp\left(\beta_{01} + \sum_{k=1}^{p} \beta_k x_{ik}\right)}{1 + exp\left(\beta_{01} + \sum_{k=1}^{p} \beta_k x_{ik}\right)} \quad (8)$$

2. Parameter Estimation

In determining parameter estimation in ordinal logistic regression, *the Maximum Likelihood Estimator* (MLE) method is used [15]. The MLE method provides β estimated value by maximizing the likelihood function. If i is a sample of a population, then the general form of the likelihood function for the sample is up to n

$$l(\beta) = \prod_{i=1}^{n} \left[\pi_0(x_i)^{y_{0i}}\, \pi_1(x_i)^{y_{1i}}\, \pi_2(x_i)^{y_{2i}}\right] \quad (9)$$

with i = 1, 2, ..., n.
To get an estimate of **β**, Equation (9) must be adjusted *to make* it easier in the differential process, so that Equation (9) becomes:

$$L(\boldsymbol{\beta}) = \sum_{i=1}^{n} [y_{0i} \ln(\pi_0(x_i)) + y_{1i} \ln(\pi_1(x_i)) + y_{2i} \ln(\pi_2(x_i))] \quad (10)$$

The maximum *value of ln-likelihood* is obtained by differentiating the function against and equalizing it with zero. The first derivative solution of a nonlinear function is carried out by the numerical method, namely Newton-Raphson iteration.$L(\boldsymbol{\beta})$ $\boldsymbol{\beta} L(\boldsymbol{\beta})$.

3. Parameter Testing

The coefficient values obtained from MLE need to be tested for the level of significance to the response variable, where the test carried out is a simultaneous and partial test. Simultaneous testing was carried out to find out how significant the coefficient ββ was to the response variable at the same time as the test statistics. The test statistics for simultaneous tests that can be used are *the G* test or *Likelihood Ratio Test*[16].
Hipotesis:

$H_0: \beta_1 = \beta_2 = \cdots = \beta_p = 0$

$H_1: paling\ sedikit\ ada\ satu \beta_k \neq 0; k = 1, 2, \ldots, p$

$$G = -2ln \left[\frac{\left(\frac{n_0}{n}\right)^{n_0} \left(\frac{n_1}{n}\right)^{n_1} \left(\frac{n_2}{n}\right)^{n_2}}{\prod_{i=1}^{n} [\pi_0(x_i)^{y_{0i}} \pi_1(x_i)^{y_{1i}} \pi_2(x_i)^{y_{2i}}]} \right] \quad (11)$$

Where $n_0 = \sum_{i=1}^{n} y_{0i}\ n_1 = \sum_{i=1}^{n} y_{1i}\ n_{2i} = \sum_{i=1}^{n} y_{2i}$

$n = n_0 + n_1 + n_2$

The area of rejection is if with a free derjad v or .$H_0 G^2 > \chi^2_{(\alpha,df)} p - value < \alpha$.

Partial testing was carried out to determine the meaning of the partial coefficient using test statistics β *Wald.*
Hipotesis :

$H_0: \beta_k = 0$

$H_1: \beta_k \neq 0; k = 1, 2, \ldots, p$

Wald test statistics

$$W = \frac{\hat{\beta}_k}{SE(\hat{\beta}_k)} \quad (12)$$

The area of rejection is or or with a free degree $H_0 |W| > Z_{\alpha/2} W^2 > \chi^2_{(\alpha,v)} p - value < \alpha v$

In addition to testing the coefficients both simultaneously and partially, a model suitability test was also carried out. This test is carried out to determine the suitability of the model in describing the existing data[17]. The test statistics used are β*Pearson* test statistics, with the following hypothesis:

$H_0: model\ sesuai$

$H_1: model\ tidak\ sesuai$

Perason's statistical test is as follows:

$$X^2 = \sum_{i=1}^{n} \sum_{j=1}^{k} \frac{(y_{ij} - \hat{y}_{ij})^2}{\hat{y}_{ij}} \quad (13)$$

Where:
y_{ij} is the observed frequency for category *j* at observation *i*
$\hat{y}_{ij}$ is the expected frequency for category *j* at observation *i*

