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TIDAL FLOOD MAPPING MODEL IN NORTH MEDAN REGION USING ORDINAL LOGISTIC REGRESSION AND GIS (Geographical Information System)

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Abstract

Tidal floods are a regular threat in the coastal area of North Medan, which includes Medan Belawan, Medan Labuhan, and Medan Marelan. This research aims to map the level of vulnerability to tidal flooding using the Ordinal Logistic Regression (RLO) approach combined with Geographic Information Systems (GIS). Nine factors were analyzed: rainfall, drainage density, land use, distance from rivers, distance from the sea, soil type, elevation, slope, and topographic aspects. The analysis showed that rainfall, elevation, and distance from the sea were the most significant factors. The vulnerability map shows that 7.6% of areas are classified as highly vulnerable, 64.74% high, 27.36% medium, and only 0.3% low. The accuracy of the model reached 87.84%. These results provide a solid foundation for spatial planning, disaster mitigation, and coastal adaptation strategies.

Keywords: ***Tidal Flood, Ordinal Logistic Regression, SPSS, Rstudio, QGIS.***

INTRODUCTION

North Medan area is a coastal region that is often affected by tidal flooding due to the rise in sea levels exceeding land elevation. Over the past few decades, flood disasters have increased and become more frequent and more destructive compared to previous times (Dubey & Katarya, 2021). The rise in sea levels has caused several losses, especially in coastal areas, such as tidal flooding disasters or rob (Arief & Aris, 2014). Saputra et al., (2020) conducted a research on the vulnerability level of tidal flooding with several factors, such as land data, environmental conditions, and social factors, in an effort to determine effective and efficient methods for handling tidal flooding. Saputra conducted data analysis using AHP (Analytical Hierarchy Process).

Farino et al., (2021) conducted a follow-up research to compare the results of Saputra et al., (2020) research. Farino conducted data analysis using Binary Logistic Regression.

The research conducted is a continuation and modification of the research by Saputra and Farino to compare the factors influencing tidal flood vulnerability. The analysis used in this research employs Ordinal Logistic Regression to determine the relationship between the dependent variable (Y) and the independent variable (X), and then combines it with Geographic Information System (GIS). Flood mapping should ideally be conducted using Geographic Information System (GIS)-based software. Software becomes the main tool of the information system for inputting, storing, retrieving, processing, analyzing, and generating geographic reference data or geospatial data.

LITERATURE REVIEW

1. Factors of tidal flood vulnerability

Several ordinal logistic regression factors for determining areas prone to tidal flood disasters in North Medan in this research were identified from existing research literature, namely rainfall, drainage density, land use, distance from rivers, distance from the sea, soil type, elevation, aspect, and slope. The explanation of these factors is as follows:

A. Rainfall

Rainfall is a significant factor contributing to flood risk, as higher rainfall levels tend to increase the likelihood of flooding (Hidayah et al., 2022).

B. Drainage Density

Urban areas often have varying levels of drainage infrastructure, and when system capacity is insufficient, factors like drainage density need to be carefully considered (Natkaniec & Godyń, 2024).

C. Land use

Land use or land cover in an area is also a key consideration in mapping flood-prone zones, as it not only represents current land utilization but also emphasizes its role in influencing soil stability and water infiltration (Ouma & Tateishi, 2014).

D. Distance from the river

Tidal flooding disasters are not solely caused by seawater overflow during high tides; they can also result from river water overflow. A natural factor influencing river overflow is rainfall, as both high and low rainfall levels can impact the river's flow rate and contribute to flooding (Yance et al., 2024).

E. Soil Type

Soil type criteria take into account the proportions of clay and sand in an area. High clay content hinders water infiltration, causing floodwaters to recede more slowly. In contrast, a high sand content can accelerate flooding, as low-permeability soils tend to retain surface water, increasing the likelihood of pooling (Simanjuntak & Gunarto, 2025).

