Geoid
Journal of Geodesy and Geomatics

Geoid Vol. 20, No. 2, 2025, 80-92

P-ISSN: 1858-2281; E-ISSN: 2442-3998

Detection of River Change in Modeling Flood Vulnerability using Support Vector Machine (SVM) Methods in Tallo River Makassar City

Atika Izzaty*[1], Syahra Dewi Aprian[1], Regita Faridatunisa Wijayanti[1], Athiya Iffaty[2], Bambang Bakri[3], Riswal Karamma[3]
[1]Geodetic Engineering, Universitas Hasanuddin, Makassar, 92171, Indonesia
[2]Urban and Regional Planning Department, Universitas Diponegoro, Semarang, 50275, Indonesia
[3]Civil Engineering Department, Universitas Hasanuddin, Makassar, 92171, Indonesia
*Corresponding author: atikaizzaty@unhas.ac.id

Received: 22 July 2025; Revised: 06 October 2025; Accepted: 07 October 2025; Published: 08 October 2025

Abstract: The transformation of river morphology and the rising frequency of flooding in urban environments have emerged as increasingly concerning environmental challenges, particularly in Makassar City. The Tallo River, one of the primary waterways traversing the city, exhibits notable dynamic changes driven by both natural processes. In the contemporary era, flooding stands as one of the most recurrent natural disasters, occurring unpredictably and posing serious risks, especially in major metropolitan areas. Such events frequently disrupt daily activities, leading to traffic congestion and obstructing ground transportation. Residential zones situated near riverbanks are particularly vulnerable to its impacts. Moreover, climate change exacerbates these conditions by contributing to increasing environmental unpredictability and need through a monitoring. The purpose of this research is to analyze river morphology changes and assess flood susceptibility in the Tallo River, Makassar City, using Support Vector Machine (SVM) classification methods. Approximately, there are 20% of the area experienced significant changes during 2018 in Tallo River. As water discharge continues to increase, the volume of water mass also rises accordingly. To detect the spatial distribution of flood vulnerability along the Tallo River, which flows through Makassar City, this study utilizes Land Use and Land Cover (LULC) data from 2017 and 2024. These datasets were classified using the Random Forest model, achieving accuracies of 0.89 and 0.87, respectively values that meet the standards for land use change accuracy. Flood vulnerability is also influenced by low elevation values, particularly areas below 0 meters, which are classified as wetland zones. In the Tallo River area, which is part of the Jeneberang Watershed, the dominant class is moderate flood vulnerability, covering approximately 138.48 hectares. Remote sensing technology combined with machine learning approaches especially supervised classification techniques widely used for both binary and multivariate classification tasks, demonstrating high accuracy in detecting and classifying flood vulnerability.

Keywords : River Change Detection; Sentinel-1; Support Vector Machine (SVM); Flood Vulnerability; Tallo River.

How to cite: Izzaty, Atika., Aprian, Syahra D., Wijayanti, Regita F., Iffaty, Athiya., Bakri, Bambang., Karamma, Riswal. (2025). Detection of River Change in Modeling Flood Vulnerability using Support Vector Machine (SVM) Methods in Tallo River Makassar City. *Geoid, 20*(2), 80-92.

Introduction

Changes in river morphology and the increasing frequency of flooding in urban areas are becoming increasingly worrying environmental issues, including in Makassar City. The Tallo River, as one of the main rivers flowing through the urban area, shows significant dynamic changes due to a combination of natural factors and human activities, such as land use change, sedimentation, and development around the riverbanks (Latief et al., 2021).These changes have a direct impact on the carrying capacity of river flows, thereby increasing the potential for flooding, especially when there is high rainfall and the drainage system is not functioning optimally (Khairina et al., 2024). In recent years, the incidence of flooding along the Tallo River has increased. This is due to the water discharge of the Tallo River reaching 268.13 m^3/s, with an average rainy day of 3,217 days/year, resulting in a flow discharge of about 5.7 billion m^3/year or equivalent to 70.67 m^3/s, which exceeds the capacity of the river (Zulfahmi et al., 2016). This condition emphasizes the importance of regular monitoring of river morphology and flood detection as a basis for disaster mitigation planning and more adaptive and sustainable regional spatial planning.

In this era, flooding is one of the most frequent natural disasters and can occur at any time, particularly in large metropolitan cities. This disaster often disrupts various activities (Tanim et al., 2022), such as causing traffic congestion and hindering ground transportation. It also significantly affects residential areas located near riverbanks. There are several aspects influenced by climate change factors, such as weather, annual rainfall, and others. Climate change effect greatly influences the dynamics of unpredictable (Xiong et al., 2019) environmental conditions. However, these changes can still be anticipated to reduce disaster risks (Jayawardena, 2015), especially in urban areas. Floods are classified as hydrometeorological disasters (Paul et al., 2018) and can be analyzed and predicted using hydraulic models (Chuan et al., 2018). They are among the easiest disasters to occur (Yousefi et al., 2018), as even a short period of heavy rainfall can lead to water accumulation. This is especially true in urban and coastal environments affected by climate change (Tanim et al., 2022); (Moftakhari et al., 2015). Urban areas in coastal regions may experience alterations in river courses, particularly as water discharge levels continue to increase.

Conventional monitoring of changes in river morphology, such as through field surveys and analysis of topographic maps, is often inefficient due to limitations in area coverage, frequency of observation, and the need for large amounts of time, energy, and cost (Rahmawaty & Hasan, 2023). The use of complementary optical imagery and aerial photography also has constraints, as they are highly dependent on weather and lighting conditions (Muhadi et al., 2020). As a result, this method is less effective when the area is covered by clouds, rain occurs, or data collection is carried out at night. To overcome these limitations, technologies such as Synthetic Aperture Radar (SAR), were developed as a superior solution in earth observation systems. SAR is able to record data in all weather and time conditions, and allows monitoring of changes in the earth's surface, including river morphology, in a multitemporal and wide coverage (Vikraldo, 2024). The superiority of SAR in detecting wetland changes and water flow has also been proven to provide high accuracy in mapping disaster-prone areas (Budiarto & Bioresita, 2023).