If the p-value > 0.05 fails to reject which means the model corresponds to the dataH_0
If the p-value < 0.05 minus it means that the model does not match the dataH_0
In addition to the Pearson test, the Deviance conformity test was also carried out , with the following hypothesis:

$H_0: model\ sesuai$

$H_1: model\ tidak\ sesuai$

Test Deviance's statistics as follows:

$$D = -2 \sum_{i=1}^{n} \left[y_{ij} ln \left(\frac{\hat{\pi}_{ij}}{y_{ij}} \right) + (1 - y_{ij}) ln \left(\frac{1 - \hat{\pi}_{ij}}{1 - y_{ij}} \right) \right] \quad (14)$$

Where:
y_{ij} is the observed value for category *j* at observation *i*

$\hat{\pi}_{ij}$ is the probability predicted by the model for category j at the time of observation i
(1-y_{ij}) is the observed value for a category other than j at the time of observation i
(1-$\hat{\pi}_{ij}$) is the probability predicted by the model for a category other than j in observation i

If the p-value > 0.05 fails to reject which means the model corresponds to the dataH_0
If the p-value < 0.05 minus it means that the model does not match the dataH_0

4. Fashion Interpretation

Model interpretation is a form of defining the unit of change in response variables caused by predictor variables and determining the functional relationship between response variables and predictor variables. To facilitate the interpretation of the model, the odds ratio value is used[18]. The *odds ratio* value used in the interpretation of ordinal regressive regressive coefficients is a value that shows the comparison of the level of tendency of two or more categories in one predictor variable with one of the categories used as a comparison. If it is assumed that the response variable with Y=0 is the comparative response variable, then the *odds ratio* for Y=I with Y=0 at the covariate value of x = a with x=b is as follows:

$$OR_i(a,b) = \frac{P(Y=i|x=a)/P(Y=0|x=a)}{P(Y=i|x=b)/P(Y=0|x=b)}$$

3. RESULTS AND DISCUSSION

In this study, to interpret the parameters and model of the relationship between the nature of rain and ENSO, IOD, monsoon and SST is to use an ordinal logistic regression model with a limitation of the analysis period only in the period of June - October. The June-October period is a dry season period that is very vulnerable to climatic anomalies.

a. Distribution of Rainfall

Based on data analysis, information was obtained that during the 1992-2023 dry season period, the percentage of rain events with below-normal rainfall tended to be more dominant (51.9%) compared to normal (38.1%) and normal (10%) rainfall, as shown in Table 2.

Table 2. Distribution of rainfall properties

Yes	Nature of Rain	Frequency	Prosentase
1	Top Normal	61	38.1
2	Normal	16	10.0
3	Top Normal	83	51.9
	Quantity	160	100

b. Simultaneous Test

The simultaneous test was carried out to determine the influence of predictor variables on the response variables simultaneously using the G *test* or *Likelihood Ratio Test,* the test results are shown in Table 3.

Table 3. Simultaneous test

DF	G	P-Value
5	67.449	0.000

Based on Table 3. it shows that the G test value is 67,449 greater than $\chi^2_{(5:0.05)}$ 11.07 and based on the *p-value is* known to have a significance level of 0 < 0.05. This means that a decision was rejected, meaning that there is at least one predictor variable that has a significant effect on the nature of monthly rain during the dry season period in the Semarang area.H_0

c. Partial Test

Based on the results of the ordinal logistics analysis, the constant values and coefficients of each variable in the model will be obtained, as shown in Table 4. Based on Table 4. There are two model constants that show the existence of two response variables in the ordinal logistic regression model. This indicates that there are two logit models that will be formed. Based on Table 4. Partial test results were obtained for each predictor variable, namely ENSO, IOD, SST and monsoon, where the variables that have a significant influence on the nature of monthly rainfall are ENSO, IOD, and air temperature with *a p-value* of < 0.05, while the monsoon is not significant because the *p-value* is > 0.05

Table 4. Parameters of the estimated result

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Const(1)	-24.1874	11.9720	-2.02	0.043			
Const(2)	-23.5872	11.9630	-1.97	0.049			
ENSO							
Netral	-0.753612	0.417073	-1.81	0.071	0.47	0.21	1.07
El Nino	-2.25122	0.689394	-3.27	0.001	0.11	0.03	0.41
IOD							
Netral	-1.63380	0.620227	-2.63	0.008	0.20	0.06	0.66
IOD+	-3.50795	0.966406	-3.63	0.000	0.03	0.00	0.20
SST	0.898005	0.397563	2.26	0.024	2.45	1.13	5.35
MONSUN	-0.0059819	0.178415	-0.03	0.973	0.99	0.70	1.41

Because monsoon is not a predictor that has a significant influence on the nature of monthly rainfall in the study area, the monsoon variable is eliminated in the ordinal logistic regression model, and new parameter estimation results are obtained as shown in Table 5.