F. Elevation

Lowland areas are more prone to flooding due to their lower elevation, as water naturally flows from higher to lower ground. (Osman & Das, 2023).

G. Slope

Slope values reflect the steepness of the terrain, where lower slope values indicate flatter topography and higher values signify steeper land. The susceptibility to flooding varies accordingly. Slopes are typically classified into five distinct categories based on their gradient. (Desalegn & Mulu, 2021).

H. Aspect

According to Papaioannou et al., (2015), the evaluation of criteria includes analyzing the river's position and the direction of storms that frequently lead to flooding in the area. Storms originating from the north make regions located between 157.0° and 202.5° south particularly vulnerable to flooding due to their exposure to these weather patterns.

I. Distance from the sea

Rising sea levels can contribute to tidal flooding in coastal regions by increasing the likelihood and intensity of seawater overflow onto land. (Jabbar et al., 2023). Tidal flooding results from the overflow of seawater, making coastal regions the first to be affected—particularly those with elevations lower than the high tide level.

2. Ordinal Logistic Regression

Regression analysis is used in various fields of study, such as health, engineering, science, economics, management, and social sciences (Hosmer and Lemeshow, 2000). Logistic Regression Analysis is used in model creation where the dependent variable is categorical (non-metric) and the independent variable can be continuous or categorical (Arofah, 2018). Regression analysis is a method used to analyze the relationship between two or more variables. If the dependent variable is ordinal, then for data classification, ordinal logistic regression analysis can be used (Gunawan et al., 2022).

The model that can be used for ordinal logistic regression is the logit model. This model is obtained by comparing the cumulative odds, which is the odds of being less than or equal to the j-th response category on p predictor variables expressed in the vector X, $P(Y \leq j|X)$, with the odds of being greater than the j-th response category, $P(Y>j|X)$ (Hosmer and Lemeshow, 2000). Cumulative probability, $P(Y \leq j|X)$, is defined as follows:

$$P(Y \leq J|X) = \frac{\exp(\beta_{0j} + \sum_{k=1}^{p} \beta_{kXk})}{1 + \exp(\beta_{0j} + \sum_{k=1}^{p} \beta_{kXk})} \qquad (1)$$

$$\hat{\pi}_i = \frac{\exp(g(x_i))}{1+(g(x_i))} \quad (2)$$

Explanation j= 1, 2, j is the response category. With

$$g(x_1) = \beta_0 - (\beta_1 x_n + \cdots + \beta_p x_{ip}), i = 1,2,\ldots,n \quad (3)$$

Ordinal logistic regression analysis can be performed using several tools as follows:

A. R Program

Ordinal logistic regression can be used to assess the relationship between predictors and ordinal outcomes. Data can fit an ordinal logistic regression model in R using MASS::polr() (proportional odds logistic regression) (James et al., 1996).

B. SPSS Program

SPSS is often the primary choice due to its ease of use for many universities and research institutions to conduct statistical training. SPSS also simplifies the process of importing data, managing variables, and executing various commands without requiring complex coding (Nanere et al., 2025).

3. Spearman Correlation

Spearman correlation (Spearman's rank correlation coefficient, ρ or "rho") is a non-parametric statistical method used to measure the strength and direction of the relationship between two variables measured on an ordinal scale or when the data do not meet the assumption of normal distribution (Frost, 2021). Spearman's correlation is more commonly used than others and is easily interpreted as a correlation coefficient, and this correlation can be empirically calculated and easily applied to continuous and discrete data (Tu et al., 2024). The formula of Spearman's correlation is as follows:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \quad (4)$$

In determining the strength of the relationship between variables, one can refer to the correlation coefficient value obtained from the SPSS output (Pamungkasih, 2023), with the following provisions:

Table 1. Criteria for Correlation Strength Levels

Correlation coefficient value	Correlation criteria
0,00 - 0,25	Very weak relationship
0,26 - 0,50	Relationship is fair
0,51 - 0,75	Strong relationship
0,76 - 0,99	Very strong relationship
1,00	Perfect Relationship

4. Geographic Information System (GIS)

Geographic Information System (GIS) has developed and applied in various fields of life. The existence of GIS also helps the community in providing various information (Agus et al., 2018). Remote sensing technology, which involves the use of satellite vehicles, has become a highly useful and effective alternative in various activities such as natural disaster studies, regional mapping, natural resource inventorying, and environmental monitoring. One of the applications of GIS is the use of the Quantum Geographic Information System (QGIS) Processing Modeler (Ezrahayu, 2024). The components that make up GIS are software, hardware, data, users, and applications (Andree Ekadinata et al., 2008).