The technology of remote sensing in supervised classification techniques are commonly employed for both binary and multivariate classification tasks. Algorithms such as the K-Nearest Neighbor (KNN) classifier, Random Forest (RF) classifier and Support Vector Machine (SVM) (Gašparović & Dobrinić, 2020) have been utilized for flood detection using Sentinel-1 SAR imagery. These various models collectively represent an integral part of machine learning, which is highly effective in predicting and detecting environmental conditions. The integration of these algorithms within the same analytical framework enhances the robustness and accuracy of flood detection results. Synthetic Aperture Radar (SAR)-based remote sensing data is an approach that is increasingly applied in urban environmental studies, especially in monitoring changes in river morphology (Kryniecka et al., 2022) and flood detection because it has the advantage of recording data consistently. One of the key advantages of remote sensing is its ability to detect floods (Munawar et al., 2022; Rahmi et al., 2024) and produce large-scale flood maps without requiring highly precise input data or computationally demanding processes, thereby supporting more efficient flood risk management. To support the classification and spatial analysis process, a machine learning approach is used, specifically the Support Vector Machine (SVM) (Langhammer, 2023; Xiong et al., 2019) method. SVM model have proven to be highly effective tools in modeling and forecasting flood inundation (Tehrany, Pradhan, & Jebur, 2015), Therefore, in this study, the same method was applied similar to the approach used in study (Chang et al., 2018) due to its high average accuracy in detecting floods, particularly in urban areas. The method used in this study was selected because it aligns with previous findings conducted under similar site conditions, demonstrating suitability for detecting floods in urban areas (Yan et al., 2018). This algorithm is proven to be able to accurately process radar data to detect spatial changes, as well as evaluate the relationship between changes in river morphology and urban flooding events (Islam & Meng, 2022). This approach makes a significant contribution to regional planning, disaster risk mitigation, and environmental management based on measurable and accurate spatial data. The purpose of this research to got a morphology changes of the river and flood susceptibility in Tallo River in Makassar City using the SVM classification methods.

Methodology

Study Area

This research was conducted in the Tallo River basin, Makassar City, South Sulawesi Province, which is geographically located at 119°24'17“ to 119°24'38” East Longitude and 5°8'6“ to 5°8'19” South Latitude. This area is one of the densely populated areas and has experienced an increase in flood intensity in recent years.

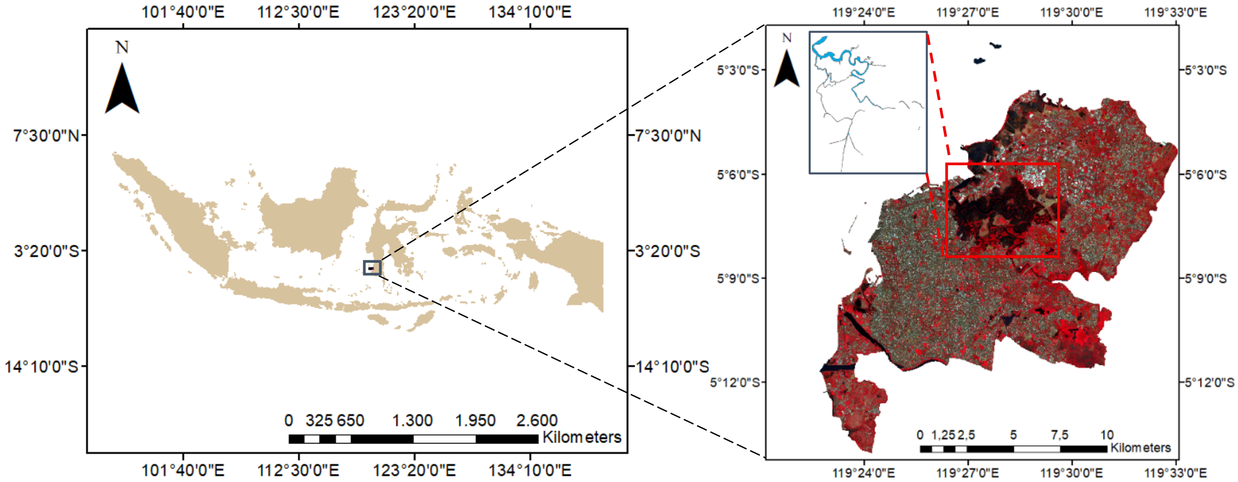

Figure 1. Study Area

Materials

This research uses Sentinel-1 SAR satellite image data with a multitemporal time span from 2017 to 2024 as the main material. The data was obtained from the Google Earth Engine (GEE) platform. The research phase began with the identification of problems related to morphological changes in the Tallo River. Furthermore, computational processing of the research study area was carried out. Research was also conducted to review environmental conditions with elevation parameters and collaboration of two machine learning methods. The final stage was analyzed for each method with all parameters that have been modeled.

The research stage consists of five main steps, starting from literature study to analysis of data processing results. The initial stage began with a literature study and problem identification based on the latest data sources and references, to understand the phenomenon of changes in river morphology and flood events in the study area, namely Tallo River, Makassar City. Next, relevant methods and modeling were determined based on the analyzed problems. The methods used include the utilization of machine learning algorithms, namely SVM for the classification of river shape changes, and Random Forest to detect and estimate areas with high flood vulnerability. The research data was collected from several sources, namely the Tallo River Region of Interest (ROI) shapefile, Sentinel-1 SAR satellite image for the period 2017-2024, and Digital Elevation Model (DEM) data. After the data was collected, the management process was carried out using a cloud-based platform such as GEE, which allows multitemporal and efficient image processing. At this stage, an assessment of the environmental conditions closely related to the elevation and flow characteristics of the river was also conducted. The final stage of the research involves analyzing the classification and modeling results, by evaluating all the parameters that have been included in the system. Visualization of the results is done in the form of thematic mapping that shows changes in river morphology and the distribution of flood potential in the study area.

Methods

a. *The Stage of Pre-processing and Processing Data*

In the initial stage of processing, pre-processing was carried out on the Sentinel-1 image dataset obtained through the Google Earth Engine (GEE) platform. This platform provides Sentinel-1 images that have gone through systematic pre-processing stages, including thermal noise removal to remove signal interference from the sensor, radiometric calibration to convert digital values into physically representative backscatter values, and terrain correction using Digital Elevation Model (DEM) data so that each image pixel has an accurate geographical position (Islam & Meng, 2022). This pre-processing stage is important to ensure that the SAR images used have good spatial and radiometric quality, so that they can be interpreted reliably in the further analysis process.

After pre-processing was completed, the data was analyzed to detect changes in river morphology and flood inundation in urban areas. Elevation data from the DEM was used to determine the contours of the area around the river, while slope was calculated through spatial derivative analysis to identify areas prone to erosion or surface flow (Desalegn & Mulu, 2021). In addition, rainfall data with a spatial resolution of 0.05° (5 km) was used to observe the relationship between rainfall intensity and flood events (Pan et al., 2024).

The detection of changes in river morphology is done by comparing the backscatter values of multitemporal Landsat-8 data using an image differencing approach (Marchetti et al., 2023). Landsat-8 data is combined to assess flood hazards and detect flood events by calculating several parameters and contributing factors, resulting in a flood hazard detection map for the Tallo River Basin. The Sentinel-1 mission comprises two polar-orbiting satellites carrying C-band synthetic aperture radar (SAR) instruments. These satellites operate with a spatial resolution of 10 meters and provide frequent image acquisition, with a revisit period of six days when operating in constellation mode. The data used in this research was the Google Earth Engine image collection comprises Sentinel-1 Ground Range Detected (GRD) from 2017 to 2024 which the scenes produced the calibrated and ortho-rectified outputs. The mission delivers reliable data independent of weather conditions or daylight (Tarpanelli et al., 2022); (Torres et al., 2012). Sentinel-1 continues the legacy of previous SAR missions such as ERS-1, ERS-2, Envisat, and RADARSAT developed by ESA and Canada. Its capability for wide-area coverage and dual polarization enhances data reliability. The identification of inundation areas is done by thresholding techniques on the sigma naught values, as water has very low reflectance in SAR images (Tran et al., 2022).

