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Unveiling regional drivers of the blue economy in Sumatra: A multiscale space–time regression analysis with variable selection

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Abstract

Indonesia, as a maritime country, positions the blue economy as a cornerstone in the 2025–2045 National Long-Term Development Plan (RPJPN) to support sustainable economic growth, particularly through the development of the fisheries sector and marine tourism. This study aims to construct a Blue Economy Index (BEI) at the district/city level and identify its key determinants using the Regression Weighted Geographic and Temporal Multiscale (MGTWR) method. The BEI is based on environmental, social, and economic dimensions using data from 2020 to 2022 across 154 districts/cities on Sumatra Island. The analysis incorporates 14 predictor variables grouped into four dimensions and selected through Group LASSO and Elastic Net methods. The best-performing model is the RTGTM with Group LASSO variable selection and a Gaussian kernel function, yielding an R^2 of 30.71% and an AIC of 1377.52. The social dimension contributes most to the BEI, while Medan City and Subulussalam City consistently record the highest and lowest scores. Significant variables influencing BEI include population factors (number of sub-districts, total population, sex ratio), education factors (number of senior high schools and vocational schools), and environmental indicators (protected drinking water sources and sanitation access). These findings underscore the importance of multi-dimensional, spatial, and temporal approaches in evaluating and advancing blue economy policies at the regional level.

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INTRODUCTION

Blue economy is a development concept that focuses on the sustainable utilization of marine resources to support economic growth, community welfare, and environmental sustainability (Martínez-Vázquez et al., 2021; Phang et al., 2023; Wuwung et al., 2022). Blue

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economy mapping is needed to identify the potential and challenges in its management. Indonesia, as a maritime country, has great potential, but its utilization is uneven. The Indonesia Blue Economy Index (IBEI) shows that Sumatra Island is still lagging behind with an average score of 40.43, far below East Java, which reached 87.36, despite Sumatra contributing 22.01% to national GDP in 2023. This shows the need for better mapping to optimize the potential of the blue economy in a sustainable manner.

Blue economy measurement tools play an important role in assessing the sustainability of marine resource utilization in various regions. ARISE+ has developed the IBEI with three main dimensions: environmental, economic, and social to measure blue economy performance at the provincial level (Kementerian PPN, 2023). The IBEI assists the government and stakeholders in comparing blue economy implementation between regions in a more structured manner. However, a more detailed measurement tool to assess blue economy development at the local level is still not available. Therefore, a Blue Economy Index (BEI) will be developed that adopts the IBEI dimensions and uses the same calculation method as the Human Development Index (HDI) in order to provide a more accurate picture of the condition of the blue economy at the local level.

Spatial modeling is essential in the blue economy to understand the distribution of potential and challenges across regions. However, traditional spatial modeling approaches are often static and do not account for changes over time. Previous research, such as Aghnyn et al. (2024), applied Statistical Downscaling (SD) and Integrated Nested Laplace Approximation (INLA) to map the blue economy, but these results were limited to global regressions that failed to capture local variations and temporal dynamics. Until now, few studies have applied spatio-temporal modeling, despite the fact that this method allows for the simultaneous analysis of changes in the blue economy in both space and time. Christina et al. (2025) made an important contribution by applying spatio-temporal modeling to analyze changes in the blue economy, although its application remains limited in terms of scope and local level. Therefore, a more accurate spatio-temporal approach is needed to fully understand the dynamics of the blue economy and map its potential at the local level. This research extends the application of spatio-temporal modeling further by using MGTWR, which enables a deeper analysis of changes in the blue economy at the regional and local levels, providing more precise insights into spatial and temporal dynamics.

Geographically Weighted Regression (GWR) is used in spatial modelling with kernel functions and bandwidth to capture local variations (Cellmer et al., 2020; Wang et al., 2020). Kernel functions such as Gaussian, Uniform, Bisquare, and Exponential assign weights based on distance from the observation point, allowing the model to emphasize the influence of nearby data and reduce the impact of data farther away. Bandwidth regulates the extent of this influence. A smaller bandwidth isolates the influence to a smaller area, while a larger bandwidth expands the scope of influence. This enables the model to dynamically capture local relationships between variables, which is crucial in analyzing the blue economy at the regional level. However, the traditional GWR model uses a single bandwidth for all variables, which means it cannot capture differences in the degree of influence that different variables might have in different locations. For example, the impact of marine resources on the blue economy may vary between coastal regions and those further inland. Geographically and Temporally Weighted Regression (GTWR) adds a time dimension to account for changes in the blue economy over time, but it still uses a single bandwidth for all variables (Liu & Dong, 2021; Zhang et al., 2019). Multiscale Geographically and Temporally Weighted Regression (MGTWR), which is used in this research, allows each variable to have a flexible bandwidth, providing greater flexibility in capturing changes across different locations and time periods (Liu et al., 2021). Kernel functions are crucial in spatial modeling because they determine the weights assigned to each observation based on proximity, which directly influences how local variations are captured. These kernel functions, such as Gaussian, Uniform, and Exponential, are essential in emphasizing relevant spatial relationships by ensuring that observations closer to the center of the analysis have more influence, while distant observations have less impact. Without the proper use of kernel functions, the model would fail to reflect the local dynamics accurately, which is essential when analyzing regional systems like the blue economy. However, in the study by Wu et al. (2019), the kernel types used in MGTWR are not specified, making it difficult to gain insights regarding the choice and comparison of kernels. The absence of this detail limits our understanding of how different kernel types may influence the results. Our research aims to fill this gap by using flexible bandwidth for each variable, allowing for a more detailed and accurate model of spatial and temporal dynamics in the blue economy. By comparing kernel types, we can better understand their impact on the model and improve the robustness of our findings.

Multicollinearity in regression causes parameter estimates to be unstable, so a variable selection method is required (Chan et al., 2022; Oghenekevwe Etaga et al., 2021). Least Absolute Shrinkage and Selection Operator (LASSO) is used to select variables by adding an L1 penalty, which can shrink the coefficient to zero (Aheto et al., 2021; Emmert-Streib & Dehmer, 2019). However, LASSO can only select one variable in a group of highly correlated variables, so it may ignore other variables that are also influential. Group LASSO and Elastic Net were developed to overcome the limitations of LASSO in variable selection. Group LASSO maintains a group of interrelated variables, while Elastic Net combines L1 and L2 penalties to be more flexible in selecting highly correlated variables so as to reduce bias due to multicollinearity (Altelbany, 2021; Bastiaan et al., 2022; Huang et al., 2024). This study aims to calculate the BEI and make it a response variable, different from previous studies that have not modeled BEI explicitly. This research will select variables that affect BEI using Group LASSO and Elastic Net before modelling it with MGTWR, which is then applied with a variety of kernels (Gaussian, Uniform, Bisquare, and Exponential) to capture spatial and temporal variations more accurately.

The next section of this paper will describe the dataset used for the study, calculate the blue economy index, select variables with Group LASSO and Elastic Net, determine kernel variation, model GTWR, determine the spatio-temporal distance function, and model MGTWR in Section 2. Section 3 will present the BEI results, variable selection results, assumption tests, model comparison, and mapping. Section 4 will provide conclusions.

METHOD

The first step in this research is the collection of variables that will be used to construct the Blue Economy Index (BEI), along with the identification of variables that may influence the BEI. This index will be developed using an approach similar to the Human Development Index (HDI) calculation, incorporating environmental, economic, and social dimensions. Once the BEI calculation is completed, the resulting BEI values will be used as the response variable in the analysis model. Subsequently, the next step involves performing variable selection on the relevant variables to identify those that significantly affect the BEI. This selection process utilizes Group LASSO and Elastic Net techniques to reduce multicollinearity among the variables and select those that have a significant impact on the BEI. Figure 1 illustrates the methodology flowchart that outlines the steps involved in the analysis process.