METHOD

This research is a type of quantitative descriptive research. This research is a type of research that aims to describe or depicting a phenomenon, condition, or problem systematically and objectively using numerical or quantitative data. The sample used in this research test consists of 170 samples from 329 neighborhoods, expected to represent the entirety of the North Medan area. The sample represents the number of neighborhoods in the North Medan area. Data on tidal flooding was taken from the tidal flood vulnerability parameter map in the North Medan region. Then, the data was analyzed using ordinal logistic regression.

In this research, ordinal logistic regression analysis uses 9 factors of tidal flood vulnerability, namely: rainfall, drainage density, distance from the river, land use, soil type, elevation, slope, aspect, and distance from the sea. Data to support the creation of the rob flood vulnerability map in this thesis was collected from the research conducted by Saputra et al., (2020) titled "Mapping Rob Flood Vulnerability Zones in the North Medan Region using AHP and GIS." The process of integrating ordinal logistic regression and GIS consists of classifying factors on the existing map and analyzing data using statistical programs such as SPSS 26 and RStudio, resulting in probability values to be later integrated into GIS. The classification process involves changing the parameters present in the existing map into values so they can be processed arithmetically. Each classification has a value as explained in Table 2. This classification is applied to all maps based on each criterion, and the classification process uses GIS.

Table 2. Risk level classification

Level of tidal flood vulnerability	Score	Color notation
Very low	1	Dark Green Light
Low	2	Green
Medium	3	Yellow
High	4	Orange
Very high	5	Red

RESULTS AND DISCUSSION

The stage before determining the logit model is to create Training Data to observe the training data with the highest percentage, which will then be used for future modeling with the logit model. Training data uses several environmental samples, namely 170 and 329 environments, as the full data set. Ordinal logistic regression analysis includes several tests, among them: Odds Ratio, Partial test, and classification. The results of the data processing can be seen in the table below, along with their interpretation.

1. Odds Ratio Software SPSS and RStudio Odds Ratio Software SPSS and RStudio

The results of the data analysis using a subset of data, namely 170 environments with normal variables, can be seen in the table below:

Table 3. Odds Ratio for a Sample of 170 Environments with 9 Factors

Symbol	Name	Variable	SPSS	R
Exp(β)	Odds Ratio	X1	-0,228	-0,228
		X2	0,821	0,821
		X3	5,586	5,586
		X4	5,847	5,847
		X5	3,281	3,281
		X6	-0,095	-0,095
		X7	.	.
		X8	3,978	3,978
		X9	20,896	20,896

Based on the results of Table 3 we can interpret the *Odds ratio* or Exp (β) column as follows:

1. The rainfall variable shows a negative sign in both statistical programs, which means that the greater the value, it can reduce the level of flood vulnerability by -0.228 times in the SPSS program and the R program.
2. The *drainage density* variable can increase the tendency of flash flood vulnerability by 0.821 times in the SPSS program and the R program.
3. The *land use* variable can increase the tendency of flash flood vulnerability by 5.586 times in

the SPSS program and the R program.