Imagery captured during or after a flood event is utilized to map the extent of inundated floodplains. By comparing it with pre-event imagery using a change detection approach, it becomes possible to distinguish permanent water bodies (Bioresita et al., 2019). Furthermore, the effectiveness of Sentinel-1 in detecting and estimating flood inundation events has been demonstrated in numerous studies. The processing results were combined with topographic and land use data to produce comprehensive spatial information on river dynamics and flood risk in urban areas. The following are the parameters or indicators used to assess the changes occurring in the river area.

Table 1. Parameter of Flood Risk Detection

Parameter	Source	Unit	Description
Rainfall model (interpolated from rain gauge locations in the river)	Central Bureau of Statistics (Makassar City in Figures 2017–2024)	mm	The proportional of standar deviation in rainfall extremes
Soil attributes types	Food and Agriculture Organization of the United Nations (Harmonized World Soil Database v2.0)	kg/m^3	Depth of soils in area Lithosol, Fluvisol, Podsol, Rendzina, and Histosol in river/catchment area
Land use	Google Earth Engine Datasets (Sentinel-2A)	Hectares	Built-up Area, Waterbody, Wetland (permanent and nonpermanent water), Bareland, Agriculture, and Vegetation

Elevation of the topograhic indicates	Geospatial Information Agency (National Digital Elevation Model (DEM) Data)	m	The mean value of catchment elevation

The rainfall model will be calculated using an interpolation method based on Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS). CHIRPS provides gridded rainfall time series by combining satellite observations with ground-based station data, supporting trend analysis and seasonal drought monitoring.

$$Xg = \sum_{i=1}^{ns} \lambda_1 Zs_i \quad (1)$$

In this context (Ly et al., 2013), *Xg* represents the interpolated value at the target location, while *Zsi* denotes the observed value at point *i*. The variable *ns* refers to the total number of observed points, and $\lambda = (\lambda_1)$ indicates the weighting factors applied in the interpolation process.

The soil attributes types is to identify the soil types distributed within the study area. The data collected are in-situ data obtained through manual calculations using the Unified Soil Classification System (USCS). This system classifies soils based on their primary characteristics, including soil type, grain size, gradation, plasticity level, and organic content. These primary data are then categorized and represented in a spatial distribution format.

To find the land use in the hectares which classify the land use and cover change. The use of the LULC model (Hasan et al., 2023)in validating land cover changes with high accuracy is applied during data processing. The Random Forest model (Junaid et al., 2023) is employed to analyze temporal changes in LULC, with its performance evaluated through a confusion matrix. This matrix classifies each object into interpretable classes and provides performance metrics such as overall accuracy (Ridhayana et al., 2022) and the kappa coefficient (Maxwell et al., 2021).

$$UA = \frac{z_{ii}}{z_{+1}} x\ 100\% \quad (2)$$

$$PA = \frac{z_{ii}}{z_{i+}} x\ 100\% \quad (3)$$

$$OA = \frac{\sum_i^r z_{ii}}{N} \quad (4)$$

The values of z_{ii}, z_{+1}, z_{i+}, and *N* are used to populate the rows and columns of the classification matrix. This is based on the results of observations and the overall classification of the previously identified LULC class points. The kappa coefficient (Rwanga & Ndambuki, 2017) is used to identify classification errors, where values approaching 1 indicate a more accurate and reliable classification. Therefore, the kappa coefficient is calculated using the following algorithm.

$$KC = \frac{N \sum_{i=1}^r z_{ii} - \sum_{i=1}^r (z_{i+} . z_{+1})}{N^2 - \sum_{i=1}^r (z_{i+} . z_{+1})} \quad (5)$$

In calculating the kappa coefficient, the parameters z_{ii}, z_{+1}, z_{i+}, *N*, and *r* are required. These parameters include the validated LULC point values (Rana & Suryanarayana, 2020) along with the total number of correctly validated points, and they also account for the calculated error factor.

Alongside other parameters used to detect changes in river morphology and flood impact on the surrounding environment, elevation derived from topographic data serves as a crucial factor in understanding surface height variations. Topographic surface values, as one of the surface factors in flood assessment, are obtained using a Digital Elevation Model (DEM) with a 30 x 30 meter resolution. These data are extracted using tools available in the QGIS raster analysis toolbox to generate contour maps and elevation points, which are essential for determining the slope conditions of the study area.

b. Machine Learning Approach

The use of machine learning models has become an increasingly popular trend alongside technological advancements. In spatial data processing, machine learning (Abdullah & Abdulazeez, 2021) offers significant convenience (Ganjirad & Delavar, 2023) by enabling automated data handling, such as in satellite image processing. As a branch of artificial intelligence, it allows computer systems to learn and make decisions based on data without the need for explicit programming for each specific task. The system learns and executes the necessary instructions to process data according to the provided input. There is a wide range of automation models within the domain of machine learning, including the SVM and RF algorithms.

Most studies have reported high-accuracy (Langhammer, 2023; Tehrany, Pradhan, et al., 2015) findings in flood monitoring by using the SVM which commonly applied machine learning algorithm utilized for both classification and regression modeling tasks (Choubin et al., 2019) and for analysis the changes of environmental condition. SVM supports various kernel functions, such as linear, nonlinear, polynomial, and radial basis functions (RBF). It is a supervised binary classification method that operates based on the principle of structural risk minimization (Tehrany et al., 2014); (Wan & Lei, 2009). The model operates on the principle of optimization and aims to fit a hyperplane to the training dataset to distinguish between different classes. This hyperplane is positioned to maximize the distance from the nearest data points of each class (Ganjirad & Delavar, 2023); (Koggalage & Halgamuge, 2004), which are referred to as support vectors. It operates by constructing a hyperplane (Tanim et al., 2022) within the data space to distinguish between water and non-water features based on Sentinel-1 pixel values. For the purpose of flood image classification, the radial basis function is selected, and its formulation (Keerthi et al., 2001) is presented in Equation (1).

$$z(a, b) = \exp(-\sigma||a - b||^2) \tag{6}$$

which the parameter of σ is the spread to controls the kernel. Adjusting the parameter σ enhances the accuracy in distinguishing between water and non-water pixels.