After the variable selection stage, the subsequent step involves modeling using Multiscale Geographically and Temporally Weighted Regression (MGTWR), which accounts for both spatial and temporal variations. This modeling process employs various kernel functions (such as Uniform, Gaussian, Bisquare, and Exponential) to capture the relationships between variables at different locations and times. With this approach, the model is expected to provide a more accurate representation of the dynamics of the blue economy affecting development in Sumatra. The final step involves result analysis, which identifies significant variables that contribute to the

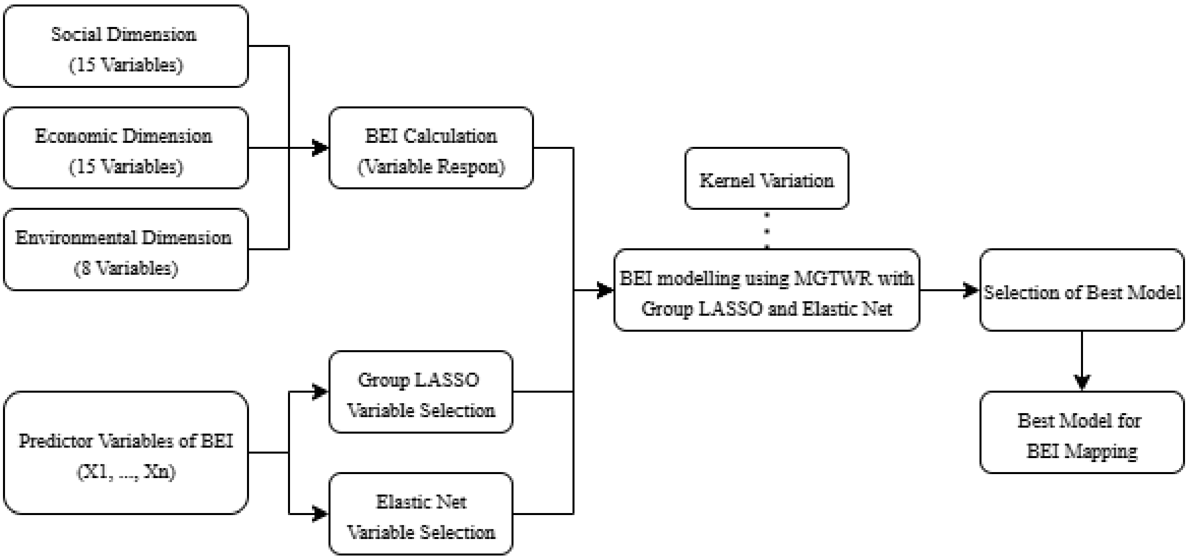


Figure 1. Research Methodology for the Development and Modelling of the BEI

BEI, as well as the BEI distribution map that illustrates variations across districts/cities during the 2020-2022 period.

Dataset

This research analyzes spatio-temporal data and calculates the index with a statistical approach. Spatio-temporal data has the unique characteristic of combining information on geographic location and time, allowing the analysis of relationships between variables in the context of space and time. This data includes response variables, predictor variables, subjects (such as place names or individuals), geographical coordinates, and time spans. This study takes the object of 154 regencies/cities in 10 provinces located on the island of Sumatra in the period 2020-2022 with data sourced from Statistic Indonesia (SI), available at https://www.bps.go.id/id; Ministry of Tourism and Creative Economy (Kemenparekraf), available at https://satudata.kemenparekraf.go.id/; National Waste Management Information System (NWMIS), available at https://sipsn.menlhk.go.id/sipsn/; and Ministry of Marine Affairs and Fisheries (KKP) of the Republic of Indonesia, available at https://statistik.kkp.go.id/home.php. Based on these data, this study calculates the BEI and analyzes the factors that influence the BEI at the district/city level on the island of Sumatra. The variables that will be used in constructing the BEI response variable and predictor variables in modelling the BEI are shown in Table 1 and Table 2. Sumatra shapefile data format is also used to view the geographic information system obtained from https://geosai.my.id/.

Table 1. Blue Economy Index Composing Variables

No	Descriptions	Pillars
1	Land Area for Quiet Water Ponds Enlargement Cultivation	Environment
2	Land Area of Freshwater Hatchery Cultivation	
3	Annual Waste Generation	
4	Annual Waste Management Amount	
5	Annual Waste Recycling Amount	
6	Percentage Distribution of Households with PLN Electric Lighting Sources	
7	Percentage Distribution of Households with Non-PLN Electric Lighting Sources	
8	Percentage Distribution of Households with Non-Electric Lighting Sources	
9	Freshwater Hatchery Aquaculture Fish Production Volume	Economy
10	Quiet Water Ponds Enlargement Aquaculture Fish Production Volume	
11	Inland Public Waters Capture Fishery Fish Production Volume	
12	Freshwater Hatchery Aquaculture Households	

No	Descriptions	Pillars
13	Quiet Water Ponds Enlargement Aquaculture Households	
14	Sea Capture Fishery Households	
15	Inland Public Waters Capture Fishery Households	
16	Number of Sea Business Vessels	
17	Number of Inland Public Waters Business Vessels	
18	Micro and Small Fish Processing Units	
19	Freshwater Hatchery Aquaculture Fish Production Value	
20	Quiet Water Ponds Enlargement Aquaculture Fish Production Value	
21	Inland Public Waters Capture Fishery Fish Production Value	
22	Number of National Tourist Trips by Regency/City of Origin	
23	Number of National Tourist Trips by Regency/City of Destination	
24	Number of Quiet Water Ponds Enlargement Aquaculture Fishermen	
25	Number of Freshwater Hatchery Aquaculture Fishermen	
26	Number of Sea Capture Fishery Fishermen	
27	Number of Inland Public Waters Capture Fishery Fishermen	
28	Open Unemployment Rate	
29	Labor Force Participation Rate	
30	Percentage of Poor Population	
31	Percentage of Population with PBI BPJS Health Insurance	
32	Percentage of Population with Non PBI BPJS Health Insurance	**Social**
33	Percentage of Population with Jamkesmas Health Insurance	
34	Percentage of Population with Private Health Insurance	
35	Percentage of Population with Company Health Insurance	
36	Percentage of Population with Access to Adequate Drinking Water Sources	
37	Number of High School Students Under the Ministry of Education and Culture	
38	Number of Vocational School Students Under the Ministry of Education and Culture	

Table 2. Predictor Variables for BEI Modelling

No	Variables	Descriptions	Dimensions
1	$X_{subdist}$	Number of sub-districts	
2	$X_{village}$	Number of Villages	
3	X_{pop}	Total Population (thousand)	**Population**
4	X_{ratio}	Sex Ratio	
5	X_{poor}	Number of Poor People (thousand)	
6	X_{HDI}	Human Development Index	
7	$X_{highschool}$	Number of High Schools under the Ministry of Education	**Education**
8	$X_{vocschool}$	Number of Vocational Schools under the Ministry of Education	
9	X_{pumped}	Percentage Distribution of Households with Pumped Drinking Water Source	
10	$X_{bottled}$	Percentage Distribution of Households with Drinking Water Sources of Bottled Water	
11	X_{well}	Percentage Distribution of Households with Protected Well Drinking Water Sources	**Environment**
12	$X_{sanitation}$	Percentage of Households with Access to Adequate Sanitation	
13	X_{food}	Average Monthly Per Capita Expenditure on Food	
14	$X_{nonfood}$	Average Monthly Expenditure per Capita on Non-Food Items	**Economy**

Table 1 presents the components of the BEI, structured around three main pillars: environment, economy, and social, each further divided into several sub-pillars. In total, 38 variables contribute to the calculation of the BEI. The social pillar includes variables related to human maritime resource welfare, health, and education. The environmental pillar covers marine resources and energy, while the economic pillar includes tourism, trade, industry, and fish catch. Table 2 shows the 14 predictor variables across four dimensions used in the MGTWR modeling approach to analyze the factors influencing the BEI. These predictor variables will undergo selection using two distinct methods: Group LASSO and Elastic Net, both designed to identify the most relevant variables influencing the BEI.

Blue Economy Index Calculation

This BEI calculation will adopt the calculation conducted by the United Nations Development Programme (UNDP) in calculating the HDI. The calculation of the BEI value will be explained in several steps as follows.

Stage 1. Data normalization using min-max. Normalization is performed so that the variable values x_{ij} have a uniform scale within each dimension. This process ensures that unit differences between variables do not affect the analysis results. The normalized values are expressed as x'_{ij} using the following formula (Henderi, 2021):

$$x'_{ij} = \frac{x_{ij} - \min(x_{ij})}{\min(x_{ij}) - \max(x_{ij})} \tag{1}$$

Stage 2. Dimensional index calculated by arithmetic mean. The I_j dimension index represents the average value of the normalized variables in one particular dimension. This value shows the general trend of the data after the normalization process. This index is calculated using the following formula:

$$I_j = \frac{\sum_{i=1}^{n} x'_{ij}}{n} \tag{2}$$

Stage 3. Overall index calculated by geometric mean. The overall index reflects the combination of all dimensions using the geometric mean method. This approach ensures that each dimension has a balanced influence on the final result. The index is calculated using the following formula:

$$BEI = \left(\prod_{j=1}^{n} I_j\right)^{\frac{1}{n}} \times 100 \tag{3}$$

This approach strengthens the credibility of the BEI by aligning it with international standards like the Human Development Index. By applying both arithmetic and geometric means, it ensures each dimension contributes fairly and prevents any single aspect from dominating the final score. Policymakers can actively use the BEI to assess regional performance, set development priorities, and track progress in building a sustainable and inclusive blue economy across Indonesia's maritime regions.

