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Multivariate Water Stress Index Model for Predicting Water Vulnerability

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Abstract

Sabu Raijua Regency is a semi-arid island region with limited water resources and increasing water demand pressure, thus potentially experiencing high water vulnerability. This study aims to develop a multivariate Water Stress Index (WSI) model to analyze the dominant factors causing water stress and predict the level of water vulnerability in the medium to long term on Sabu Island. The study uses a predictive quantitative approach by combining multivariate regression analysis and spatial analysis based on Geographic Information Systems (GIS). The WSI value for the base year 2023 and the projection for 2033 were calculated using the Water to Availability (WTA) method which has been validated through the reliable discharge from the FJ Mock simulation results and field data. Eight independent variables were analyzed, including population density, water demand, dry spell and wet spell conditions, water availability, and clean water service coverage. The analysis results show that water demand (X3) is the most dominant factor in increasing the WSI value, while water availability (X7) plays a significant role in reducing water stress. Seasonal climate variables and clean water service coverage show relatively weak statistical effects. Spatial analysis identified West Sabu District as the area with the highest and persistent water stress, while Central Sabu and Sabu Liae Districts were at medium vulnerability levels, and Hawu Mehara and East Sabu were relatively lower.

Introduction

The availability of drinking water in a region not only plays a role in improving public health but also drives productivity and economic growth, particularly in underdeveloped and drought-prone areas. However, the coverage of drinking water services in several regions of Indonesia, particularly East Nusa Tenggara (NTT), including Sabu Raijua Regency, remains far from the target. Based on 2022 data from the Central Statistics Agency (BPS), clean water coverage in Sabu Raijua Regency only reached 44.54%, encompassing piped, non-piped, and tanked water networks (Central Statistics Agency of Sabu Raijua Regency, 2023). This situation indicates that the majority of the population still relies on surface water sources, which are highly vulnerable to climate change and extreme weather (Delpla et al., 2009; Koutroulis et al., 2019; Hoque et al., 2016).

This situation is expected to become increasingly complex due to the pressures of population growth and environmental degradation, thus necessitating an in-depth study of the balance

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between water demand and availability at the village level (Biswas et al., 2025; Nachibi & Morgan, 2025; Simanihuruk et al., 2025; Jiang et al, 2024). One widely used scientific approach is the Water Stress Index (WSI), which measures the ratio between total water demand and total water availability in a region (Falkenmark, 1989; Rijsberman, 2006; Zhou et al., 2016; Nilsalab & Gheewala, 2018; Nilsalab et al., 2017; Gao et al., 2011; Ghulam et al., 2008). This index value can be used as an indicator to classify regions based on their level of water vulnerability, ranging from safe to extreme.

Several previous studies at the local level have used the conventional WSI approach to map water-vulnerable villages, including in Sabu Raijua Regency. However, this approach tends to be static and fails to integrate multidimensional variables that influence water vulnerability, such as climatological factors, water infrastructure, socioeconomic characteristics, and geographic conditions (Gain, 2012; El Garouani et al., 2024; Ahmadalipour, 2017; Pandey et al., 2010; Aroca-Jiménez et al., 2022; Tanim et al., 2022; Mengistu et al., 2025). Water vulnerability is a complex phenomenon that requires comprehensive analysis through a modeling approach capable of capturing the interactions between variables.

Based on these conditions, this study aims to develop a predictive multivariate model based on the Water Stress Index that is able to estimate the level of water vulnerability of villages in Sabu Raijua Regency until 2045. This model will be built based on data on water availability (river discharge, springs, reservoirs), water needs (household, agriculture, livestock), as well as other explanatory variables such as rainfall, population growth, access to water infrastructure, and geographical conditions. The development of this model also considers climate change projections and regional development trends, so that the results can be used as a basis for long-term drought adaptation planning (Liu et al., 2025; Bayatavrkeshi et al., 2023; Lee et al., 2022; Zellou et al., 2023). The problem formulation in this study is to analyze the influence of the main variables determining WSI in the NTT archipelago region which tends to have a semi-arid climate based on multivariate analysis, as well as mapping the level of water vulnerability in the future spatially-temporally, and providing data-based information for planning targeted clean water policies in Sabu Raijua Regency.

The scope of this study is limited to the Sabu Island region. The analysis does not include Raijua District due to differences in biophysical conditions, geographical separation, and water source characteristics that are not comparable to the five sub-districts on Sabu Island. This focus is necessary to maintain model consistency and the validity of the multivariate analysis.