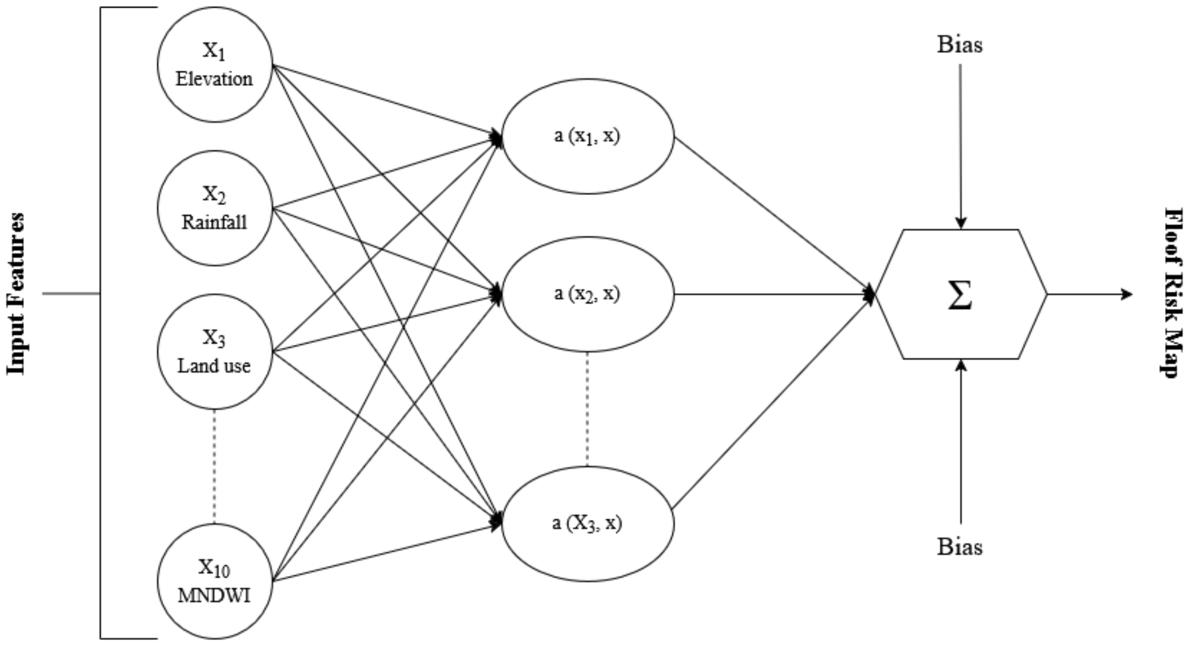

Figure 2. General Structure of the SVM Models
(Adapted and modified from (Xu et al., 2021))

Results and Discussion

River Morphology Changes

Changes in river conditions are key factors analyzed in the case study of the Tallo River. For many years, the Tallo River has been one of the main rivers flowing through the center of Makassar City, where daily activities such as waste disposal, land use changes, river discharge, and industrial waste influence its dynamics. The river also serves as a waterway for transportation, connecting the city center to the neighboring Gowa Regency. The Tallo River forms a watershed that is part of the larger Jeneberang River Basin, which also extends into Gowa Regency.

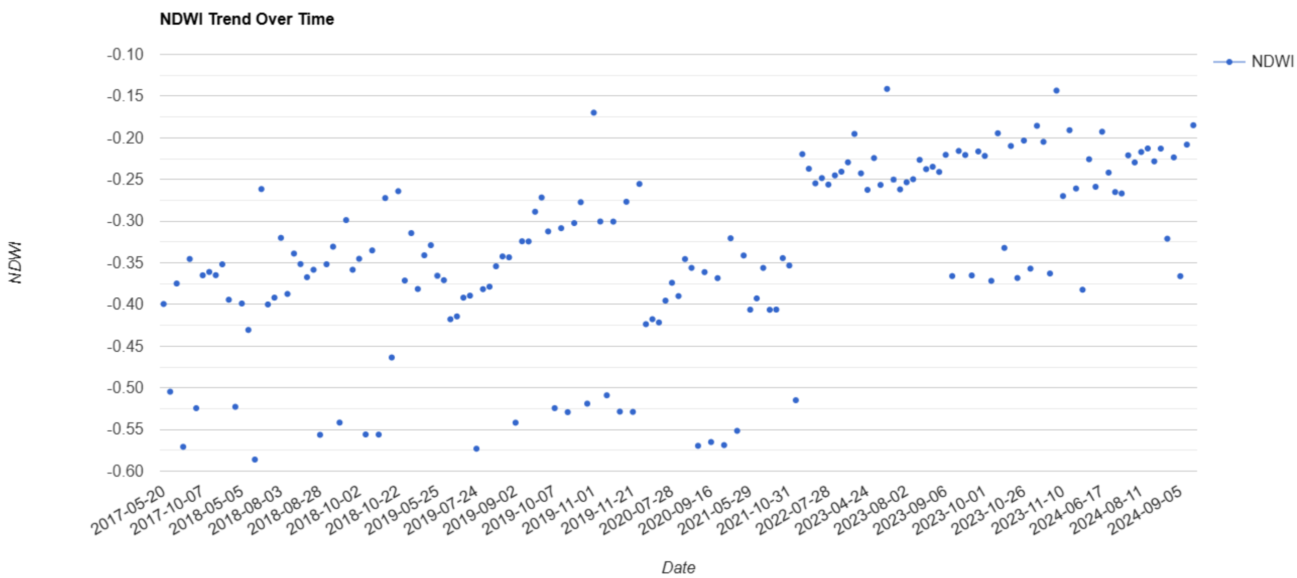

Figure 3. NDWI Trend Point 2017 - 2024

The process of NDWI detection is employed to distinguish aquatic areas from terrestrial ones and to map the presence of wetlands around riverbanks. For seven years, the Tallo River's water index has steadily declined. This reduction, however, raises hydrometeorological worries because, concurrently, rainfall has escalated, leading to recurrent inundation of urban centers, notably those close to the Tallo River. Fig.4a and Fig.4b provides a clear depiction of how water distribution has transformed from 2017 to 2024.