Variable Selection Method

Group Least Absolute Shrinkage Selection Operator

In statistical modeling, variable selection is crucial, especially when the dataset includes many correlated or irrelevant predictors. The goal is to improve model accuracy, reduce complexity, and enhance interpretability. This process starts with Multiple Linear Regression (MLR), which assumes a linear relationship between the dependent variable and predictors (Shao & Qin, 2024). The model for MLR is written as:

$$y_i = \sum_{j=1}^{p} x_{ij}\beta_j + \varepsilon_i \tag{4}$$

where y_i represents the response value for the i-th sample, x_{ij} is the value of the j-th predictor variable, β_j is the regression coefficient indicating the influence of predictor j, and ε_i is the error term assumed to follow a normal distribution with mean zero and constant variance, $\varepsilon_i \sim N(0, \sigma^2)$. When expressed in matrix form, the model becomes:

$$y = X\beta + \varepsilon \tag{5}$$

where, X is the matrix of predictor variables, and β is the vector of unknown regression coefficients that need to be estimated. The goal is to minimize the residual sum of squares. The traditional method is Ordinary Least Squares (OLS), where the coefficients are estimated by (Shin et al., 2021):

$$\hat{\beta}^{OLS} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y} \tag{6}$$

However, when the matrix X^TX is not invertible due to multicollinearity, Least Absolute Shrinkage and Selection Operator (LASSO) is used. LASSO adds an L1-norm penalty to the OLS objective, shrinking the coefficients toward zero. The LASSO optimization problem is formulated as (Khattak et al., 2021):

$$\hat{\beta}^{L_1} = arg\ min\left\{\frac{1}{2n}\sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda\|\beta\|_1\right\} \tag{7}$$

where, λ controls the regularization strength. The optimal λ is chosen using Cross-Validation (CV), which minimizes prediction error (Takano & Miyashiro, 2020):

$$CV(\lambda) = \frac{1}{K}\sum_{k=1}^{K} e(\lambda)_k \tag{8}$$

While LASSO handles large predictor sets, it treats each predictor individually. Group LASSO addresses this limitation by penalizing entire groups of related predictors, ensuring they are selected or discarded together. The Group LASSO objective is (Li et al., 2020):

$$\hat{\beta} = arg\ min\left\{\frac{1}{2n}\left\|y - \sum_{g=1}^{G} X_g\beta_g\right\|_2^2 + \lambda\sum_{g=1}^{G}\sqrt{p_g}\left\|\beta_g\right\|_2\right\} \tag{9}$$

In this formulation, X_g represents the matrix of predictors within group g, β_g is the vector of coefficients for group g, and p_g is the number of predictors in group g. The term $\sqrt{p_g}$ adjusts for the size of each group, ensuring that larger groups are appropriately penalized. This method allows for a more structured selection process, where entire groups of related variables are chosen or discarded based on their collective importance. Group LASSO is particularly valuable when predictors come from natural groupings, as it preserves the interrelationships between variables within each group, ensuring that the underlying structure of the data is respected.

Elastic Net

Elastic Net combines the strengths of LASSO and Ridge Regression to address issues with correlated predictors. While LASSO can perform variable selection by shrinking some coefficients to zero, it becomes unstable with highly correlated predictors, potentially excluding important variables. Elastic Net overcomes this by combining the L1 penalty (from LASSO) with the L2 penalty (from Ridge Regression), handling multicollinearity effectively and preserving model stability (Altelbany, 2021; Araveeporn, 2021; Tay et al., 2023). The objective function for Elastic Net is as follows:

$$\hat{\beta} = arg\ min\left\{\frac{1}{2n}\|y - X\beta\|_2^2 + \lambda_1\|\beta\|_1 + \lambda_2\|\beta\|_2^2\right\} \tag{10}$$

where, the first term in the Elastic Net objective function, $\frac{1}{2n}\|y - X\beta\|_2^2$ represents the residual sum of squares (RSS), which measures the difference between the observed values y and the predicted values $X\beta$. The RSS reflects how well the model fits the data, with smaller values indicating a better fit (Sloboda et al., 2023). The second term, $\lambda_1\|\beta\|_1$, is the L1 penalty applied to the coefficients β_j. The L1 penalty encourages sparsity in the model by shrinking some of the coefficients to zero (Gollamandala & Kampa, 2021). This results in the selection of only the most important variables, effectively performing variable selection. As a result, less relevant predictors are excluded from the model, leading to a simpler and more interpretable solution. The third term, $\lambda_2\|\beta\|_2^2$ is the L2 penalty, which helps stabilize the model. The L2 penalty reduces the impact of correlated predictors by shrinking their coefficients toward zero, but unlike the L1 penalty, it does not set them exactly to zero. This ensures that the coefficients of correlated predictors are scaled down smoothly, rather than eliminated entirely, providing a balance between variable selection and model stability (Ren et al., 2023).

The Elastic Net penalty combines these two regularization terms, enabling the model to reduce the influence of correlated predictors while performing effective variable selection. The balance between the L1 and L2 penalties is controlled by a parameter α, defined as:

$$\alpha = \frac{\lambda_1}{\lambda_1 + \lambda_2} \tag{11}$$

when, $\alpha = 1$, the model behaves like LASSO (only L1 penalty), and when $\alpha = 0$, it behaves like Ridge Regression (only L2 penalty). This allows Elastic Net to adapt to different situations based on the dataset's characteristics. The parameters λ_1 and λ_2 control the strength of the L1 and L2 penalties, respectively, and their optimal values are typically selected through CV. CV involves testing different values of λ_1 and λ_2 to identify the combination that minimizes the prediction error.

Multiscale Geographically and Temporally Weighted Regression

Geographically Weighted Regression (GWR) is an extension of Ordinary Least Squares (OLS) regression, designed to handle spatial heterogeneity (Cellmer et al., 2020). Unlike traditional regression, GWR allows relationships between predictors and the response to vary spatially. The general form of GWR is:

$$y_i = \beta_{i0} + \sum_{j=1}^{k} \beta_{ij}x_{ij} + \epsilon_i\,,\ \ i = 1, \dots, n \tag{12}$$

where, y_i represents the observed response at location i, β_0 is the intercept, x_{ij} is the j-th predictor at location i, and β_j is the local coefficient for predictor j at location i, while ε_i is the residual at location i.

The coefficient β_j are estimated using OLS with a spatial weight matrix W. The weight matrix W is constructed using a kernel function based on the distance between locations. The model parameters are then estimated by:

$$\hat{\beta}_i = [X^T W_i X]^{-1} X^T W_i y \tag{13}$$

where, X is the matrix of predictor variables; W is the spatial weight matrix, reflecting the distance between location i and all other locations; y is the vector of observed responses.

One limitation of GWR is that it assumes a fixed bandwidth, or spatial scale, for all locations, which may not be appropriate when the spatial relationship between variables changes at different locations Multiscale Geographically Weighted Regression (MGWR) addresses this by allowing the bandwidth to vary locally, optimizing the bandwidth for each location using the backfitting algorithm (Jo & Kim, 2022). The general form of the MGWR model is:

$$y_i = b_{w0}(\beta_{0i}) + \sum_{j=1}^{k} b_{wj}(\beta_{ij}x_{ij}) + \epsilon_i, i = 1, \dots, n \tag{14}$$

where, b_{w0}, b_{w1},…., b_{wk} are the varying bandwidths for each model component. The MGWR model can also be written in Generalized Additive Model (GAM) form as:

$$y = f_{b_{w0}}(\beta_{0i}) + \sum_{j=1}^{k} f_{b_{wk}}(X_k) + \epsilon_i, i = 1, \dots, n \tag{15}$$

where, $f_{b_{w0}}$, $f_{b_{w1}}$,…., $f_{b_{wk}}$ are smoothing functions applied to predictors and b_{wj} are bandwidths for each predictor, optimized to minimize residuals. The bandwidths are calculated as:

$$A_k = \begin{pmatrix} x_{1k}\left(X_k^T W_1 X_k\right)^{-1} X_k^T W_1 \\ \vdots \\ x_{nk}\left(X_k^T W_n X_k\right)^{-1} X_k^T W_n \end{pmatrix}_{n\times n} \tag{16}$$

The covariance matrix of the estimated parameters is given by:

$$C_i = [X^T W_i X]^{-1} X^T W_i \tag{17}$$

where, C_i is the variance-covariance matrix for the estimated coefficients at location i. The standard error of the estimated coefficients is calculated as:

$$V_i = C_i C_i^T \hat{\sigma}^2 \tag{18}$$

where, $\hat{\sigma}^2$ is the estimated variance of the residuals.