4. The variable distance to the river can increase the tendency to be prone to flash flooding by 5.847 times in the SPSS program and in the R program.
5. The soil type variable can increase the tendency to be vulnerable to flash flooding by 3.281 times in the SPSS program and in the R program.
6. The elevation variable is marked negative in both statistical programs, which means that the greater the value, it can reduce the level of tidal flooding prone by 0.095 times in the SPSS program and the R program.
7. The slope variable is a redundant variable, therefore this variable can be ignored.
8. The aspect variable can increase the tendency to be prone to flash flooding by 3.978 in the SPSS program and in the R program.
9. The distance to the sea variable can increase the tendency to be threatened to 20.896 times in the SPSS program and in the R program.

The *Threshold* value of 170 environmental samples is:

Table 4. Threshold Value 170 Environment 9 Factors

Threshold	Coef β
g(3)	0,496
g(4)	30,437

The ordinal logistic regression model will produce a predictive value in the form of logit (log odds), and the logit model requires a threshold to convert that value into a category. The logit model produced from the training data for sample 170 is as follows:

g(3) = 0,496 – (-0.228(X1) + 0,821(X2) + 5,586(X3) + 5,847(X4) + 3,281(X5) + (-0,095(X6)) + 3,978(X8) + 20,896(X9))

g(4) = 30,437 – (-0.228(X1) + 0,821(X2) + 5,586(X3) + 5,847(X4) + 3,281(X5) + (-0,095(X6)) + 3,978(X8) + 20,896(X9)).

The results of data analysis using some data, namely 329 environments with normal variables, can be seen in the following table:

Table 5. Odds Ratio for a Sample of 329 Environments with 9 Factors

Symbol	Name	Variable	SPSS	R
Exp(b)	Odds Ratio	X1	3,887	3,887
		X2	-0,073	-0,073
		X3	3,178	3,178
		X4	6,008	6,008
		X5	0,951	0,951
		X6	5,610	5,610
		X7	.	.
		X8	2,896	2,896
		X9	3,473	3,473

Based on the results of Table 5 we can interpret the *Odds ratio* or Exp (β) column as follows:

1. The bulk variable can increase the level of flash flood vulnerability by 3.887 times in the SPSS and R programs.
2. The *drainage density* variable shows a negative sign in both statistical programs, which means that the greater the value, it can reduce the level of tidal flood vulnerability by 0.073 times in the SPSS and R programs.
3. The *land use* variable can increase the tendency of flash flood vulnerability by 3.178 times in the SPSS and R programs.
4. The distance variable to the river can increase the tendency to be prone to flash flooding by 6.008

times in the SPSS and R programs.
5. The soil type variable can increase the tendency to be prone to being threatened by flooding by 0.951 times in the SPSS and R programs.
6. The elevation variable can increase the level of flood prone by 5.610 times in the SPSS and R programs.
7. The slope variable is a redundant variable, therefore this variable can be ignored.
8. Aspect variables can increase the tendency to be prone to flash flooding by 2,896 in the SPSS and R programs.
9. The distance to the sea variable can increase the tendency to be threatened to 3.473 times in the SPSS and R programs.

The *Threshold* value of 329 environmental samples is:

Table 6. Threshold Value 329 Environment 9 Factors

Threshold	Coef β
g(2)	2,645
g(3)	9,831
g(4)	20,256

The ordinal logistic regression model will produce a predictive value in the form of logit (log odds), and the logit model requires a threshold to convert that value into a category. The logit model produced from the training data for sample 329 is as follows:

$$g(2) = 2,645 – (3,887(X1) + (-0,073(X2)) + 3,178(X3) + 6,008(X4) + 0,951(X5) + 5,610(X6) + 2,896(X8) + 3,473(X9))$$

$$g(3) = 9,831 – (3,887(X1) + (-0,073(X2)) + 3,178(X3) + 6,008(X4) + 0,951(X5) + 5,610(X6) + 2,896(X8) + 3,473(X9))$$

$$g(4) = 20,256 – (3,887(X1) + (-0,073(X2)) + 3,178(X3) + 6,008(X4) + 0,951(X5) + 5,610(X6) + 2,896(X8) + 3,473(X9))$$

2. *p-value* Software SPSS and RStudio 9 Factors

Table 7. p-value Partial Test for 170 samples with 9 Factors

Simbol	Nama	Variabel	SPSS	R
Sig.	p-value	X1	0,912	0,912
		X2	0,425	0,425
		X3	0,000	0,000
		X4	0,000	0,000
		X5	0,043	0,043
		X6	0,972	0,972
		X7	.	.
		X8	0,008	0,008
		X9	0,000	0,000