Methods

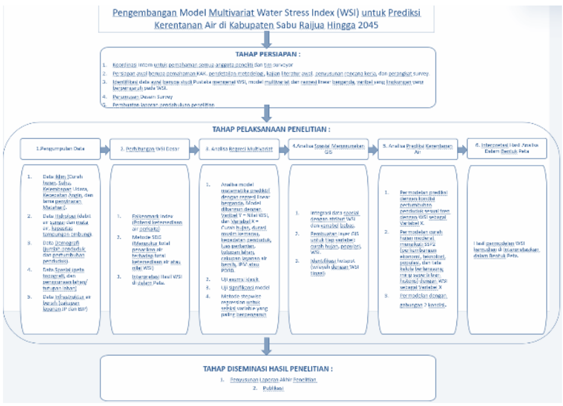

Figure 1. Research Flowchart

The approach used in this research is quantitative predictive, with multivariate and spatial analysis. This research aims to predict by examining the complex relationships between several independent and dependent variables, as well as understanding relationship patterns

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and trends using geographic information systems (Santikayasa, 2022). A detailed overview of the work flow can be seen in Figure 1, a flowchart of the research plan.

The steps of the research plan are as follows:

The explanation of the steps for implementing the research is as follows:

Preparation Stage

The initial phase began with internal coordination between the research team and surveyors to ensure a shared understanding of the work plan, methods, and survey tools to be used. This phase also included developing the methodology design, reviewing literature related to WSI and multivariate regression, and conducting an in-depth literature review of the variables determining WSI. The team also conducted an initial identification of the availability of secondary data through communication with government agencies in Sabu Raijua Regency. The formulation of the survey design and the preparation of a preliminary report were carried out at this stage to serve as technical guidance before entering the field.

Research Implementation Stage

This stage involves the main technical activities of the research. It begins with data collection, including climate data (rainfall, temperature, humidity, wind, and sunshine duration), hydrological data (river discharge, reservoir capacity, and spring discharge), demographic data (population size and growth), and spatial data (topographic and land use maps from satellite imagery). Clean water infrastructure data is also collected from the local BLUD SPAM and the PUPR Department.

Next, the basic WSI calculation is carried out using two approaches, namely:

Falkenmark Index :

$$WSI_{kapita} = \frac{Annual\ water\ availability(m^3)}{Total\ population} \qquad (1)$$

The WSI value is then classified with a value of <1700 m^3/capita/year meaning water stress, <1000 m^3/capita/year meaning water scarcity, and <500 m^3/capita/year meaning extreme scarcity (Falkenmark, 1989).

SDG Method 6.4.2,:

$$WSI = \frac{Total\ water\ intake}{Total\ Water\ Availability} \times 100 \quad (2)$$

Classified into values <25% meaning low pressure level (safe), 25-50% meaning medium pressure level, 50-75% meaning high pressure level, >75% meaning very high pressure level (United Nations, 2022).

The results of the 2 WSI models are then presented in the form of a WSI value distribution map.

Multivariate regression analysis was conducted to model the relationship between WSI (as the dependent variable) and several independent variables such as rainfall, dry season duration, population density, agricultural area, land cover, clean water service coverage, HDI, or GRDP. The model was developed using multiple linear regression and evaluated through classical assumption tests (normality, multicollinearity, homoscedasticity) and significance tests (t- and F-tests) (Gain, 2012; Santikayasa, 2022; Iheaka, 2025; Fransisca et al., 2026; Pratiwi & Septiani, 2025). To obtain the best model, a variable selection technique using stepwise regression was used.

General model of multivariate regression:

$$WSI = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn + \varepsilon (3)$$

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WSI = Water Stress Index value (dependent variable), $X_1 \ldots X_n$ = independent variable, β = regression coefficient, ε = error.

Spatial analysis using GIS was conducted by integrating attribute data (WSI, population, rainfall) into a spatial map of the Sabu Raijua region. Thematic map layers were created for each variable, and WSI values were classified to identify hotspot areas with high vulnerability levels (Santikayasa, 2022; Mubarak, 2024; Jasim et al., 2024; Sola-Caraballo et al., 2025).

Results and Discussion

Compilation of Research Variables

Variable Y

This study uses a quantitative approach with the aim of building a multivariate Water Stress Index (WSI) model to predict the level of water vulnerability in Sabu Raijua Regency. Therefore, the research variables are arranged into two groups, namely the dependent variable (Y) and the independent variable (X). The Water Stress Index (WSI) values for the base year 2023 and the projection for 2033 used as the dependent variable (Y) in this study were obtained from previous research conducted by the author. The WSI calculation is explained in detail in the manuscript "Water Criticality Analysis Based on the Water Stress Index in Sabu Raijua Regency, NTT" which is currently under review in the Civil Engineering Journal of Maranatha University.