The backfitting process in MGWR begins by setting initial values for the local parameters and iterating to converge these values. Convergence is achieved when the change in the RSS between iterations is less than a specified threshold, typically 10^{-5}. The Score of Change (SOC) criterion is used to monitor convergence:

$$SOC_{RSS} = \frac{RSS_{new} - RSS_{old}}{RSS_{new}} \tag{19}$$

where the convergence is met when this value falls below the threshold.
The model's flexibility is also measured by the Effective Number of Parameters (ENP), which is calculated as the trace of the matrix R_k for each predictor:

$$ENP_k = tr(R_k) \tag{20}$$

where, R_k is the spatial weight matrix for the k-th predictor. The total ENP for the model is the sum of the ENPs for all predictors:

$$ENP_{model} = \sum_k ENP_k \tag{21}$$

The final predicted values are obtained using the projection matrix S, which maps the observed data to the predicted values:

$$\hat{y} = Sy \tag{22}$$

where S is the projection matrix that gives the predicted values based on the model parameters. The model's coefficients are updated iteratively to ensure the best fit.

Geographically and Temporally Weighted Regression (GTWR) is an extension of GWR that incorporates both spatial and temporal dimensions (Liu & Dong, 2021; Sifriyani et al., 2022). While GWR captures the spatial variability of relationships between predictor variables and the response variable, GTWR extends this idea by incorporating temporal variation, allowing the model to capture how the relationships change over both space and time. The general form of GTWR is given by:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{j=1}^{p} \beta_k(u_i, v_i, t_i)x_{ij} + \varepsilon_i \tag{23}$$

where, y_i is the response variable at observation point i; $\beta_0(u_i, v_i, t_i)$ is the constant term at location (u_i, v_i) and time (t_i); $\beta_k(u_i, v_i, t_i)$ is the regression coefficient for predictor k; x_{ij} is the j-th predictor at observation i; ε_i is the error term at observation i.

The coefficients are estimated using Weighted Least Squares (WLS) with a spatio-temporal weight matrix W. Based on spatial (d_{ij}^s) and temporal (d_{ij}^T) distances. The combined spatio-temporal distance is:

$$\left(d_{ij}^{sT}\right)^2 = \phi^s\left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \phi^T\left[\left(t_i - t_j\right)^2\right] \tag{24}$$

where, ϕ^s and ϕ^T are factors adjusting the influence of spatial and temporal distances. The geographic weights are computed as:

$$w_{ij} = exp\left\{-\left(\frac{\left(d_{ij}^s\right)^2}{b_s^2} + \frac{\left(d_{ij}^T\right)^2}{b_T^2}\right)\right\} \tag{25}$$

where, b_s is the spatial bandwidth and b_t is the temporal bandwidth. These bandwidths control the extent to which observations at different locations and times influence each other. These bandwidths are optimized to improve model accuracy.

Once the spatial and temporal weights are computed, the model parameters can be adjusted further. The τ parameter is used to either enhance or reduce the temporal effect relative to the spatial distance. The validation of the model is done by calculating the following:

$$(\tau) = \sum_i\left(y_i - \hat{y}_{\neq i}(\tau)\right)^2 \tag{26}$$

with the spatial-temporal weights and bandwidths, the predicted values $\hat{y}_i$ can be computed using the following formula:

$$\hat{y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix} = Sy \tag{27}$$

This model allows for more accurate predictions by considering both spatial and temporal variations, capturing relationships that change over time and space.

The kernel functions used in this method are essential for measuring the relationships between variables within the model. These kernels assign weights to data points based on the distance between them, considering both spatial and temporal variability (Al-Hasani et al., 2021). Table 3 shows the kernel functions used in the study, including: Gaussian, Uniform, Bisquare, and Exponential. Each kernel function provides a different weighting scheme depending on the distance between the data points.

Table 3. Kernel Function

Function	Specifications	
Gaussian	$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{\lvert d_{ij}^{sT}\rvert}{b}\right)^2\right)$	(28)
Uniform	$w_{ij} = \begin{cases} 1, \text{ if } d_{ij} \leq b \\ 0, \text{ otherwise} \end{cases}$	(29)
Bisquare	$w_{ij} = \begin{cases} \left(1-\left(\frac{\lvert d_{ij}^{sT}\rvert}{b}\right)^2\right), \text{if } d_{ij} \leq b \\ 0, \text{otherwise} \end{cases}$	(30)
Exponential	$w_{ij} = \exp\left(-\left(\frac{\lvert d_{ij}^{sT}\rvert}{b}\right)\right)$	(31)

The Multiscale Geographically and Temporally Weighted Regression (MGTWR) model is an advanced extension of both GWR and GTWR (Liu et al., 2021; Wu et al., 2019). It incorporates both spatial and temporal heterogeneity in a more flexible way by considering multiple scales of spatial variation and temporal dynamics. The MGTWR model is expressed as follows:

$$Y = \beta_{bwt_0s_0} + \beta_{bwt_1s_1} \otimes x_1 + \cdots + \beta_{bwt_ps_p} \otimes x_p + \varepsilon \tag{32}$$

where, $\otimes$ is the matrix element-wise multiplication, and bwt_ps_p is the spatial and temporal bandwidth used for variable coefficient determination. The concept of the MGTWR backfitting algorithm is the same as that of MGWR.

The backfitting algorithm is applied in MGTWR, where all additive terms are calculated iteratively. The error term is calculated as the difference between observed and predicted values and is minimized during each iteration:

$$\varepsilon = y - \hat{f}_0^0 - \hat{f}_1^1 - \cdots - \hat{f}_p^p \tag{33}$$

The iterative process continues until the error reaches an acceptable level, with each iteration refining the model coefficients. This ensures that both spatial and temporal factors are considered optimally, improving the model's predictive accuracy.

RESULTS AND DISCUSSIONS

This section discusses the steps in constructing the BEI and MGTWR models to identify predictor variables affecting the BEI. The pillars of the BEI are calculated using the arithmetic mean, while the BEI itself is computed using the geometric mean. After calculating the BEI, variable selection is performed on 14 predictor variables using Group LASSO and Elastic Net to identify the most influential variables. The MGTWR model is applied with different kernel weight functions (Uniform, Gaussian, Bisquare, and Exponential) using the selected variables from Group LASSO and Elastic Net to analyze their impact on BEI. Descriptive analysis of the BEI pillar indices is conducted before proceeding with the BEI construction.

Formulation of Blue Economy Index

The descriptive analysis of the BEI pillars in Sumatra from 2020 to 2022 shows significant variation across the regions. The Environmental pillar had a minimum value of 0.0095 in 2021 and a maximum of 0.5006 in 2020, with the highest rate in 2020 at 0.1848. The Economic pillar showed a minimum of 0.0105 in 2020 and a maximum of 0.4107 in 2021, with the highest rate at 0.0758 in 2022. The Social pillar ranged from a minimum of 0.1293 in 2020 to a maximum of 0.5558 in 2022, with the highest rate at 0.2369 in 2021. These results underscore the importance of addressing the factors affecting BEI to improve the overall quality of life across the regions. Table 4 shows the detailed descriptive analysis of the BEI pillars for the years 2020 to 2022.

Table 4. Descriptive Analysis of BEI Pillars

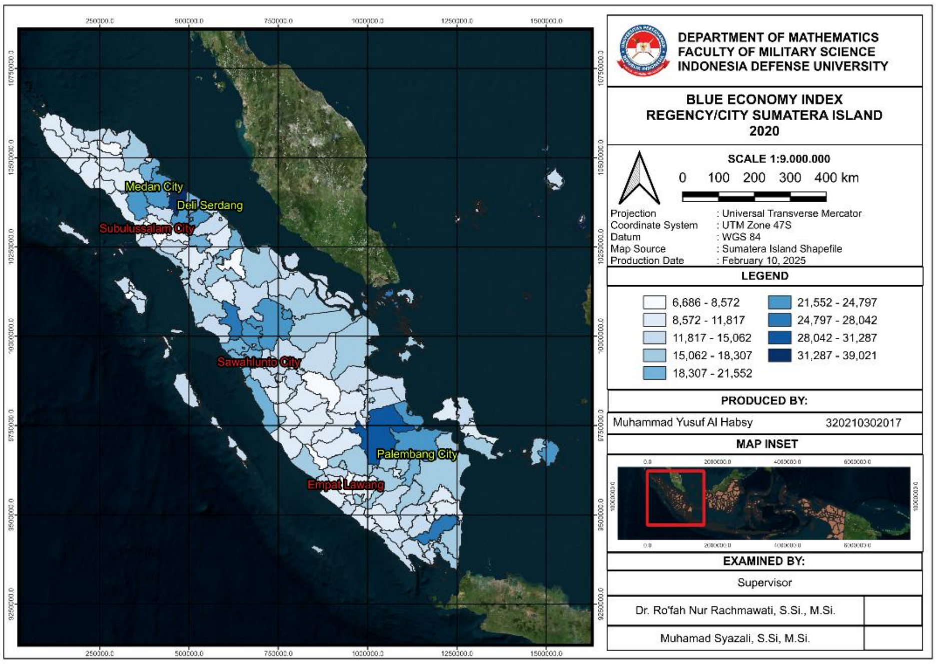
Pillars	Year	Min	Mean	Max	Std
Environment	2020	0,1297	0,1848	0,5006	0,0775
	2021	0,0095	0,0701	0,3334	0,0672
	2022	0,1284	0,1723	0,4245	0,0540
Economic	2020	0,0105	0,0847	0,4107	0,0672
	2021	0,0060	0,0689	0,3095	0,0574
	2022	0,0084	0,0758	0,3691	0,0595
Social	2020	0,1293	0,2338	0,4558	0,0524
	2021	0,1288	0,2269	0,5177	0,0533
	2022	0,1269	0,2336	0,4385	0,0524