Table 7 presents several independent variables, some of which have significance (p-values) below 0.05, indicating a partial effect on the dependent variable (flood vulnerability), while others have p-values above 0.05, suggesting no significant partial effect. Specifically, variable X1 (rainfall) has a significance value of 0.912 (>0.05), indicating no significant partial influence. Similarly, X2 (drainage density) with a p-value of 0.425 also shows no significant effect. In contrast, X3 (land use) has a significance value of 0.000 (<0.05), signifying a significant partial influence. The same applies to X4 (distance to the river), which has a p-value of 0.000. X5 (soil type) is significant as well, with a value of 0.043. Meanwhile, X6 (elevation) has a p-value of 0.972, suggesting no partial effect. X7 (slope) is identified as a redundant variable, indicating it does not contribute significantly. X8 (aspect), with a p-value of 0.008, and X9 (distance to the sea), with a value of 0.000, both demonstrate significant partial influences on flood vulnerability.

Table 8. p-value Partial Test for sample 329 with 9 Factors

Simbol	Nama	Variabel	SPSS	R
		X1	0,000	0,000
Sig.	p-value	X2	0,894	0,894
		X3	0,000	0,000
		X4	0,000	0,000
		X5	0,247	0,247
		X6	0,000	0,000
		X7	.	.
		X8	0,038	0,038
		X9	0,000	0,000

Table 8 displays several independent variables, some of which have p-values below 0.05, indicating a significant partial effect on the dependent variable (flood vulnerability), while others have p-values above 0.05, indicating no significant effect. Specifically, X1 (rainfall) has a significance value of 0.000 (<0.05), showing a significant partial influence. X2 (drainage density), with a p-value of 0.894 (>0.05), does not show a significant effect. X3 (land use) and X4 (distance to the river) both have significance values of 0.000, suggesting strong partial influences. X5 (soil type), with a significance value of 0.247, does not have a significant effect. In contrast, X6 (elevation) shows a significant influence with a p-value of 0.000. X7 (slope) is identified as a redundant variable, indicating no significant contribution. X8 (aspect), with a p-value of 0.038, and X9 (distance to the sea), with a value of 0.000, both exert significant partial influences on flood vulnerability.

3. SPSS and R Program Classification Scores

Table 9. Accuracy Rate for a Sample of 170 Environments with 9 Factors

SPSS dan R			
Medium	High	Very High	Accuracy
4	190	27	66,26%

Based on Table 9, the number of samples that received a difference in the level of flood prone to flooding compared to the previous data after the logit model was applied to the entire data set with a moderate level of vulnerability was 4 environments. The sample that received a high level of flooding prone to flooding was 190 neighborhoods. The sample that received a very high level of vulnerability to flash floods was 27 neighborhoods. Meanwhile, the overall percentage value is 66.26%, which means that the accuracy of the logit model for the training data of 170 samples is 66.26%.

Table 10. Accuracy Rate for 329 Environments Sample with 9 Factors

SPSS dan R			
Medium	High	Very High	Accuracy
71	195	23	87,84%

Based on Table 10, the number of samples that received a difference in the level of flood prone to flooding compared to the previous data after the logit model was applied to the entire data set with a moderate vulnerability level was 71 environments. The sample that received a high level of flooding prone to flash floods was 195 neighborhoods. The sample that received a very high level of vulnerability to flash floods was 23 neighborhoods. Meanwhile, the overall percentage value was 87.84%, which means that the accuracy of the logit model for the training data of 329 samples was 87.84%.