The WSI value is calculated based on the Water To Availability (WTA) method and the WSI classification of Samsudin et al. (2015), by considering the total water demand and total water availability that have been validated using the mainstay discharge from the FJ Mock simulation and field measurements. The distribution of WSI values in the study area is as shown in Figure 2.

Variable X

The independent variables in this study consist of eight variables (X1–X8), selected based on their theoretical relevance to water stress formation, data availability, and the results of initial correlation analysis. These eight variables represent demographic aspects, water demand, seasonal climate conditions, water supply, and clean water services.

Population Density: This variable reflects the population pressure on domestic water demand. The higher the population density, the greater the potential water demand. The highest values are found in Hawu Mehara (307.47) and East Sabu (265.92). The lowest is in Central Sabu (116.75). This variable is one of the main indicators of demand pressure in the WSI model.

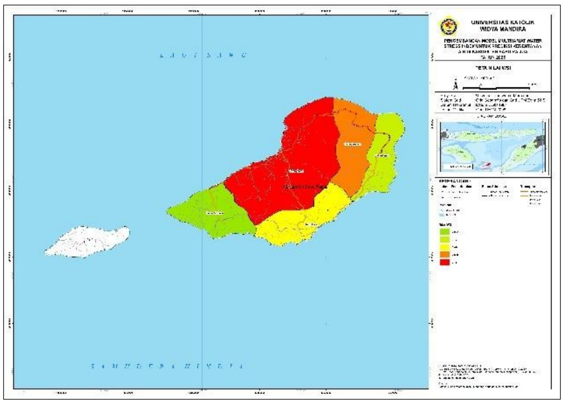

Figure 2. WSI Value in Sabu Raijua Regency

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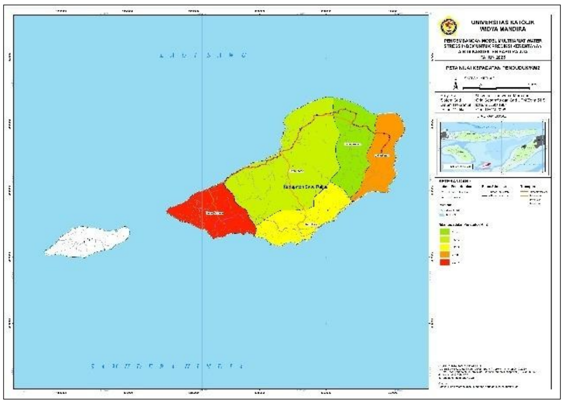

Figure 3. Population Density Value of Sabu Raijua Regency

Area: Area is considered to assess ecological capacity to accommodate water resources and population distribution. Largest area: West Sabu (185.16 km²) Smallest area: East Sabu (37.21 km²). This variable serves more as a control variable and is used to normalize several ratios.

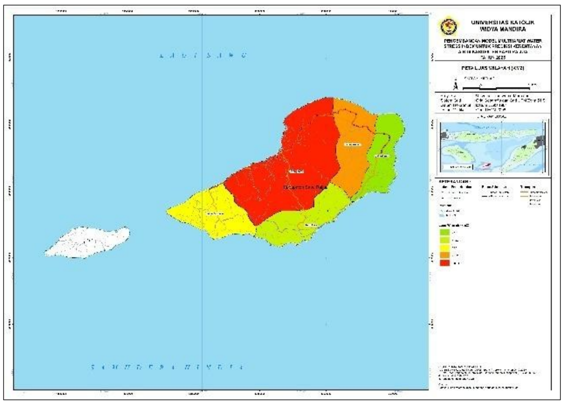

Figure 4. Area of Sabu Raijua Regency

Water Needs in 2023: This variable is the result of medium-term water demand projections based on population growth over the next 10 years. Highest: West Sabu (2,32017 m³/second) Lowest: Hawu Mehara (0.02614 m³/second) This variable is used for the WSI prediction model in 2033.

Water Demand in 2033: This variable represents the projection of medium-term water demand based on population growth over the next 10 years. Highest: West Sabu (2,32017 m³/second), Lowest: Hawu Mehara (0.02614 m³/second). This variable is used for the WSI prediction model in 2033.