Table 5. Parameters of the estimated result

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Const(1)	-24.0221	10.8740	-2.21	0.027			
Const(2)	-23.4219	10.8639	-2.16	0.031			
ENSO							
Netral	-0.753195	0.416271	-1.81	0.070	0.47	0.21	1.06
El Nino	-2.25129	0.688986	-3.27	0.001	0.11	0.03	0.41
IOD							
Netral	-1.62842	0.602290	-2.70	0.007	0.20	0.06	0.64
IOD+	-3.50042	0.944229	-3.71	0.000	0.03	0.00	0.19
SST	0.893249	0.370407	2.41	0.016	2.44	1.18	5.05

Based on Table 5. Information was obtained that partial testing of each coefficient value of the constant and the predictor variable showed *a p-value* of < 0.05, meaning that the independent variable used had a significant influence on the response variable except for the Neutral ENSO variable.

d. Model Fit Test

Based on the results of the model match, it shows that the *Chi-square* value of Pearson*'s test* is 311,544 with *a p-value* of 0.513 and the *Deviance* test is 232,829 with *a p-value* of 1, so the decision taken is that the decision to fail to reject Ho because of *the p-value* > 0.05. Thus, at a 95% confidence level, it can be said that the ordinal logistic regression model obtained appropriately describes the existing data conditions.

e. Model Logit

In the ordinal logistic regression model with 3 response variables, 2 logit models will be obtained, where the value of the constant coefficient and the independent variable is shown in Table 5. The equation of the formed logit model can be written as follows:

$$Logit\ (Y_1) = -24.022 - 2.251X_{1,3} - 1.628X_{22} - 3.5X_{23} + 0.892X_3$$

$$Logit\ (Y_2) = -23.422 - 2.251X_{1,3} - 1.628X_{22} - 3.5X_{23} + 0.892X_3$$

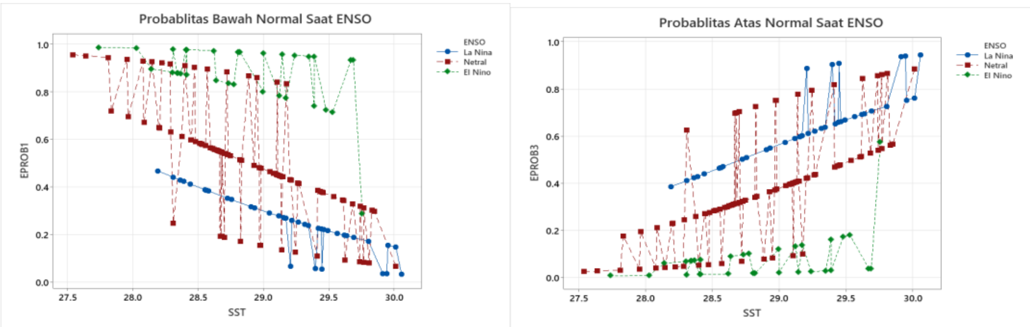
There are 2 logit models formed, where the log model 1 is a logit model that distinguishes between the normal upper category to normal and below normal, while the logit 2 model distinguishes between the normal upper and normal lower categories. The value of the negative constant at logit 1 and logit 2 means that when all the free variables (*El Nino*, neutral IOD, IOD+ and SST) are zero, then the chance of rain in the upper normal and normal categories is very low respectively.

f. Odds Ratio

The odds *ratio value* for each variable is calculated so that the risk of each independent variable can be determined against the response variable. Based on Table 5, it shows the *El Nino odds ratio* value of 0.11, meaning that when the ENSO condition is *El Nino*, the chance of normal or normal upper category rain is 0.11 times with below normal rain conditions (89% smaller) compared to *La Nina* conditions. When IOD is Neutral and IOD+, the chance of rain above normal or normal is 0.20 and 0.03 times respectively with below-normal rain conditions (smaller 80% and 97% respectively) compared to IOD-. Meanwhile, the *odd ratio* for SST is 2.44, meaning that SST can increase the chance of rain in the upper normal or normal category by 2.44 compared to the lower normal conditions.