According to Table 4, the results of the BEI dimensioning show that the social pillar plays the most dominant role. The dominance of the social pillar in the BEI calculation reflects the population's dependence on fisheries and marine resources for livelihoods. After performing the descriptive analysis of the BEI pillars, we proceed to analyze the BEI as a whole. Table 5 shows the BEI values for Sumatra's districts/cities from 2020 to 2022, revealing significant variation. The minimum value was 6.8683 in 2020, while the maximum reached 39.0204 in the same year. This analysis highlights the fluctuations in BEI values, reflecting regional and temporal differences across Sumatra.

Table 5. Descriptive Analysis of the Blue Economy Index

Year	Min	Mean	Max	Std
2020	6,6863	14,5763	39,0204	5,4065
2021	2,5448	9,2226	31,5204	5,0229
2022	5,9987	13,7766	33,6480	5,1360

Figure 2 illustrates the distribution of the BEI from 2020 to 2022 to make the results easier to visualize. The darker shades of blue indicate regions with the highest BEI values, while the lighter shades represent areas with lower BEI values. From 2020 to 2022, Medan City consistently had the highest BEI, while Subulussalam City consistently had the lowest. This visual helps highlight the spatial variations in BEI across Sumatra's regions over the three years.



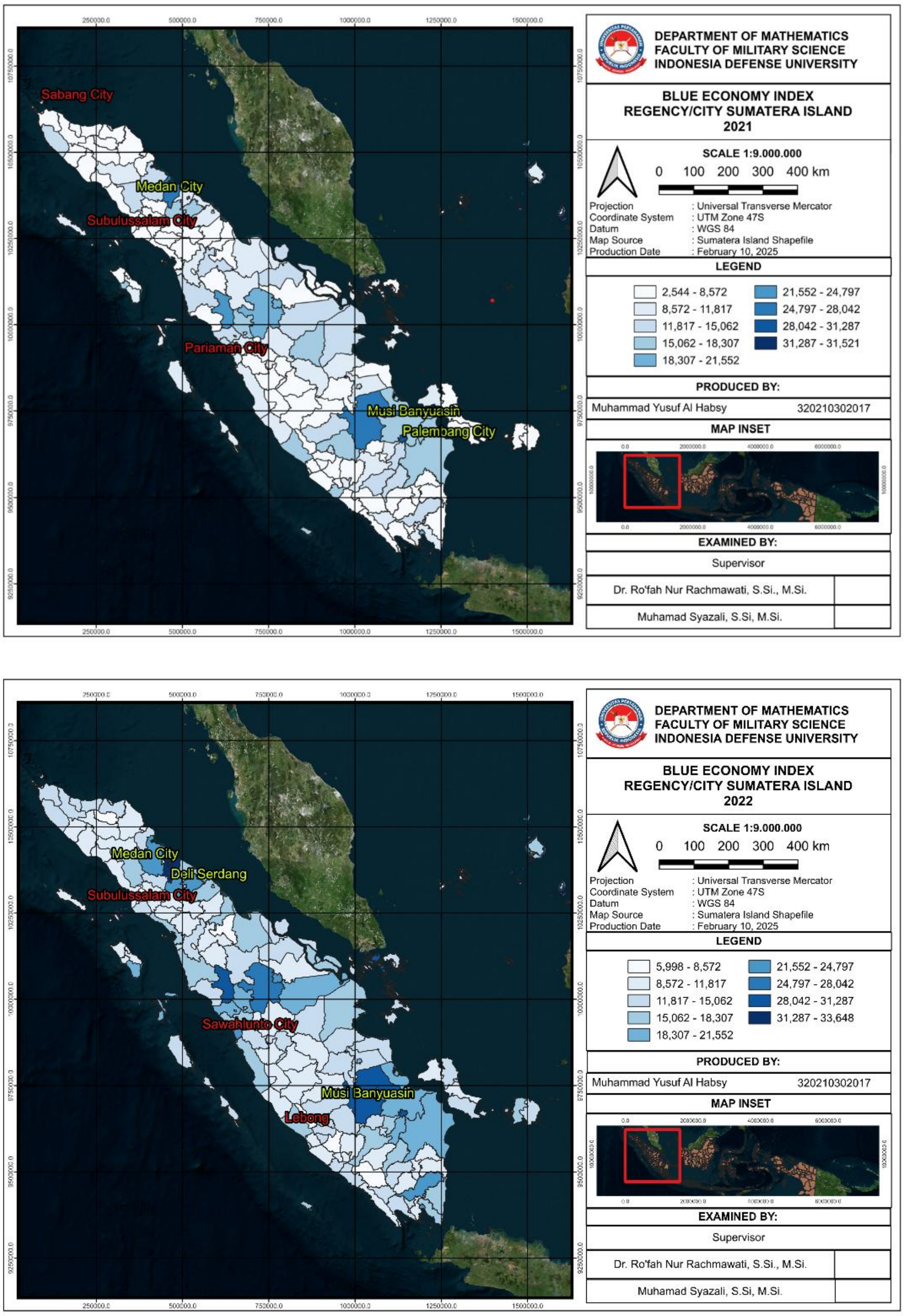


Figure 2. Distribution of the Blue Economy Index in Sumatra (2020-2022)

Medan City, as the capital of North Sumatra, consistently holds the highest BEI from 2020 to 2022. This success results from better infrastructure and widespread access to public services, which drive the city's growth and competitiveness across various economic sectors (Safnul et al., 2020). The local government's policies promoting investment and infrastructure development have been pivotal in improving the BEI. Social media platforms like Instagram and Twitter have also enhanced communication on infrastructure projects, fostering public engagement and ensuring that development policies meet the community's needs (Budi et al., 2023).

Subulussalam in Aceh Province, on the other hand, consistently ranks lowest in the BEI during the same period. This is due to inadequate infrastructure, limited access to public services, and poor resource management, which hinder economic growth and reduce competitiveness (Tatang et al., 2021). ARISE+ calculations for 2022 show that Sumatra's BEI scores range between

30 and 40. While Medan performs well, the overall blue economy management in Sumatra remains relatively low, reflecting challenges like underdeveloped infrastructure and unsustainable practices, especially in fisheries. To improve the BEI, effective policies for managing the blue economy, upgrading infrastructure, and enhancing access to public services are necessary. Overcoming these challenges requires a comprehensive and collaborative approach to foster long-term, sustainable growth and well-being for the people of Sumatra.

After calculating the BEI, we will model it using MGTWR, beginning with variable selection through Group Lasso and Elastic Net. This approach will help identify the significant variables influencing BEI, with BEI serving as the core response variable in the model.

Variable Selection Results

This section presents the results of the variable selection process using Group LASSO and Elastic Net. The goal is to identify variables that significantly affect the BEI. Before selecting the variables, the researcher performed CV to determine the optimal penalty parameter (λ) for both methods, which minimizes prediction error (Oyedele, 2023). The selection of the number of folds is denoted by K, which has no strict rules. Commonly used K values in research are 5 or 10 (Liu et al., 2023). This study uses K=5 to analyse the log(λ) value that produces the lowest Mean Squared Error (MSE). Figure 3 shows the cross-validation results, helping to identify the best model configuration.