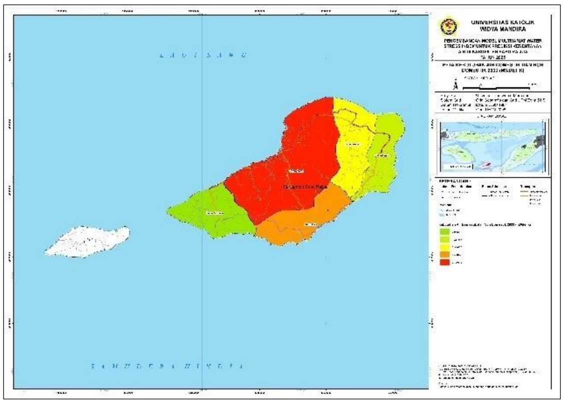

Figure 5. Water Requirements in 2033 for Sabu Raijua Regency

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Wet Spell: Wet spell indicates the length of consecutive rainy periods and reflects the level of natural water availability from rainfall. Across all sub-districts on Sabu Island, the value ranges from 7 to 9 days. Due to its small variation, this variable is used as a climate control, although its statistical impact is weak.

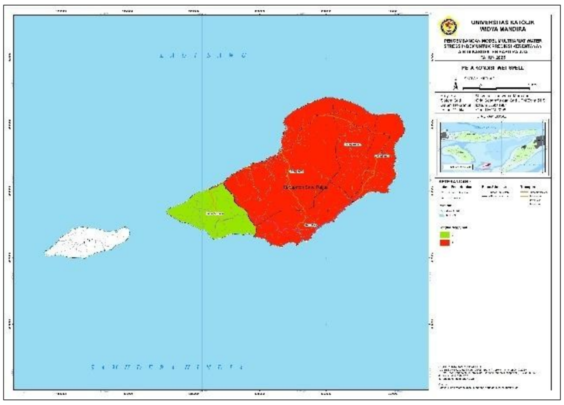

Figure 6. Wet-Spell Conditions in Sabu Raijua Regency

Dry Spell: Dry spell measures the length of consecutive periods without rainfall and is related to drought risk. Values range from 105 to 140 days. Hawu Mehara District exhibited the highest dry spell (140 days). This variable is theoretically important, but initial analysis showed relatively limited variability between districts.

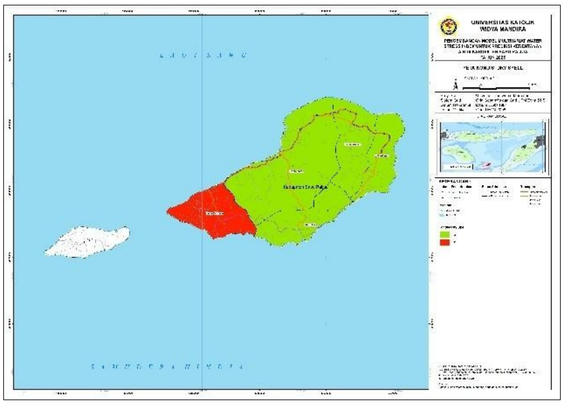

Figure 7. Dry-Spell Conditions in Sabu Raijua Regency

Water Availability: This is the water supply capacity from springs, reservoirs, and other water sources. Highest: West Sabu (0.59007 m³/second) Lowest: Central Sabu (0.1434 m³/second). This variable is the main factor that reduces WSI in the multivariate model.

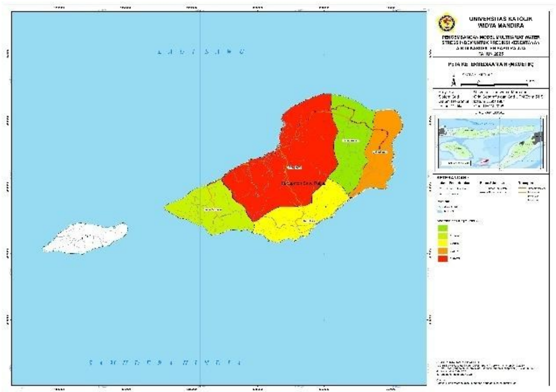

Figure 8. Water Availability Conditions in Sabu Raijua Regency

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Clean Water Service Coverage: Percentage of the population served by the SPAM/BLUD network. Highest: East Sabu (27%) Lowest: Sabu Liae (0%). This variable is important in the context of basic public services, although its statistical impact on WSI is relatively small.

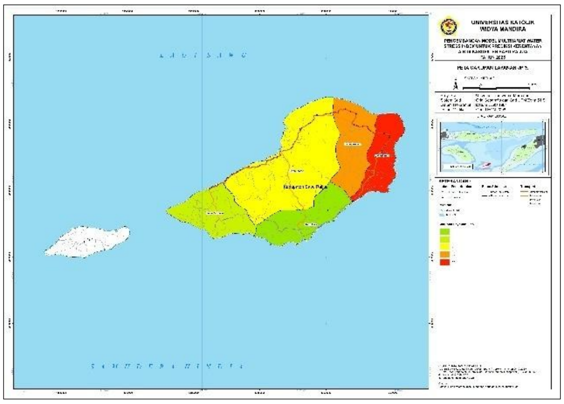

Figure 9. Conditions of Water Service Coverage in Sabu Raijua Regency

These eight variables were used as input in a multivariate model to analyze the factors that most influence the Water Stress Index (WSI) values in five sub-districts on Sabu Island. By combining variables such as water demand, water availability, population conditions, and climate factors, the developed multivariate model is able to describe water vulnerability conditions more comprehensively.