g. Influence of ENSO, IOD and SST

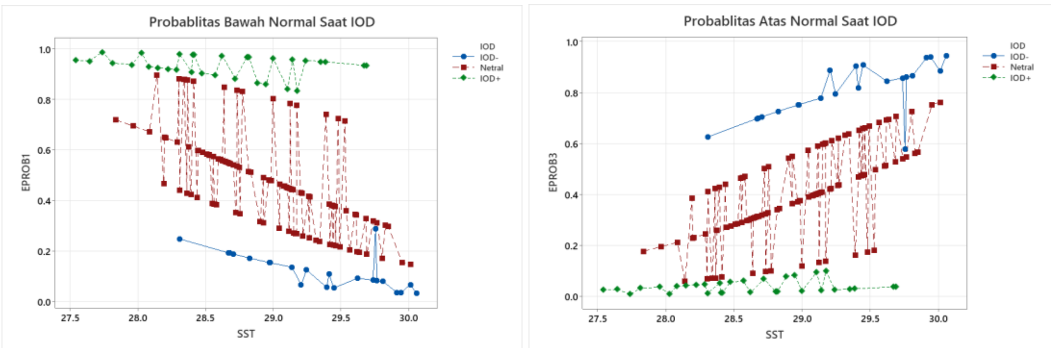
Based on the results of ordinal logistic regression, it is shown that ENSO, IOD and SST have a significant influence on the nature of rain in the dry season. When *El Nino* coincides with the cooling of sea surface temperatures in the Java Sea, the probability of normal below-normal rainfall is higher than during neutral and *La Nina* conditions, on the other hand, when *La Nina* occurs followed by warming SST in the Java Sea, the probability of normal upper rainfall is higher than during Neutral and *El Nino* conditions, as shown in Figure 1.



a b

Figure 1. Probability of Below Normal (a) and Above Normal (b) rainfall at the time of ENSO

At the time of IOD+ along with the cooling of the sea surface temperature in the Java Sea, the probability of below-normal rainfall is higher than during neutral and IOD-conditions, on the other hand, when IOD-is followed by the warming of SST in the Java Sea, the probability of normal upper rainfall is higher than during Neutral and IOD+ conditions, as shown in Figure 2.



A b

Figure 2. Probability of Below Normal (a) and Above Normal (b) rain at the time of IOD

4. CONCLUSION

Based on the results of data processing and ordinal logistic regression analysis, several conclusions were obtained as follows:

1. Based on the analysis of the distribution of rainfall data during the June-October dry season for the period 1992-2023, it shows that the incidence of below-normal rainfall is more dominant, namely 51.9% and above normal at 38.1% of the total data, this indicates that the climatic variability/rainfall in the Semarang area is quite high in the dry season.
2. The ordinal logistic regression that is formed can describe the existing climatic conditions (rainfall properties) characterized by a significant *Pearson* and *Deviance* model match test with a *p-value* of > 0.05.

3. Based on partial tests, it was shown that *El Nino*, neutral IOD and IOD+ and SST in the Java Sea were significant in influencing the nature of rain in the study area.
4. In general *El Nino*, Neutral IOD and IOD+ have a very small chance of triggering normal or normal rain compared to below normal rainfall when compared to *La Nina* and IOD- (for reference), characterized by odds *ratios* of 0.11, 0.20 and 0.03 respectively. Conversely, SST can increase the chance of normal or normal upper category rain by 2.44 compared to its below normal conditions.
5. The probability of rain above normal will be higher in the event of *La Nina* and/or IOD- accompanied by a warming SST in the Java Sea. On the other hand, the probability of below-normal rainfall will be higher if *El Nino* and or IOD+ occur accompanied by the increase in SST in the Java Sea.