4. Spearman Correlation Analysis Results

The results of the spearman correlation analysis carried out in this research are as follows:

Table 11. Spearman Correlation Values

	X1	X2	X3	X4	X5	X6	X7	X8	X9
Spearman's rho	.684	-.347	.037	.453	.249	.680	.	.122	.563
(ρ) Sig.	.000	.000	.509	.000	.000	.000	.	.027	.000

Based on the table above, there is a spearman correlation value. There is a strong and positive relationship between the variables X1 and Y. The value of the ρ coefficient of 0.684 indicates that when the value of X1 increases, the value of Y also tends to increase. The significance value is 0.000 < 0.05, hence this relationship is statistically significant. There is a negative and sufficient relationship between the variables X2 and Y of -0.347, meaning that an increase in X2 is likely to be followed by a decrease in the value of Y. This relationship is statistically significant because the significance value is 0.000 < 0.05. There is a very weak and insignificant relationship between X3 and Y with a ρ value of 0.037 and a significance of 0.509 > 0.05, so statistically there is no significant relationship between X3 and Y. There is a sufficient and positive relationship between X4 and Y, namely ρ of 0.453. This means that when the value of X4 increases, the value of Y tends to increase as well. Since Sig. 0.000 < 0.50, this relationship is statistically significant. The relationship between X5 and Y is very weak and positive, i.e. ρ is 0.249. The increase in X5 slightly correlated with the increase in Y by sig. 0.000 < 0.05, this relationship is statistically significant although weak.

There is a strong and positive relationship between X6 and Y with a ρ value of 0.680. This value is almost equivalent to X1, indicating that the higher X6, the higher the Y. This relationship is also statistically significant because of the sig value. 0.000 < 0.05. The relationship between X7 and Y has no Spearman correlation data or significance value for X7, so it cannot be interpreted because the data is not diverse or the data value is too homogeneous so that there is no correlation between the two. The relationship between X8 and Y is very weak and positive with a ρ value of 0.122. However, because of the value of sig. 0.027 < 0.05, this relationship is statistically significant, although the strength is low. There is a strong and positive relationship between X9 and Y which is ρ of 0.563. This means that the increase in X9 is quite correlated with the increase in Y. With the value of sig. 0.000 < 0.05 of this relationship is statistically significant.