Multivariate Analysis

The Pearson correlation test was conducted to examine the linear relationship between variables and provide a statistical basis for determining which variables are suitable for inclusion in the multivariate model. The correlation table shows the direction, strength, and significance of the relationship between the X variables (population density, water demand, water availability, climate conditions, and water service coverage) and the Y variable (WSI).

Main findings of the correlation test:

Variables with strong correlation to WSI:

X3 – Water Needs ($r \approx 0.86$) → very strong positive relationship

X7 – Water Availability ($r \approx 0.66$) → strong negative relationship

X1 – Population Density ($r \approx -0.75$) → inverse relationship but theoretically significant

Variables with weak correlation:

X8 – Clean water service coverage

X5 – Wet spell condition

X6 – Dry spell condition

X2 – Area

Weakly correlated variables are considered only as alternative or theoretically controlled variables, not as the main variables of the model.

Implications of correlation test:

X3 and X7 are the most empirically influential variables on WSI.

X1 is maintained because of its high theoretical relevance (demand driver).

Climate variables (X5, X6) have small variations between sub-districts so their influence on WSI is not strong.

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Variable X8 (service coverage) is policy-important but not statistically significant.

The results of this correlation form the basis for selecting variables for the next step in multivariate modeling.

Variable selection for multivariate modeling was based on a combination of correlation test results, theoretical considerations, and consistent data availability for five sub-districts on Sabu Island. This step is crucial to ensure the resulting model is parsimonious (simple but able to optimally explain data variability) and relevant to the hydrological context of a dry area like Sabu Island.

The selection of variables takes into account three main aspects:

Significance of Correlation

Variables that have a strong correlation with the WSI are more suitable for inclusion in the main model.

From the Pearson correlation results:

X3 (Water Needs) → strongest correlation with WSI

X7 (Water Availability) → strong correlation and opposite direction

X1 (Population Density) → moderate–strong correlation and theoretically important

Theoretical Relevance

Literature shows that water stress is determined by two main components:

Water demand pressure → influenced by population size/density and water needs

Water supply capacity → determined by spring discharge, reservoir capacity, and effective rainfall

Variables X1, X3, and X7 are in accordance with the structure of the theory.

Consistency and Range of Data Variation

Climate variables such as X5 (wet spell) and X6 (dry spell) have too small a range of variation between sub-districts, causing their contribution to be very weak in the model.

Variable X8 (clean water service coverage) is important for policy analysis, but its statistical correlation is low.

Based on the evaluation results:

Main Models use X1, X3, X7

Alternative Model using X1, X3, X8

The main model is used for predictive analysis and technical policy formulation, while the alternative model is used to see the sensitivity of the results to water service variables.

The next step is to perform multivariate modeling using the regression/SEM-PLS method to determine the direction, magnitude, and significance of each variable's influence on the Water Stress Index. The results of the multivariate modeling are presented in the following subsection.

Model 1 Analysis Results

Model 1 is the main model developed in this study with the aim of predicting the Water Stress Index (WSI) value based on three main independent variables, namely:

X1 – Population Density,

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X3 – Water Requirements, and

X7 – Water Availability.

The relationship structure between variables in Model 1 is constructed as follows:

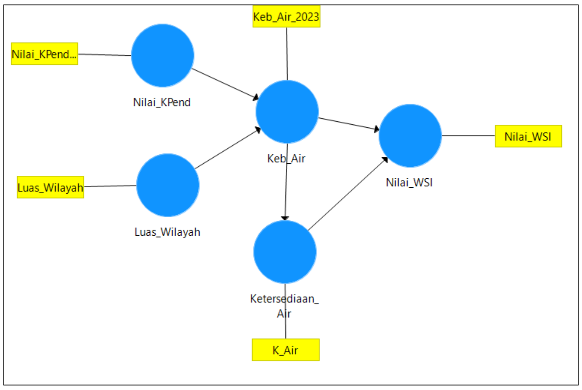

Figure 10. Model 1

With the interpretation that population density affects water needs, water needs affect WSI, while water availability has a direct influence in reducing WSI.