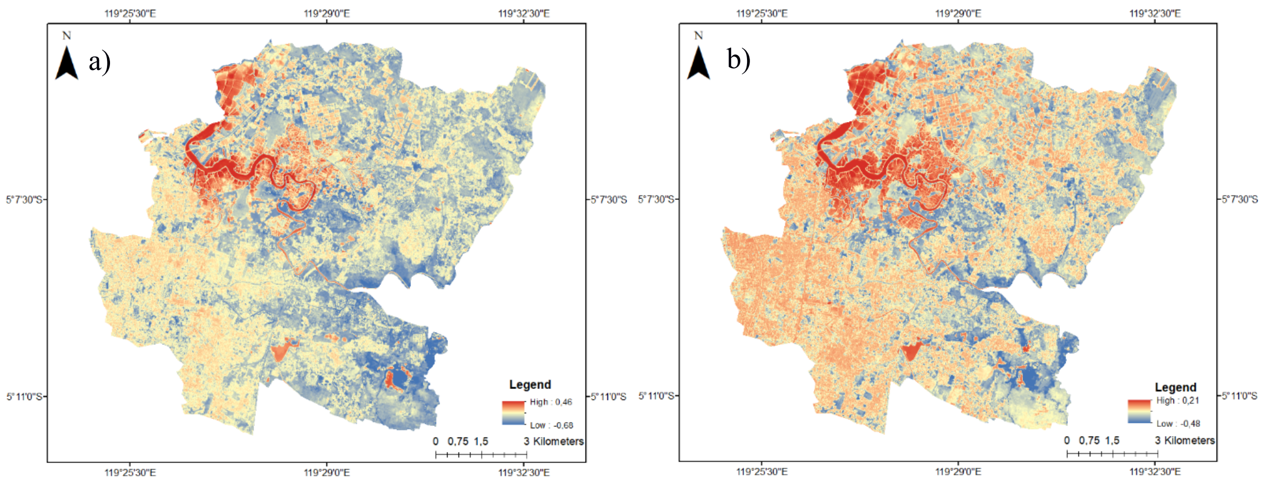

Figure 4. Distribution of NDWI a) 2017 and b) 2024

In 2017, low-lying areas were mainly concentrated around the Tallo River. However, by 2024, the extent of wetlands, classified as water-saturated areas, has significantly increased. The number of locations with detectable water content, as indicated by the water index, has grown. This can be observed in Fig. 3b. The figure also illustrates morphological changes in the river, showing a noticeable transformation in the shape of the Tallo River. Land cover changes in 2018 were more prominent compared to subsequent years, which showed only minor variations. Notably, approximately 20% of the area marked in purple experienced significant changes during 2018. Permanent water bodies can be observed in Fig.5a, indicated by dark blue areas, highlighting changes along the Tallo River in those permanent water zones.

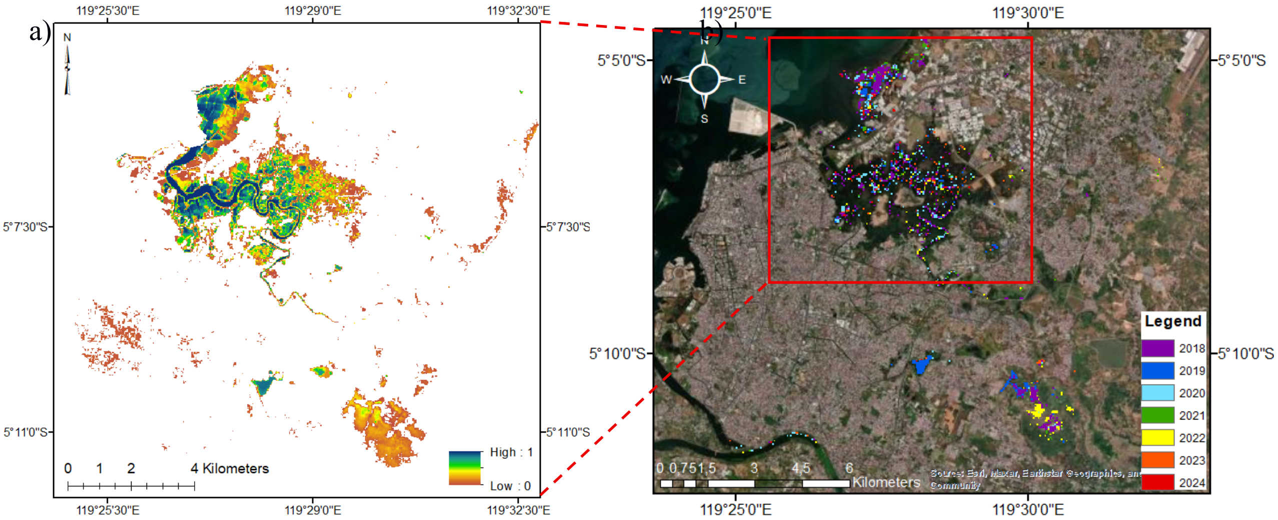

Figure 5. a) Permanent Water and the wetland Area of Tallo River; and b) River Change from 2017 – 2024

Flood Inundation Vulnerability

a. Land Use Changes and Elevation Model Detection Parameters

Land cover changes around and along the Tallo River can be observed by comparing the years 2017 and 2024. Over the span of seven years, five land cover classes were selected: Waterbody, Vegetation, Built-up Area, Bareland, and Wetland. These classes were used as samples for both training and validation data, applying the Random Forest algorithm under a supervised classification approach. A classification accuracy of over 85% was required for reliable results. Significant changes were identified in several areas of Makassar City, particularly along the banks of the Tallo River, which is part of the Jeneberang Watershed conservation area. Notably, in the northernmost region near the airport, there has been a considerable increase in residential development by 2024 compared to 2017. This northern section of the Tallo River has transformed into a built-up area. The expansion of development around the river has also led to a loss of vegetation due to land conversion activities and land clearing, resulting in increased bareland.

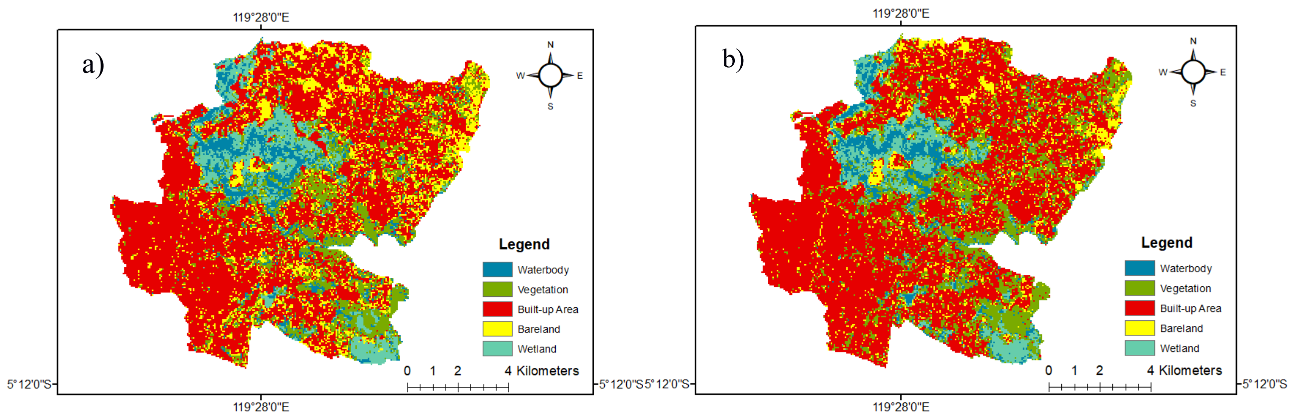

Figure 6. LULC Changes in 2017 and 2024

Based on the figure above, an evaluation was conducted using overall accuracy and the Kappa coefficient to assess the accuracy level of the land cover classification model. For the five land cover classes classified, the overall accuracy achieved in 2017 was 89%, with a Kappa coefficient of 0.86. In contrast, for the year 2024, the overall accuracy was 87% and Kappa coefficient was 0.83. These results are presented in Tables 1 and 2, which display the confusion matrices for the years 2017 and 2024, respectively.