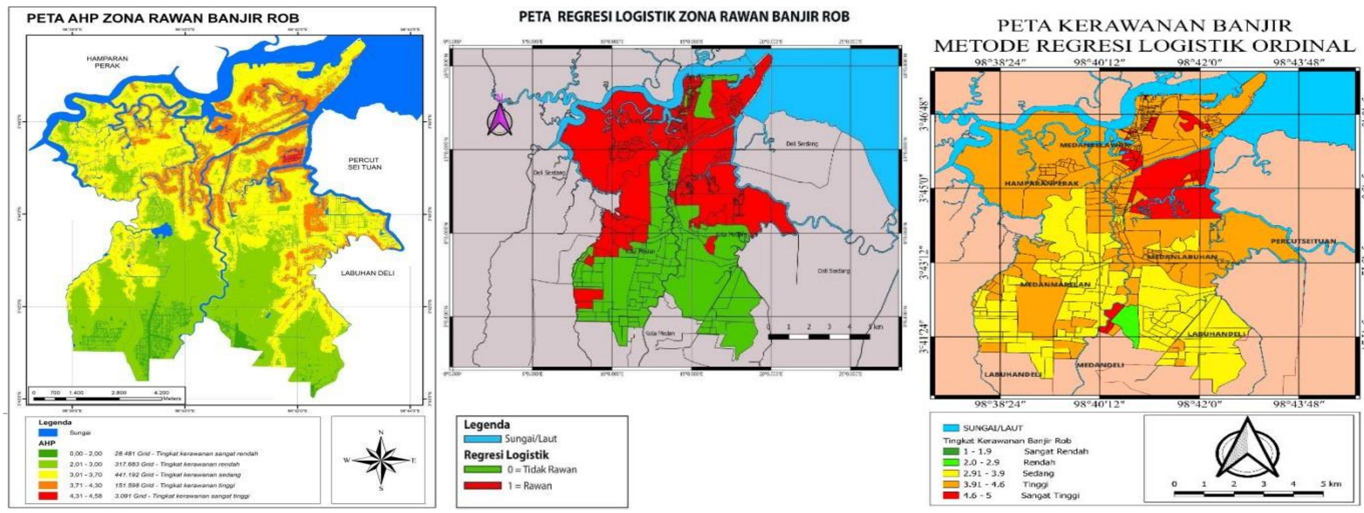

Figure 1. Tidal Flood Maps AHP, RLB, dan RLO

CONCLUSION

The application of Ordinal Logistic Regression and GIS methods has proven to be effective in accurately mapping flash flood vulnerability zones in the North Medan area. This method makes a positive contribution to spatial planning and disaster risk mitigation. The map of flash flood vulnerability using the ordinal logistic regression method in this research has a fairly high accuracy (87.84%), but is still below the accuracy of the Binary Logistic Regression method from Farino's research (93.7%). However, the ordinal logistic regression approach is more flexible in accommodating various environmental factors than the AHP method from the Saputra research and the binary logistic regression from Farino's research. The next research recommendation is the development of a spatial- based early warning system and the integration of actual seawater tidal data.

REFERENCES

Agus, F., Ramadiani, Silalahi, W., Armanda, A., & Kusnandar. (2018). Mapping urban green open space in Bontang city using QGIS and cloud computing. *IOP Conference Series: Earth and Environmental Science*, *144*(1). https://doi.org/10.1088/1755-1315/144/1/012032

Andree Ekadinata; Sonya Dewi; Danan Prasetyo Hadi; Dudy Kurnia Nugroho; Feri Johana. (2008). *Sistem Informasi Geografis Untuk Pengelolaan Bentang Lahan Berbasis Sumber Daya Alam* (1st ed.). World Agroforestry Centre (ICRAF).

Arief, A. K., & Aris, M. A. (2014). Spatial Modeling of ROB Flood AND Assessment of Potential Loss to Rice Field Agricultural Land Case Sudy of The Coastal Area of Pekalongan District, Centeral Java. *Geo Eduksi*, *III*(2), 83–91. https://www.neliti.com/id/publications/56109/pemodelan-spasial-genangan-banjir-rob-dan-penilaian-potensi-kerugian-pada-lahan

Arofah, I. (2018). Analisis Persepsi Biaya Kuliah Perguruan Tinggi dengan Menggunakan Metode Regresi Logistik Ordinal. *Jurnal Statistika Dan Aplikasinya*, *2*(1), 21–29. https://doi.org/10.21009/jsa.02103

Desalegn, H., & Mulu, A. (2021). Flood vulnerability assessment using GIS at Fetam watershed, upper Abbay basin, Ethiopia. *Heliyon*, *7*(1), e05865. https://doi.org/10.1016/j.heliyon.2020.e05865

Dubey, V., & Katarya, R. (2021). *BNDNN: Batch Normalization Based Deep Neural Network for Predicting Flood in Urban Areas*. https://doi.org/10.21203/rs.3.rs-1027530/v1

Ezrahayu, P. (2024). Penggunaan Aplikasi QGIS Processing Modeler dalam Menentukan Potensi Bencana Tanah Longsor di Kabupaten Bogor. *Geodika: Jurnal Kajian Ilmu Dan Pendidikan Geografi*, *8*(1), 41–52. https://doi.org/10.29408/geodika.v8i1.25729

Frost, J. (2021). *Spearman's Correlation Explained*. Statistics By Jim. https://statisticsbyjim.com/basics/spearmans-correlation/

Gunawan, K., Ruhiyat, & Purnaba, I. G. P. (2022). Penerapan Analisis Regresi Logistik Ordinal pada Asuransi Kredit Perdagangan Domestik. *Jurnal Statistika Dan Aplikasinya*, *6*(2), 366–380. https://doi.org/10.21009/jsa.06220