Path Coefficients

The results of the calculation of Model 1 using SmartPLS show the path coefficient values as follows:

Table 1. Direct Effect of Model 1

Track	Coefficient	Meaning
X1 → X3	0.003	very small positive influence (not significant)
X3 → Y (WSI)	2,040	very strong and significant positive influence
X7 → Y (WSI)	–1,253	strong and significant negative influence

Water demand (X3) is the most dominant variable in increasing WSI. The higher the total water demand, the greater the water pressure (WSI) in the sub-district.

Water availability (X7) has a direct impact on reducing the WSI value. This means that districts with a greater water supply have lower levels of water vulnerability.

Population density (X1) does not have a direct significant effect on water demand (X3), but in theory still plays a role as a determinant of water demand.

Indirect Effects

Based on the results:

Table 2. Indirect Effect of Model 1

Indirect Path	Mark	Meaning
X1 → X3 → Y	0.003 × 2.040 = 0.00612	indirect contribution is very small
X7 → X3 → Y	no path	–

The indirect effect of X1 through X3 is almost insignificant. This means that X1's contribution to WSI in this model is very small and is mostly influenced by the other two variables (X3 and X7).

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Total Effects

Table 3. Total Influence of Model 1

Variables	Total Effect on WSI	Information
X3 – Water Requirements	2,040	greatest influence (positive)
X7 – Water Availability	−1,253	big negative impact
X1 – Population Density	≈ 0.006	almost no effect

Interpretation:
The model shows that water stress on Sabu Island is primarily caused by the large water demand and limited water availability, not by direct demographic factors.

From the results of the analysis of Model 1, it can be concluded that:

Water requirements (X3) are the factors that have the greatest influence on increasing WSI.

Water availability (X7) is a factor that significantly suppresses the WSI value, so that areas with low water supply have the potential to experience high water stress.

Population density (X1) does not show a statistically significant influence, although theoretically it remains relevant as a driving factor for water needs.

Model 1 can be used as the main WSI prediction model for Sabu Island because it is in accordance with the supply–demand theory and has the most stable statistical results.

Model 2 Analysis Results

Model 2 was developed as an alternative model to examine the extent to which the clean water service variable (X8 – Clean Water Service Coverage) influences the Water Stress Index (WSI) value. In this model, variable X7 (water availability) is replaced with X8, so the analysis path structure becomes:

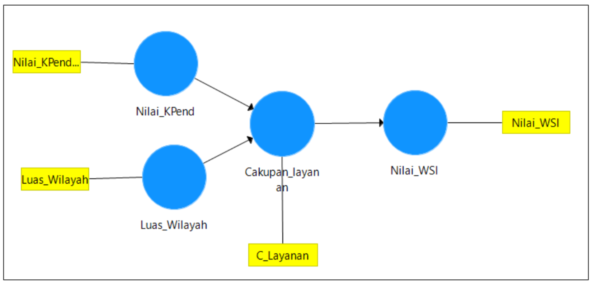

Figure 11. Model 2

The aim of Model 2 is to test the sensitivity of WSI to clean water infrastructure, and compare it with Model 1 which uses pure hydrological variables (water availability).

Path Coefficients

The SmartPLS calculation results for Model 2 show the following values:

Table 4. Direct Effect of Model 2

Track	Coefficient	Interpretation
X1 → X3	0.003	very small, insignificant
X3 → Y (WSI)	2,040	remains the dominant, significant variable
X8 → Y (WSI)	0.017	very small, insignificant

Main Interpretation:

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X3 → Y remains the most influential path, just like Model 1.

X8 → Y has a very low coefficient value, indicating that the coverage of clean water services does not directly affect WSI.

Low service coverage in almost all sub-districts causes small data variability → statistical contribution becomes weak.

Indirect Effects

Table 5. Indirect Effect of Model 2

Indirect Path	Mark	Information
X1 → X3 → Y	0.00612	very small and insignificant
X8 → X3 → Y	no path	—

There is no mediation path from X8 to WSI because the model does not connect X8 → X3.

Total Effects (Total Influence on WSI)

Table 6. Total Influence of Model 2

Variables	Total Effect	Meaning
X3 – Water Requirements	2,040 (dominant)	main factors causing water stress
X8 – Water Service Coverage	0.017 (almost zero)	has no significant influence
X1 – Population Density	0.006	insignificant

Total Effect Conclusion:

Model 2 shows that clean water services (X8) are not a determining factor for WSI on Sabu Island.

Clean water infrastructure is low across the board → causing its statistical impact to be small.

Model 2 is statistically weaker than Model 1.