Table 2. Confusion Matrix of LULC 2017

Classification LULC	Waterbody	Vegetation	Built-up Area	Bareland	Wetland
Waterbody	19	5	1	0	2
Vegetation	4	35	1	0	1
Built-up Area	0	2	74	2	0
Bareland	0	0	1	37	0
Wetland	1	2	0	2	35
Producers Accuracy	70%	85%	94%	97%	87%
Overall Accuracy			89%		
Kappa Coefficient			0.86		

Table 3. Confusion Matrix of LULC 2024

Classification LULC	Waterbody	Vegetation	Built-up Area	Bareland	Wetland
Waterbody	24	2	2	0	1
Vegetation	2	36	1	0	2
Built-up Area	1	4	56	3	0
Bareland	0	1	3	37	0
Wetland	3	1	1	1	40
Producers Accuracy	82%	87%	87%	90%	86%
Overall Accuracy			87%		
Kappa Coefficient			0.83		

In addition to elevation differences, which are commonly used as key indicators for identifying flood-prone areas, surface elevation plays a crucial role in determining topographical variations and the distribution of wetlands, as well as higher-elevation areas such as mountainous regions. The highest elevation within the Jeneberang Watershed area passing through Makassar City is 50 meters, while the lowest point located along the banks of the Tallo River lies below sea level, reaching as low as -16 meters.

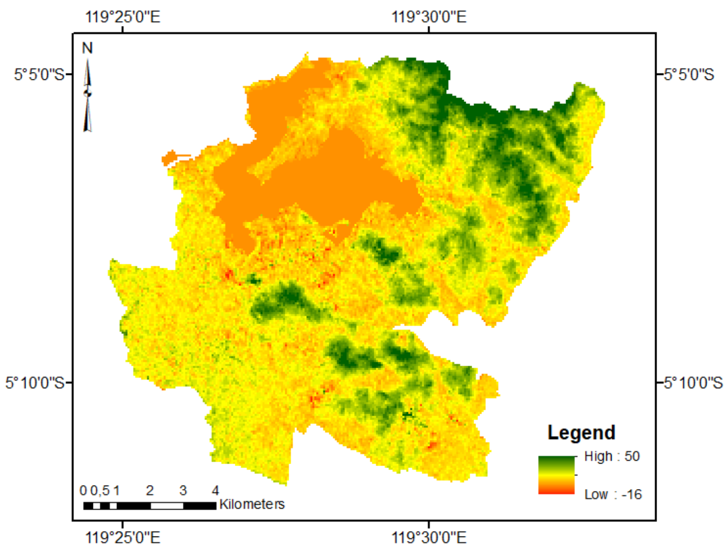

Figure 7. DEM (Digital Elevation Model) of Tallo River in Makassar City

The land cover along the riverbanks is situated at an elevation of 0–2 meters. Therefore, during periods of heavy rainfall with high precipitation intensity, this area is frequently affected by prolonged flooding. This is supported by Fig.8, which illustrates the increasing trend in rainfall from 2017 to 2024.

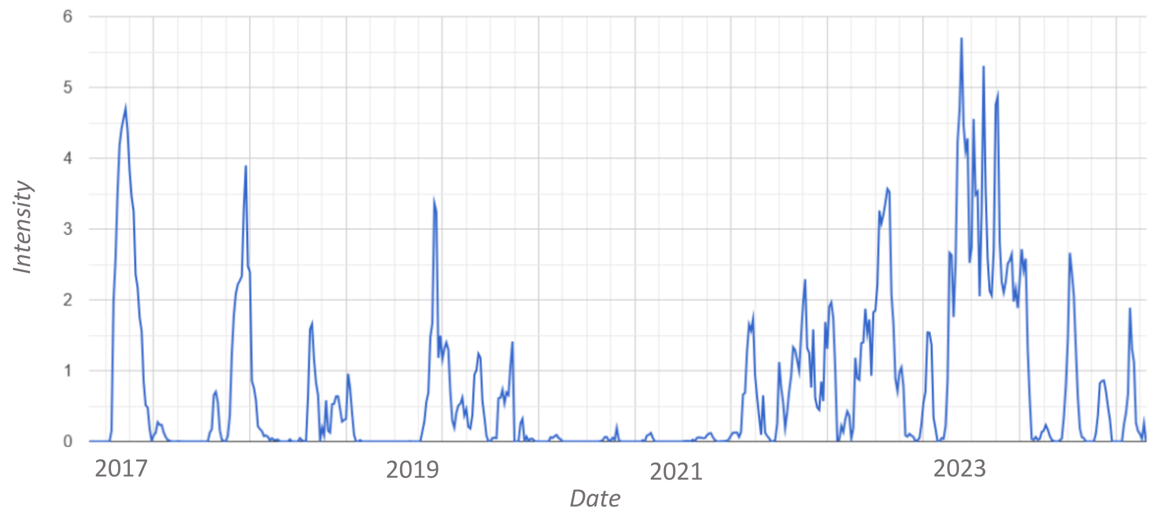

Figure 8. Intensity of Rainfall in 2017 – 2024

b. The Model of Flood Hazardous Classification

Based on the results of the SVM (Support Vector Machine) classification, the model demonstrated excellent accuracy in identifying classification classes using several parameters to determine flood vulnerability. This method considers topographic conditions, land cover around the river, proximity to permanent water bodies, vegetation indices, and water indices. Areas near the riverbanks show a significant concentration of red zones, indicating high flood intensity. In contrast, green-colored areas, which are located on higher ground <15 meters, are identified as regions with very low flood vulnerability. The highest intensity is observed in residential land cover areas located in the northernmost part of Makassar City.

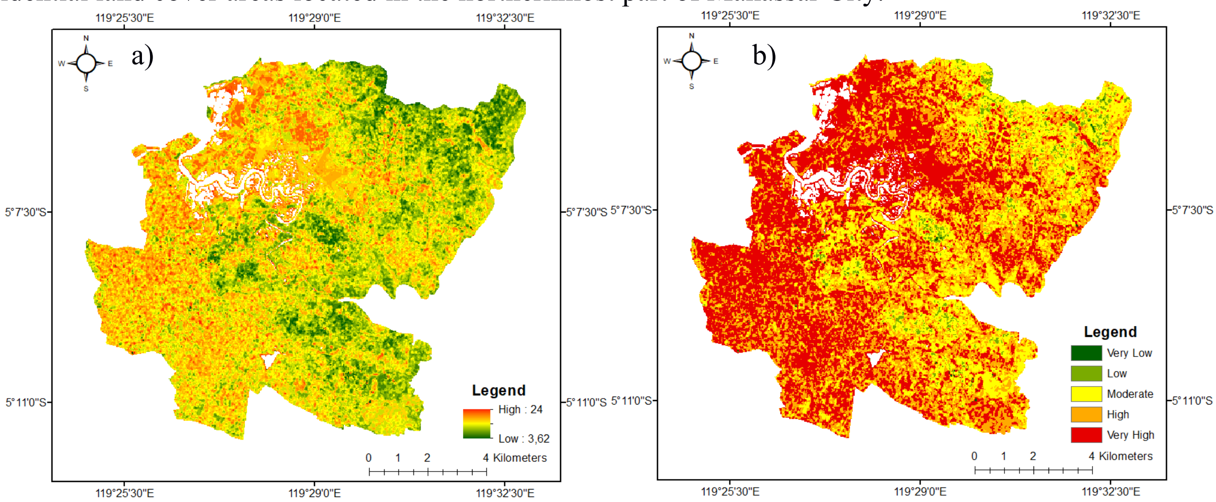

Figure 9. a) Intensity of Flood Hazard in Tallo River Makassar City; and b) The Flood Vulnerability Classification