Hidayah, E., Indarto, Lee, W. K., Halik, G., & Pradhan, B. (2022). Assessing Coastal Flood Susceptibility in East Java, Indonesia: Comparison of Statistical Bivariate and Machine Learning Techniques. *Water (Switzerland)*, *14*(23). https://doi.org/10.3390/w14233869

Jabbar, A., Fariz, T. R., Putri, S. D., Rahmawati, D., Prahmani, Y. S., Putri, R. A., Siregar, Z. G. T., Holeng, V. A., & Chasanah, A. N. (2023). Tidal Flood Susceptibility Mapping and Community Adaptation Assesment in Semarang Utara District. *Journal of Environmental and Science Education*, *3*(1), 56–62. https://doi.org/10.15294/jese.v3i1.64910

James, D. A., Venables, W. N., & Ripley, B. D. (1996). Modern Applied Statistics with S-PLUS. In *Technometrics* (Vol. 38, Issue 1). https://doi.org/10.2307/1268908

Nanere, M., Tabelessy, W., Leuhery, F., & Tubalawony, J. (2025). *Global Trends in SPSS Training for Students : A Step Towards Improved Research Competence*. *4*(1), 73–80.

Natkaniec, W., & Godyń, I. (2024). Urban Flood Risk Assessment and Mapping Using GIS-DEMATEL Method: Case of the Serafa River Watershed, Poland. *Water (Switzerland)*, *16*(18). https://doi.org/10.3390/w16182636

Osman, S. A., & Das, J. (2023). GIS-based flood risk assessment using multi-criteria decision analysis of Shebelle River Basin in southern Somalia. *SN Applied Sciences*, *5*(5). https://doi.org/10.1007/s42452-023-05360-5

Ouma, Y. O., & Tateishi, R. (2014). Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: Methodological overview and case study assessment. *Water (Switzerland)*, *6*(6), 1515–1545. https://doi.org/10.3390/w6061515

Pamungkasih, P. (2023). Penerapan Uji Korelasi Rank Spearman Untuk Mengetahui Hubungan Pengeluaran Rumah Tangga Untuk Makanan Dan Tingkat Kemiskinan Di Nusa Tenggara Timur Selama Pandemi Covid-1. *Jurnal Statistika Terapan*, *3*(2), 1–12.

Papaioannou, G., Vasiliades, L., & Loukas, A. (2015). Multi-Criteria Analysis Framework for Potential Flood Prone Areas Mapping. *Water Resources Management*, *29*(2), 399–418. https://doi.org/10.1007/s11269-014-0817-6

Pyanto, F., Mulia, A. P., & Surbakti, M. S. (2021). Pemetaan Banjir Rob Wilayah Medan Utara Menggunakan Regresi Logistik dan GIS. *Syntax Literate: Jurnal Ilmiah Indonesia*, *6*(9). https://doi.org/10.36418/syntax-literate.v6i9.1579

Saputra, N. A., Perwira, A., Tarigan, M., & Nusa, A. B. (2020). Penggunaan Metode AHP dan GIS Untuk Zonasi Daerah Rawan Banjir Rob di Wilayah Medan Utara. In *Media Komunikasi Teknik Sipil* (Vol. 26, Issue 1).

Simanjuntak, N. R., & Gunarto, D. (2025). *Flood Hazard Level Analysis of Kapuas Hulu Sub-watershed Using*. *24*(4), 1437–1448.

Tu, S., Li, C., & Shepherd, B. E. (2024). *Between- and Within-Cluster Spearman Rank Correlations*. https://doi.org/10.1002/sim.10326

Yance, Y., Soeryamassoeka, S., & Nurhayati, N. (2024). Analysis of Flood Vulnerability Levels in Landak Regency Using Geographic Information System. *Jurnal Teknik Sipil*, *24*(2), 885. https://doi.org/10.26418/jts.v24i2.7853