Some reasons why Model 2 is statistically weak:

Water service coverage (X8) is low and similar across sub-districts. Only East Sabu has relatively better coverage. The other four sub-districts have very low coverage (0–5%). Therefore, small data variability → low correlation → weak path coefficient. The WSI is much more determined by pure water supply and demand (X3–X7). The WSI is by definition a hydrological index, not a water service index. X8 only indicates access, not water source capacity. The supply-demand model (Model 1) is more in line with the theoretical structure of the WSI. Therefore, Model 2 is naturally weak.

From the results of the analysis of Model 2, it can be concluded that:

Clean water service coverage (X8) does not have a significant influence on the WSI value at the sub-district level on Sabu Island.

Water demand (X3) remains the variable with the greatest influence on WSI, the same as in Model 1.

Model 2 is less recommended as the main model for WSI prediction due to its low statistical significance and theoretical inconsistency compared to Model 1.

However, Model 2 provides an illustration that improving clean water services does not automatically reduce the WSI value, because the WSI is more determined by physical-hydrological factors.

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Comparison of Model 1 and Model 2

After analyzing Model 1 and Model 2, the next step is to compare the performance of the two models to determine the most appropriate model for predicting the Water Stress Index (WSI) level in the Sabu Island area. The comparison is based on three main indicators, namely: (1) the significance of the variable's influence, (2) the strength of the path coefficient, and (3) the model's suitability to the water supply-demand theory. Comparison Based on Path Coefficients

Path Coefficients of Model 1

X1 → X3 = 0.003

X3 → Y = 2.040

X7 → Y = –1.253

Path Coefficients of Model 2

X1 → X3 = 0.003

X3 → Y = 2.040 (same as Model 1)

X8 → Y = 0.017

Interpretation:

X3 (Water Needs) is the dominant variable in both models (largest and most significant influence).

X7 (Water Availability) in Model 1 has a strong negative influence (–1.253), thus clearly reducing WSI.

X8 (Clean Water Service Coverage) in Model 2 has a very small coefficient (0.017), which means it has no significant influence on WSI.

Table 7. Comparison of Total Effects Across Model 1 and Model 2

Variables	Model 1 (Total Effect)	Model 2 (Total Effect)	Notes
X3	2,040	2,040	Consistently dominant
X7	–1,253	—	Big & significant influence
X8	—	0.017	Very little influence
X1	0.006	0.006	Not statistically significant

Model 1: High Theoretical Relevance

Model 1 aligns with the basic theory of WSI:

WSI = f(Demand, Supply)

Demand → X3

Supply → X7

WSI is a hydrological indicator, so water availability factors must be a major part of the model.

Model 2: Weak Theoretical Relevance

Clean water service coverage (X8) is not included in the basic components of WSI because:

ISSN: 2716-3865 (Print), 2721-1290 (Online)

WSI does not assess the quality of service, but rather the physical pressure between water demand and supply.

X8 only describes community access, not water supply capacity.

Table 8. Model Performance Comparison (Summary)

Aspect	Model 1	Model 2	Conclusion
Dominant variable	X3	X3	Same
WSI suppressor variables	X7 (strong)	There isn't any	Model 1 is more valid
Additional variables	X1	X1	Same
Theoretical suitability	Very suitable	Weak	Model 1 is superior
Significance of variables	Tall	Very low	Model 1 is superior
Model stability	Tall	Low	Model 1 is superior

From all the indicators compared, it can be concluded that:

Model 1 is the most appropriate and most valid model used to predict the Water Stress Index on Sabu Island.

This is supported by:

Conformity with WSI (supply–demand) theory.

Strong and significant path coefficients.

Variable X7 (water availability) is the main determinant of WSI.

Model 2 does not show a significant influence of X8 (water service coverage).

Model 1 has a more stable relationship structure and can be used as a basis for regional water policy.

Thus, Model 1 is used as the main model of WSI prediction analysis in this study.

The modeling results indicate that water demand (X3) is the most dominant factor in increasing the Water Stress Index (WSI) value, where population growth, domestic activities, and productive needs directly contribute to increasing water stress. Conversely, water availability (X7) acts as a WSI stressor and is the main determinant of water security on Sabu Island, so increasing supply through strengthening springs, reservoir rehabilitation, rainwater storage technology, and reducing network leakage are key mitigation strategies. Although population density (X1) is not statistically significant, this variable remains important as a structural indicator of long-term water demand and should be considered in spatial planning and settlement development policies. Clean water services (X8) also do not directly influence the WSI because this index by definition reflects physical hydrological conditions, not service access; therefore, clean water network expansion is only effective if accompanied by increased supply capacity. The model also indicates a priority of water vulnerability, with Sabu Tengah and Sabu Liae Districts as the most vulnerable areas, followed by East Sabu, while West Sabu and Hawu Mehara are relatively safer. Based on all these findings, the direction of water security policy needs to be focused on controlling demand (demand management), increasing supply (supply enhancement), integrating water capacity-based spatial planning, and optimizing clean water infrastructure with a priority on increasing production capacity and reducing water loss to strengthen Sabu Island's water security.