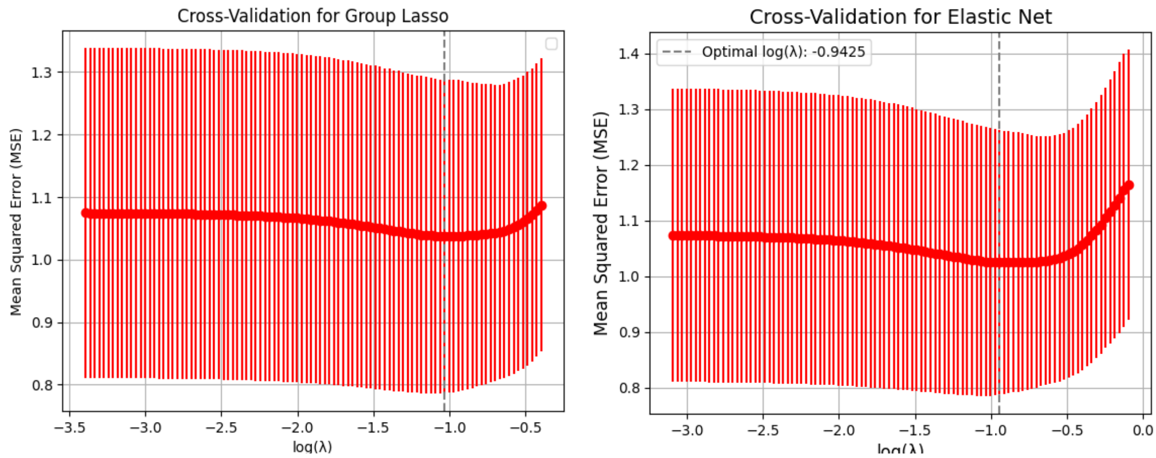


Figure 3. Cross Validation Group LASSO and Elastic Net

Figure 3 shows the cross-validation results for both Group LASSO and Elastic Net methods. The visualization compares the relationship between log(λ) values and the MSE for each method. For Group LASSO, the best log(λ) value that results in the smallest MSE is -1.0314, with an MSE of 1.0368. The red line represents the average MSE, which exhibits small fluctuations, indicating model stability across the tested range of λ. The vertical dashed line indicates the optimal log(λ). Similarly, for Elastic Net, the best log(λ) value is -0.9425, yielding an MSE of 1.0251. The optimal log(λ) for Elastic Net is also marked on the graph. These results are used to select significant variables for inclusion in the final model, with the optimal λ values determining which variables to retain.

Table 6. Variable Selection Results of Group LASSO and Elastic Net

Method	Variable Significant
Group LASSO (GLASSO)	$X_{subdist}$: Number of sub-districts $X_{village}$: Number of Villages X_{pop}: Total Population (thousand) X_{ratio}: Sex Ratio X_{poor}: Number of Poor People (thousand) X_{HDI}: Human Development Index

Method	Variable Significant
	$X_{highschool}$: Number of High Schools under the Ministry of Education $X_{vocschool}$: Number of Vocational Schools under the Ministry of Education X_{pumped}: Percentage Distribution of Households with Pumped Drinking Water Source $X_{bottled}$: Percentage Distribution of Households with Drinking Water Sources of Bottled Water X_{well}: Percentage Distribution of Households with Protected Well Drinking Water Sources $X_{sanitation}$: Percentage of Households with Access to Adequate Sanitation
Elastic Net (ENET)	$X_{subdist}$: Number of sub-districts X_{pop}: Total Population (thousand) X_{poor}: Number of Poor People (thousand) $X_{highschool}$: Number of High Schools under the Ministry of Education $X_{bottled}$: Percentage Distribution of Households with Drinking Water Sources of Bottled Water X_{well}: Percentage Distribution of Households with Protected Well Drinking Water Sources

Table 6 shows the significant variables selected through Group LASSO and Elastic Net methods. The results indicate that Group LASSO retains 12 variables, eliminating the Economy dimension. The significant dimensions retained by Group LASSO include Population, Education, and Environment. On the other hand, Elastic Net retains only 6 variables, which include the following: the number of sub-districts, total population, number of poor people, number of high schools under the Ministry of Education, percentage distribution of households with drinking water source of bottled water, and the percentage distribution of households with protected well drinking water sources. These selected variables will be used in subsequent modeling steps to understand their impact on the BEI.

Classical Assumption Test

This section presents the results of assumption tests following the MGTWR GLASSO and MGTWR ENET modeling to ensure the best model selection. The assumption tests include normality, heteroscedasticity, multicollinearity, Moran's I, and temporal heterogeneity tests (Ilori & Tanimowo, 2022; Ou et al., 2017; Podbregar et al., 2020; Rai et al., 2021). These tests ensure the model meets the necessary criteria for further analysis, such as normal distribution and constant errors. Additionally, the results of spatial, temporal, and spatio-temporal bandwidths provide insight into the interactions between variables in both spatial and temporal contexts. Table 7 shows the results of the assumption tests for the MGTWR GLASSO and MGTWR ENET models. These assumption tests are crucial for determining the best model, ensuring that the selected model meets the necessary criteria for further analysis.

Table 7. Model Assumption Test

Test	Kernel	*p*-value	
		MGTWR GLASSO	MGTWR ENET
Normality Test (Kolmogorov Smirnov)	**Uniform**	0,4192	0,2002
	Gaussian	0,0594	0,0000
	Bisquare	0,0000	0,0000
	Exponential	0,0362	0,0000
Heteroscedasticity Test (Breusch-Pagan)	**Uniform**	0,0656	0,0439
	Gaussian	0,5754	0,3407
	Bisquare	0,1561	0,1663
	Exponential	0,5056	0,3295
Multicollinearity Test		It is shown in Table 8	

Test	Kernel	p-value	
		MGTWR GLASSO	MGTWR ENET
Moran's I Test		It is shown in Table 9	
Temporal Heterogeneity Test		Boxplot in Figure 4	

Table 7 presents the assumption test results for the MGTWR GLASSO and MGTWR ENET models. The results show that MGTWR GLASSO with the Gaussian and Exponential kernels, as well as MGTWR ENET with the Uniform kernel, meet the normality assumption with p-value greater than 0.05, indicating a normal data distribution. Regarding heteroscedasticity, all kernels in MGTWR GLASSO satisfy the constant error assumption, with p-values greater than 0.05. However, for MGTWR ENET, the Uniform kernel does not meet the constant error assumption, as its p-value is less than 0.05, indicating the presence of heteroscedasticity. The results of the multicollinearity test can be found in Table 8.

Table 8. Multicollinearity Test MGTWR GLASSO and MGTWR ENET

Method	Variable Significant	VIF
Group LASSO	$X_{subdist}$	4,1657
	$X_{village}$	3,048
	X_{pop}	10,3793
	X_{ratio}	1,1948
	X_{poor}	5,4603
	X_{HDI}	1,9913
	$X_{highschool}$	5,7330
	$X_{vocschool}$	7,1892
	X_{pumped}	1,2542
	$X_{bottled}$	1,9587
	X_{well}	1,4789
	$X_{sanitation}$	1,4057
Elastic Net	$X_{subdist}$	2,0860
	X_{pop}	6,1026
	X_{poor}	4,9710
	$X_{highschool}$	4,4650
	$X_{bottled}$	1,557
	X_{well}	1,3219

Table 8 shows the multicollinearity test results for the MGTWR GLASSO and MGTWR ENET models. Several variables selected by Group LASSO have VIF values above 10, indicating multicollinearity. This occurs because Group LASSO groups related variables within the same dimension, reducing the entire group rather than individual variables. In contrast, Elastic Net shows VIF values below 10 for all significant variables, indicating no multicollinearity.

Table 9. Moran's I Test Results

Year	Moran's I	
	GLASSO	ENET
2020	-0,0037	0,0057
2021	0,0152	0,0343
2022	-0,0132	-0,0022

Table 9 shows the Moran's I test results. Positive values indicate spatial clustering, meaning that similar values are grouped together in space, while negative values suggest spatial dispersion, meaning that similar values are spread apart. This test helps identify the spatial autocorrelation present in the data, providing insights into how the variables are distributed across the study area. Figure 4 shows the boxplot for temporal heterogeneity of BEI from 2020 to

2022. The plot reveals fluctuations in BEI values across all three years, indicating variability over time.

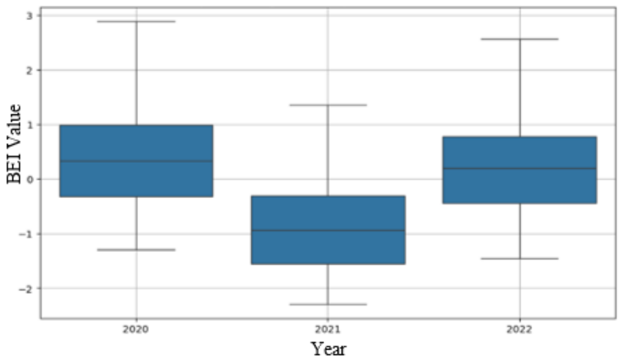


Figure 4. Boxplot of Temporal Heterogeneity of BEI

Table 10. Spatial Bandwidth (bw), Temporal Bandwidth (bw_ts), and Spatio-Temporal Scale (τ) for Uniform (U), Gaussian (G), Bisquare (B), and Exponential (E) Kernels