REFERENCES

[1] Supari, Tangang, F., Salimun, E., Aldrian, E., Sopaheluwakan, A., Juneng, L., 2017. ENSO modulation of seasonal rainfall and extremes in Indonesia. Climate Dynamics 51:2559-2580. https://doi.org/10.1007/s00382-017-4028-8

[2] Utami, M., N., Hidayat, R., 2016. Influence of IOD and ENSO to Indonesian rainfall variability: role of atmosphere-ocean interaction in the Indo-Pacisif sector. The 2nd International Symposium on LAPAN-IPB Satellite for Food Security and Environmental Monitoring 2015, LISAT-FSEM 2015. doi: 10.1016/j.proenv.2016.03.070

[3] Mulsandi, A., Sopaheluwakan, A., Faqih, A., Hidayat, Koesmaryono, Y., 2021. Evaluation of WNPMI and AUSMI Monsoon Index Performance Over Indonesian Region. Journal of Weather Modification Science & Technology, Vol. 22, 2021: 61-70.

[4] Kartika, Q., A., Faqih, A., Santikayasa, I., P., Setiawan, A., M., 2023. Sea Surface Temperature Anomaly Characteristics Affecting Rainfall in Western Java Indonesia. Agromet 37 (1): 54-65, 2023.

[5] https://www.cnbcindonesia.com/research/20230509120356-128-435738/10-lumbung-padi-nasional-jawa-sing-ada-lawan retrieved 17 June 2024 retrieved 6 June 2024

[6] Setyarini, E., A., Salamah, M., 2015. Ordinal Logistic Regression Analysis to Determine the Level of Disability Disorders in Ponorogo Regency Based on Internal Factors Causing Disability. ITS Journal of Science and Arts Vol. 4, No.2, (2015) 2337-3520.

[7] Saraswati, F., D., 2017. Ordinal Logistics Regression Modeling on the Welfare Level of Household Business Actors in the Kenjeran Marine Tourism Area of Surabaya. Final Project of the Undergraduate Study Program, Department of Statistics, FMIPA ITS

[8] Zakariyah, 2015. Ordinal Logistics Regression Analysis on the Learning Achievement of S1 ITS Surabaya Students Based on SKEM. Final Project of the Undergraduate Study Program, Department of Statistics, FMIPA ITS

[9] Rohmania, I., 2020. Ordinal Logistics Regression Model in Traffic Accidents in Malang City. Thesis, Faculty of Science and Technology, Maulana Malik Ibrahim State Islamic University, Malang.

[10] https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php retrieved June 8, 2024

[11] https://psl.noaa.gov/gcos_wgsp/Timeseries/Data/dmi.had.long retrieved June 8, 2024

[12] https://psl.noaa.gov/data/gridded/data.cobe2.html retrieved June 8, 2024

[13] https://psl.noaa.gov/data/gridded/data.ncep.reanalysis2.html retrieved 8 June 2024 retrieved June 8, 2024

[14] Hosmer, D., W., & Lemeshow, S., 2000. Apllied Logistic Regression. New York: John Wiley & Sons, Inc.

[15] Agresti, A., 1990. Categorial Data Analysis. New York: John Wiley & Sons, Inc.

[16] Palisoa, N. F., Sinay, L. J., Matdoan, M. Y., Yudistira, Y., & Bakarbessy, L. (2023). Penerapan Support Vector Machine (SVM) untuk Klasifikasi Kabupaten Tertinggal Di Provinsi Maluku. *PARAMETER: Jurnal Matematika, Statistika Dan Terapannya*, *2*(02), 79-86.

[17] Lopies, C., Matdoan, M. Y., Loklomin, S. B., & Wattimena, A. Z. (2023). Analisis dan Klasifikasi Tingkat Kebahagiaan Masyarakat Berdasarkan Propinsi di Indonesia dengan Pendekatan Statistik. *PARAMETER: Jurnal Matematika, Statistika Dan Terapannya*, *2*(1), 33-46.

[18] Rosanti, L., Matdoan, M. Y., Bakarbessy, L., Loklomin, S. B., Yudistira, Y., & Seknun, M. F. (2022). Penerapan Regresi Linier Berganda Untuk Mengetahui Pengaruh Kinerja Dosen dan Motivasi Belajar Terhadap IPS Mahasiswa dalam Pembelajaran Daring. *PARAMETER: Jurnal Matematika, Statistika dan Terapannya*, *1*(2), 87-96.