Based on the modeling results, Model 1, which combines the variables of population density (X1), water demand (X3), and water availability (X7), is then used as a basis for projecting

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the Water Stress Index (WSI) until 2045. Although the model is calibrated using data from the base year 2023 and projections until 2033, the stable causal relationship structure between X3 and X7 on the WSI allows this model to be applied for a long-term horizon through a scenario approach. The 2045 WSI projection is carried out by projecting water demand variables based on population growth and assumed per capita needs, as well as modeling water availability based on scenarios of existing conditions, increased water source capacity, and potential declines due to climate change. With this approach, the 2045 WSI value is not positioned as a deterministic prediction, but rather as a depiction of a long-term water vulnerability scenario that can be used as a basis for planning water security policies on Sabu Island.

Table 9. Projected Population and Water Needs in 2045

Amount of Water Required (ltr/sec)	
Population (People)	**Domestic and Non-Domestic Water Needs (ltr/second)**
2045	2045
40489	2,323
24201	0.034
14648	0.217
13768	0.435
9179	0.350

To calculate the WSI value with Model 1, namely the equation:

$$Y = 2.040X3 - 1.253X7$$

So the WSI value results are as follows:

Table 10. WSI Analysis Model Results

Subdistrict	WSI Value			
Parameter	**2023 analysis results**	**2023 multivariate model results**	**2033 multivariate model results**	**2045 multivariate model results**
West Sabu	3,888	3.940165083	3.993794027	3.998673245
Hawu Mehara	0.092	-0.196957243	-0.178276177	-0.161866854
East Sabu	0.728	0.064705597	0.0764028	0.087875334
Sabu Liae	2,024	0.602355559	0.613781459	0.623039459
Central Sabu	2,399	0.520942395	0.530451305	0.533802875

The Mean Absolute Error (MEA) value of 0.86 and RMSE of 1.07 indicate that the multivariate model has a moderate error rate in predicting the absolute value of the WSI in 2023. However, the model is able to consistently represent the spatial pattern of water vulnerability between sub-districts, especially in identifying areas with high and low water stress. The large relative error in sub-districts with low WSI values is due to the sensitivity of the percentage metric to the actual value which is close to zero, so it does not indicate a structural weakness of the model. The analysis results table shows that the Water Stress Index (WSI) value on Sabu Island has a consistent spatial and temporal pattern from 2023 to the 2045 projection. West Sabu Sub-district consistently recorded the highest WSI value and experienced a gradual increase, indicating a very high and sustainable level of water vulnerability. Central Sabu and Sabu Liae Sub-districts are at a medium level of water stress

ISSN: 2716-3865 (Print), 2721-1290 (Online)

with a moderate increasing trend over time. East Sabu District exhibited a low but gradually increasing WSI value, while Hawu Mehara maintained its lowest WSI value throughout the analysis period. The alignment between the analysis results for the 2023 base year and the multivariate model results for 2023, 2033, and 2045 indicates that the model consistently represents the dynamics of water vulnerability across districts and is suitable for use in long-term projections. Negative WSI values in several districts reflect the modeling results relative to reference conditions and do not indicate an absolute absence of water stress.

Conclusion

This study shows that the level of water vulnerability on Sabu Island is influenced primarily by the dynamics of water demand and water availability capacity in each sub-district. The results of multivariate modeling confirm that water demand (X3) is the most dominant factor in increasing the Water Stress Index (WSI) value, while water availability (X7) plays a significant role in reducing water stress levels and is the main determinant of regional water security. Population density (X1) and clean water service coverage (X8) do not have a statistically significant effect on WSI, but remain relevant as structural indicators of water demand and access to basic services in long-term planning. Spatial and temporal analysis shows that West Sabu Sub-district consistently has the highest level of water stress until the projection year 2045, while Central Sabu and Sabu Liae Sub-districts are at a medium level of vulnerability, and East Sabu and Hawu Mehara Sub-districts are relatively lower. The consistency of the pattern between the analysis results for the base year 2023 and the results of the multivariate model in 2023, 2033, and 2045 indicates that the developed model has good structural validity and stability. Therefore, this WSI multivariate model is suitable for use as a predictive tool and support for the formulation of water security policies, with an emphasis on controlling water demand, increasing supply capacity, integrating spatial planning based on water carrying capacity, and optimizing clean water infrastructure to strengthen the long-term water security of Sabu Island.

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