The spatial distribution of flood vulnerability is presented in the figure below, indicating that the majority of areas within Makassar City particularly those located in the Jeneberang Watershed and along the Tallo River are predominantly classified under the high and very high vulnerability categories. Specifically, approximately 97.44 hectares fall under the very high vulnerability class, while an additional 77.34 hectares are categorized as high vulnerability. The most extensive classification, however, is the moderate vulnerability class, encompassing an area of 136.48 hectares. In contrast, areas classified as low and very low vulnerability account for 49.4 hectares and 18.39 hectares, respectively. These lower vulnerability zones are primarily situated in higher elevation regions toward the northernmost part of Makassar City.

Conclusions

Changes in river morphology and the increasing discharge of river water are closely influenced by fluctuations in rainfall intensity. The volume of water retained along the river can overflow due to declining groundwater levels and land use conversion, particularly in urban areas. This is evident in the case of the Tallo River, which is part of the Jeneberang Watershed in Makassar City. The Tallo River area is situated at a relatively lower elevation compared to other urban zones. Moreover, land use changes observed through LULC (Land Use and Land Cover) modeling over a seven-year period provide insight into the increasing number of hydrometeorological issues occurring in the surrounding area. In the northernmost part of Makassar City, significant land use conversion has occurred, where areas previously dominated by vegetation and open land have been transformed into residential developments. This is consistent with the 2024 LULC map, which confirms a notable increase in built-up areas, contributing to the frequent occurrence of flooding in the northern part of the city. The increased rainfall intensity especially during the peak in 2024 has further intensified the frequency of rain events, leading to the overflow of the Tallo River. Through the use of remote sensing technology and Support Vector Machine (SVM) machine learning methods, the spatial distribution of flood-prone areas has been accurately classified into vulnerability levels ranging from very low to moderate and very high. To enhance the accuracy of the results, future studies could integrate additional machine learning systems to strengthen flood mapping and detection efforts. These findings can also serve as a reference for future planning and research, particularly in developing hazardous resilience and mitigation strategies for urban areas traversed by rivers.

Acknowledgment

The authors would like to extend our deepest appreciation to Faculty of Engineering, Universitas Hasanuddin in the funding scheme of Laboratory Based Education (LBE) Basic Inovation for their unwavering support under the research grant, Grant Number 15300/UN4.7.2/PM.01.01/2025, which made this research well implemented.

References

Abdullah, D. M., & Abdulazeez, A. M. (2021). Machine learning applications based on SVM classification a review. *Qubahan Academic Journal*, *1*(2), 81-90.

Bioresita, F., Puissant, A., Taufik, M., & Gasica, T. (2019). Identification of permanent surface water in Bengawan Solo River downstream area, Indonesia using Sentinel-1 imagery. IOP Conference Series: Earth and Environmental Science,

Budiarto, F. A., & Bioresita, F. (2023). Pemanfaatan Citra Sentinel-1 SAR dan Metode Change Detection Approach Untuk Analisis Sebaran Spasial Wilayah Banjir dan Area Terdampak (Studi Kasus: Banjir Kabupaten Aceh Utara 2022). *JGISE: Journal of Geospatial Information Science and Engineering*, *6*(2), 153-162.

Chang, M.-J., Chang, H.-K., Chen, Y.-C., Lin, G.-F., Chen, P.-A., Lai, J.-S., & Tan, Y.-C. (2018). A support vector machine forecasting model for typhoon flood inundation mapping and early flood warning systems. *Water*, *10*(12), 1734.

Choubin, B., Moradi, E., Golshan, M., Adamowski, J., Sajedi-Hosseini, F., & Mosavi, A. (2019). An ensemble prediction of flood susceptibility using multivariate discriminant analysis, classification and regression trees, and support vector machines. *Science of the Total Environment*, *651*, 2087-2096.

Chuan, N. M., Thiruchelvam, S., Ghazali, A., Mustapha, K. N., Sabri, R., Muda, N. Y. J., Norkhairi, F. F., & Yahya, N. (2018). A review of key activities in hydro meteorological disaster management. *International Journal of Engineering & Technology*, *7*(4.35), 839-843.

Desalegn, H., & Mulu, A. (2021). Flood vulnerability assessment using GIS at Fetam watershed, upper Abbay basin, Ethiopia. *Heliyon*, *7*(1).

Ganjirad, M., & Delavar, M. (2023). Flood risk mapping using random forest and support vector machine. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *10*, 201-208.

Gašparović, M., & Dobrinić, D. (2020). Comparative assessment of machine learning methods for urban vegetation mapping using multitemporal sentinel-1 imagery. *Remote Sensing*, *12*(12), 1952.

Hasan, M. M., Nilay, M. S. M., Jibon, N. H., & Rahman, R. M. (2023). LULC changes to riverine flooding: a case study on the Jamuna River, Bangladesh using the multilayer perceptron model. *Results in Engineering*, *18*, 101079.

Islam, M. T., & Meng, Q. (2022). An exploratory study of Sentinel-1 SAR for rapid urban flood mapping on Google Earth Engine. *International journal of applied earth observation and geoinformation*, *113*, 103002.

Jayawardena, A. (2015). Hydro-meteorological disasters: Causes, effects and mitigation measures with special reference to early warning with data driven approaches of forecasting. *Procedia IUTAM*, *17*, 3-12.

Junaid, M., Sun, J., Iqbal, A., Sohail, M., Zafar, S., & Khan, A. (2023). Mapping lulc dynamics and its potential implication on forest cover in malam jabba region with landsat time series imagery and random forest classification. *Sustainability*, *15*(3), 1858.

Keerthi, S. S., Shevade, S. K., Bhattacharyya, C., & Murthy, K. R. K. (2001). Improvements to Platt's SMO algorithm for SVM classifier design. *Neural computation*, *13*(3), 637-649.

Khairina, S. H., Hans, A., & Arif, I. A. (2024). Efektivitas Kebijakan Penanggulangan Bencana Dalam Konteks Pembangunan Daerah: Studi Kasus Kota Makassar.

Koggalage, R., & Halgamuge, S. (2004). Reducing the number of training samples for fast support vector machine classification. *Neural Information Processing-Letters and Reviews*, *2*(3), 57-65.