Method	Variable	bws				bw_ts			
		U	G	B	E	U	G	B	E
MGTWR GLASSO	$X_{subdist}$	7.1	18	18	18	5.7971	9.2338	9.2338	9,2338
	$X_{village}$	7.1	15.2	18	18	5.7971	7.7974	9.2338	9.2338
	X_{pop}	7.1	18	18	18	5.7971	13.8054	9.2338	12.4212
	X_{ratio}	7.1	18	18	18	5.7971	9.4868	9.2338	9.4868
	X_{poor}	7.1	18	18	18	5.7971	13.0586	9.2338	13.8054
	X_{HDI}	7.1	18	18	18	5.7971	12.4212	9.2338	10.0623
	$X_{highschool}$	7.1	18	18	18	5.7971	9.2338	9.2338	9.4868
	$X_{vocschool}$	7.1	18	18	18	5.7971	13.0586	9.2338	13.8054
	X_{pumped}	7.1	18	18	18	5.7971	13.0586	11.3842	13.0586
	$X_{bottled}$	7.1	18	18	18	5.7971	13.0586	9.2338	13.8054
	X_{well}	7.1	18	18	18	5.7971	10.3923	10.9545	10.0623
	$X_{sanitation}$	7.1	18	18	18	5.7971	11.3842	9.2338	11.3842
MGTWR ENET	$X_{subdist}$	7.1	7	17.4	5,5	5.7971	3.5909	8.9260	2.8214
	X_{pop}	7.1	13	17.4	17.4	5.7971	29.0689	8.9260	38.9076
	X_{poor}	7.1	17.4	17.4	17.4	5.7971	17.4000	9.1706	10.0459
	$X_{highschool}$	7.1	17.4	17.4	17.4	5.7971	17.4000	9.7269	17.4000
	$X_{bottled}$	7.1	17.4	17.4	17.4	5.7971	10.5893	8.9260	9.4365
	X_{well}	7.1	9	17.4	9	5.7971	20.1246	10,0459	20.1246

Method	Variable	τ			
		U	G	B	E
MGTWR GLASSO	$X_{subdist}$	1.5	3.8	3.8	3.8
	$X_{village}$	1.5	3.8	3.8	3.8
	X_{pop}	1.5	1.7	3.8	2.1
	X_{ratio}	1.5	3.6	3.8	3.6
	X_{poor}	1.5	1.9	3.8	1.7
	X_{HDI}	1.5	2.1	3.8	3.2
	$X_{highschool}$	1.5	3.8	3.8	3.6
	$X_{vocschool}$	1.5	1.9	3.8	1.7
	X_{pumped}	1.5	1.9	2.5	1.9
	$X_{bottled}$	1.5	1.9	3.8	1.7
	X_{well}	1.5	3	2.7	3.2
	$X_{sanitation}$	1.5	2.5	3.8	2.5
	$X_{subdist}$	1.5	3.8	3.8	3.8

Method	Variable	bws				bw_ts			
		U	G	B	E	U	G	B	E
MGTWR ENET	X_{pop}	1.5		0.2		3.8		0.2	
	X_{poor}	1.5		1		3.6		3	
	$X_{highschool}$	1.5		1		3.2		1	
	$X_{bottled}$	1.5		2.7		3.8		3.4	
	X_{well}	1.5		0.2		3		0.2	

Table 10 presents the spatial bandwidth (bw), temporal bandwidth (bw_ts), and spatio-temporal scale (τ) for the Uniform (U), Gaussian (G), Bisquare (B), and Exponential (E) kernels. Spatial bandwidth measures the influence of each location based on physical distance, while temporal bandwidth gauges the influence based on time. The spatio-temporal scale combines both spatial and temporal aspects, providing a more comprehensive understanding of variable interactions in both space and time. The values for each kernel represent how the model captures spatial and temporal dependencies, allowing for a more detailed analysis of the dynamics between variables across different locations and time periods.

Model Comparison

Diagnostic tests are performed to evaluate the performance of each proposed model. The R^2 value measures the proportion of variability explained by the model, with higher values indicating better fit. The Akaike Information Criterion (AIC) is used to compare models, where lower AIC values indicate better models with a penalty for complexity. Analyzing R^2 and AIC values helps determine the best model, balancing fit and simplicity. The results of this analysis are shown in Table 11.

Table 11. Model Comparison Based on R^2 and AIC

Model	MGTWR GLASSO		MGTWR ENET	
	R^2	AIC	R^2	AIC
Uniform	0.2263	1456.4245	0.1997	1460.6445
Gaussian	0.3071	1377.5212	0.6779	1014.6825
Bisquare	0.9033	907.4792	0.8743	957.6086
Exponential	0.3514	1364.7681	0.6979	1011.8859

Table 11 presents the R^2 and AIC values for various models in the MGTWR GLASSO and MGTWR ENET analysis. The Bisquare approach shows the highest R^2 value of 0.9033 and the lowest AIC value of 907.4792 for MGTWR GLASSO compared to other models. However, the highest R^2 value from Bisquare does not meet the normality assumption, which is a key consideration in model selection. This study selects the MGTWR GLASSO model with the Gaussian kernel, as it satisfies the assumption tests and provides the best R^2 and AIC values among the models that also meet the assumptions. The MGTWR GLASSO model with the Gaussian kernel has an R^2 value of 0.3071 and an AIC value of 1377.5212. The R^2 value of 0.3071 indicates that approximately 30.71% of the data variation is explained by the model. The model selection is based on the principle that the reliability of the analysis results is more important than simply achieving the highest R^2 value.

After comparing the models, it is concluded that the best model is MGTWR GLASSO using the Gaussian kernel. A partial test is conducted to determine the significance of the variables, with the hypothesis defined as follows:

$H_0: \beta_k = 0$, for $k = 1, 2, \dots, p$ (Variable k is not significant)

$H_1: \beta_k \neq 0$, for $k = 1, 2, \dots, p$ (Variable k is significant)

The study involves 154 observations and 12 variables selected by Group LASSO. The degrees of freedom are 141, and the critical t-value for α = 0.05 is 1.9769. Significant variables are identified based on the t-statistic, where variables with t-values greater than 1.9769 or less than -

1.9769 are considered significant. Table 12 shows the coefficients for Banda Aceh and Gayo Lues, with both regions consistently showing significant variables over the three-year period.

Table 12. Significant Variable Coefficient Banda Aceh City and Gayo Lues. The Sign (*) Indicates that the Coefficient of the Variables is Significant to the BEI

District/City	Year	Variable Coefficient (β)					
		$X_{subdist}$	$X_{village}$	X_{pop}	X_{ratio}	X_{poor}	X_{HDI}
Banda Aceh City	**2020**	-0,0056	-0,1207	-0,0432	**0,5430***	-0,0817	0,1953
	2021	0,0432	-0,0894	-0,1472	**0,6053***	-0,0765	0,1607
	2022	0,0557	-0,0584	-0,2252	**0,5435***	-0,0955	0,0611
		$X_{highschool}$	$X_{vocschool}$	X_{pumped}	$X_{bottled}$	X_{well}	$X_{sanitation}$
	2020	0,1859	0,2505	-0,0566	-0,0089	0,0793	-0,1744
	2021	0,2311	0,1827	-0,1016	0,0296	0,0557	-0,1211
	2022	0,2502	0,1584	-0,0605	0,0383	0,0827	-0,1513
Gayo Lues		$X_{subdist}$	$X_{village}$	X_{pop}	X_{ratio}	X_{poor}	X_{HDI}
	2020	-0,0841	-0,0786	0,0590	**0,3633***	-0,0124	0,1870
	2021	0,0678	-0,0084	-0,1741	**0,3212***	-0,0035	0,1384
	2022	0,0726	0,0041	-0,2739	0,2672	0,0095	-0,0133
		$X_{highschool}$	$X_{vocschool}$	X_{pumped}	$X_{bottled}$	X_{well}	$X_{sanitation}$
	2020	0,2308	0,2789	0,0000	-0,1540	0,1482	-0,2207
	2021	**0,2926***	0,1573	-0,0232	-0,0174	0,0999	-0,1747
	2022	**0,3350***	0,0693	-0,0024	0,1485	0,0963	0,0003

Table 12 shows the significant variable coefficients affecting the BEI in Banda Aceh City and Gayo Lues from 2020 to 2022. Variables marked with an asterisk (*) have a significant impact on BEI. The gender ratio has a positive correlation with BEI in both regions. In Banda Aceh, the gender ratio coefficient increased from 0.5430 in 2020 to 0.5435 in 2022, indicating that a higher gender ratio is linked to an increase in BEI. This suggests that the blue economy sectors, such as fisheries and maritime industries, which predominantly employ male workers, benefit from a more balanced or dominant gender ratio (Sohilauw et al., 2019). In Gayo Lues, the number of high schools also shows a positive correlation with BEI. The coefficient for high schools rose from 0.2926 in 2021 to 0.3350 in 2022. An increase in high schools contributes to improving human resource quality, which, in turn, supports sustainable management of marine resources (Laheng et al., 2022). Access to secondary education helps the population better understand sustainable fishing practices and environmental management, essential for fostering a blue economy. These results demonstrate that socio-economic factors like gender balance and educational access significantly influence the growth of the blue economy. Therefore, policies that balance human resource development with marine ecosystem sustainability are crucial.