Kryniecka, K., Magnuszewski, A., & Radecki-Pawlik, A. (2022). Sentinel-1 satellite radar images: A new source of information for study of river channel dynamics on the lower Vistula river, Poland. *Remote Sensing*, *14*(5), 1056.

Langhammer, J. (2023). Flood simulations using a sensor network and support vector machine model. *Water*, *15*(11), 2004.

Latief, R., Barkey, R. A., & Suhaeb, M. I. (2021). Perubahan Penggunaan Lahan Terhadap Banjir di Kawasan Daerah Aliran Sungai Maros. *Urban Reg. Stud. J*, *3*(2), 52-59.

Ly, S., Charles, C., & Degré, A. (2013). Different methods for spatial interpolation of rainfall data for operational hydrology and hydrological modeling at watershed scale: a review. *Biotechnologie, agronomie, société et environnement*, *17*(2).

Marchetti, A., Di Dio, C., Cangelosi, A., Manzi, F., & Massaro, D. (2023). Developing ChatGPT's theory of mind. *Frontiers in Robotics and AI*, *10*, 1189525.

Maxwell, A. E., Warner, T. A., & Guillén, L. A. (2021). Accuracy assessment in convolutional neural network-based deep learning remote sensing studies—Part 2: Recommendations and best practices. *Remote Sensing*, *13*(13), 2591.

Moftakhari, H. R., AghaKouchak, A., Sanders, B. F., Feldman, D. L., Sweet, W., Matthew, R. A., & Luke, A. (2015). Increased nuisance flooding along the coasts of the United States due to sea level rise: Past and future. *Geophysical research letters*, *42*(22), 9846-9852.

Muhadi, N. A., Abdullah, A. F., Bejo, S. K., Mahadi, M. R., & Mijic, A. (2020). Image segmentation methods for flood monitoring system. *Water*, *12*(6), 1825.

Munawar, H. S., Hammad, A. W., & Waller, S. T. (2022). Remote sensing methods for flood prediction: A review. *Sensors*, *22*(3), 960.

Pan, Y., Birdsey, R. A., Phillips, O. L., Houghton, R. A., Fang, J., Kauppi, P. E., Keith, H., Kurz, W. A., Ito, A., & Lewis, S. L. (2024). The enduring world forest carbon sink. *Nature*, *631*(8021), 563-569.

Paul, S. H., Sharif, H. O., & Crawford, A. M. (2018). Fatalities caused by hydrometeorological disasters in Texas. *Geosciences*, *8*(5), 186.

Rahmawaty, M. A., & Hasan, A. F. (2023). Mapping The Location of Flood Shelters in Demak Regency using The Spatial Multi Criteria Evaluation Method. IOP Conference Series: Earth and Environmental Science,

Rahmi, R., Ahmad, A., Yulianur, A., Ramli, I., & Izzaty, A. (2024). Spatial Analysis of Flood Vulnerability Base on Biophysics Factor the Krueng Baro Watershed in Flood Mitigation Efforts at Aceh, Indonesia. BIO Web of Conferences,

Rana, V. K., & Suryanarayana, T. M. V. (2020). Performance evaluation of MLE, RF and SVM classification algorithms for watershed scale land use/land cover mapping using sentinel 2 bands. *Remote Sensing Applications: Society and Environment*, *19*, 100351.

Ridhayana, A., Darmawan, A., Santoso, T., Yuwono, S. B., & Febryano, I. G. (2022). Perubahan Tutupan Lahan Pada Daerah Aliran Sungai Sekampung Hulu, Lampung Menggunakan Data Pengindraan Jauh. *MAKILA*, *16*(2), 104-113.

Rwanga, S. S., & Ndambuki, J. M. (2017). Accuracy assessment of land use/land cover classification using remote sensing and GIS. *International Journal of Geosciences*, *8*(04), 611.

Tanim, A. H., McRae, C. B., Tavakol-Davani, H., & Goharian, E. (2022). Flood detection in urban areas using satellite imagery and machine learning. *Water*, *14*(7), 1140.

Tarpanelli, A., Mondini, A. C., & Camici, S. (2022). Effectiveness of Sentinel-1 and Sentinel-2 for flood detection assessment in Europe. *Natural Hazards and Earth System Sciences*, *22*(8), 2473-2489.

Tehrany, M. S., Pradhan, B., & Jebur, M. N. (2014). Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS. *Journal of Hydrology*, *512*, 332-343.

Tehrany, M. S., Pradhan, B., & Jebur, M. N. (2015). Flood susceptibility analysis and its verification using a novel ensemble support vector machine and frequency ratio method. *Stochastic environmental research and risk assessment*, *29*(4), 1149-1165.

Tehrany, M. S., Pradhan, B., Mansor, S., & Ahmad, N. (2015). Flood susceptibility assessment using GIS-based support vector machine model with different kernel types. *Catena*, *125*, 91-101.

Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., Potin, P., Rommen, B., Floury, N., & Brown, M. (2012). GMES Sentinel-1 mission. *Remote Sensing of environment*, *120*, 9-24.

Tran, V.-T., Porcher, R., Pane, I., & Ravaud, P. (2022). Course of post COVID-19 disease symptoms over time in the ComPaRe long COVID prospective e-cohort. *Nature communications*, *13*(1), 1812.

Vikraldo, R. (2024). *Identifikasi Longsor menggunakan Metode Change Detection Amplitude di Daerah Aliran Sungai Salu Battang* Universitas Hasanuddin].

Wan, S., & Lei, T. C. (2009). A knowledge-based decision support system to analyze the debris-flow problems at Chen-Yu-Lan River, Taiwan. *Knowledge-Based Systems*, *22*(8), 580-588.

Xiong, J., Li, J., Cheng, W., Wang, N., & Guo, L. (2019). A GIS-based support vector machine model for flash flood vulnerability assessment and mapping in China. *ISPRS International Journal of Geo-Information*, *8*(7), 297.

Xu, D., Qi, X., Li, C., Sheng, Z., & Huang, H. (2021). Wise information technology of med: human pose recognition in elderly care. *Sensors*, *21*(21), 7130.

Yan, J., Jin, J., Chen, F., Yu, G., Yin, H., & Wang, W. (2018). Urban flash flood forecast using support vector machine and numerical simulation. *Journal of Hydroinformatics*, *20*(1), 221-231.

Yousefi, S., Mirzaee, S., Keesstra, S., Surian, N., Pourghasemi, H. R., Zakizadeh, H. R., & Tabibian, S. (2018). Effects of an extreme flood on river morphology (case study: Karoon River, Iran). *Geomorphology*, *304*, 30-39.

Zulfahmi, Z., AS, N. S., & Jufriadi, J. (2016). Dampak Sedimentasi Sungai Tallo terhadap Kerawanan Banjir di Kota Makassar. *Plano Madani: Jurnal Perencanaan Wilayah dan Kota*, *5*(2), 180-191.