Figure 5 presents a combined visualization of all significant variables across various regions for each year. This visualization helps in understanding the pattern of variable significance changes from year to year. A detailed analysis can be conducted to identify the factors influencing the BEI in different regions. The comparison of results across years reveals trends of increasing or decreasing significance of certain variables in specific regions. The color distribution on the map provides insights into the consistency of variable significance across regions. This information can serve as a foundation for region-based policy recommendations.

Figure 5 illustrates the spatial distribution of significant variables across Sumatra for the years 2020, 2021, and 2022. The map provides a visual representation of how the significance of each variable varies from year to year. Variables that are significantly correlated with BEI are indicated by distinct colors, while non-significant variables are shown in gray. This mapping highlights the changes in the significance of variables across the three years, allowing for a deeper understanding of regional patterns and trends in the spatial dynamics of the BEI. The shifting patterns of significance across different years provide valuable insights into the evolving factors influencing BEI in various regions of Sumatra. Figure 5 presents the temporal trends of significant variable coefficients for Medan and Subulussalam, highlighting regions with the highest and lowest BEI values. Although no variables were identified as significant, as indicated by the red dots, the trends reveal how these variables have influenced the BEI in these regions over the years.

Figure 6 illustrates the temporal trends of variable coefficients for Medan and Subulussalam, representing the regions with the highest and lowest BEI values, respectively. The trends highlight how the coefficients of key variables evolved from 2020 to 2022, providing insights into the relationship between these variables and the BEI. Administrative factors, such as the number of sub-districts and villages, show an increasing influence on BEI, especially in Subulussalam, suggesting that administrative factors are becoming more important in shaping the region's Blue Economy. In contrast, the gender ratio coefficient sharply decreases, particularly in Subulussalam, indicating that gender balance is having less of an impact on the region's Blue Economy over time. Similarly, the number of poor people, initially influential, shows a declining trend, reflecting socio-economic improvements in Subulussalam. HDI remains positively correlated with BEI but fluctuates, revealing the changing role of human development in the Blue Economy. The distribution of drinking water sources exhibits more dynamic changes in Subulussalam, likely influenced by varying infrastructure development and policy, whereas Medan remains more stable in this regard. The analysis of these trends provides valuable insights into the evolving factors affecting the Blue Economy across these regions.

The findings of this study offer valuable insights for local governments to enhance the BEI by focusing on sustainable resource management. The research also contributes to the academic field, particularly in the area of spatial modeling for maritime economics, offering potential for further studies and deeper understanding. Based on the analysis, the following recommendations are proposed:

a. Dominance of the Social Pillar: The social pillar plays a significant role in shaping BEI. Given its substantial contribution, policies that emphasize social development can be highly effective in boosting BEI. Key actions should include increasing social assistance, improving access to education and healthcare, and providing training programs to enhance human capital in coastal areas. Strengthening coastal communities and empowering local fishermen will not only improve livelihoods but also ensure the sustainability of maritime-based economies. As highlighted by Okafor-Yarwood et al. (2020), active community involvement and social inclusion are key to the success of sustainable blue economy initiatives. Their research shows that successful blue economy projects in Africa consistently involve local communities in all stages, from planning to implementation, creating alignment between economic, social, and environmental goals. Therefore, strengthening the social pillar through cross-regional collaboration and more inclusive policies is critical to ensuring sustainable and equitable economic development.
b. Economic Growth in Medan and Subulussalam: Despite Medan and Subulussalam having the highest and lowest BEI values respectively, their economic growth is not strongly influenced by the variables included in the current model. This suggests the need for a more comprehensive approach. To enhance the blue economy, it is recommended that local governments focus on investments in maritime infrastructure, strengthen the maritime industry, and introduce new indicators such as fisheries sustainability, efficient marine resource management, and the impact of blue economy policies. Additionally, boosting the industrial sector through technology and improving the competitiveness of coastal industries are strategic steps for long-term economic growth. Capacity building for local populations, especially fishermen and small-scale entrepreneurs, is vital for fostering a resilient and sustainable workforce. As noted by Schutter et al. (2021), the blue economy plays a crucial role in driving economic growth from marine resources, and this concept is

becoming increasingly dominant in marine governance, emphasizing sustainable economic growth that considers social, economic, and environmental aspects. Therefore, deepening the blue economy sector through integrated cross-regional collaboration is essential to maximize the economic potential of coastal areas.

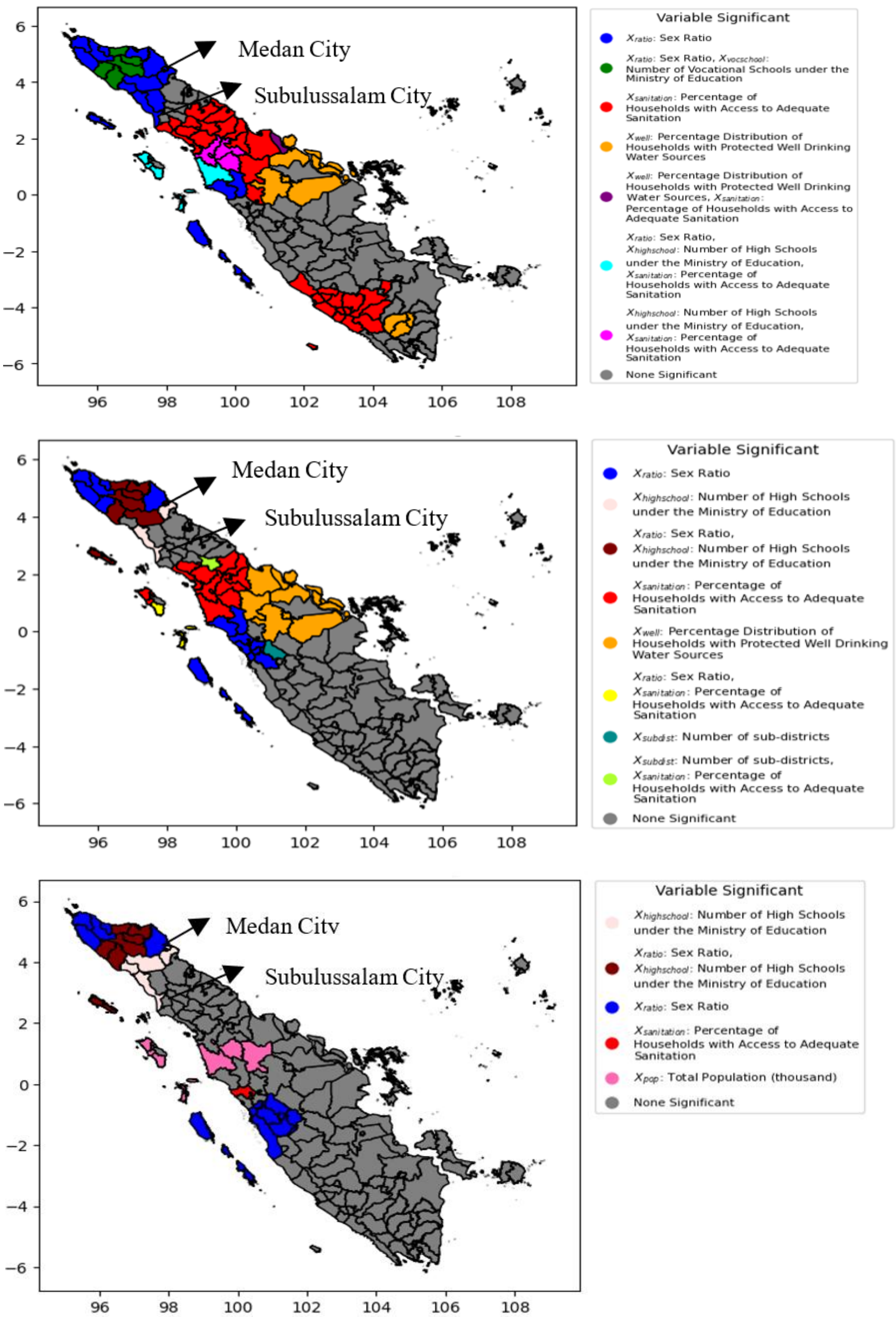


Figure 5. Visualization of Significant Variables Across Regions and Years

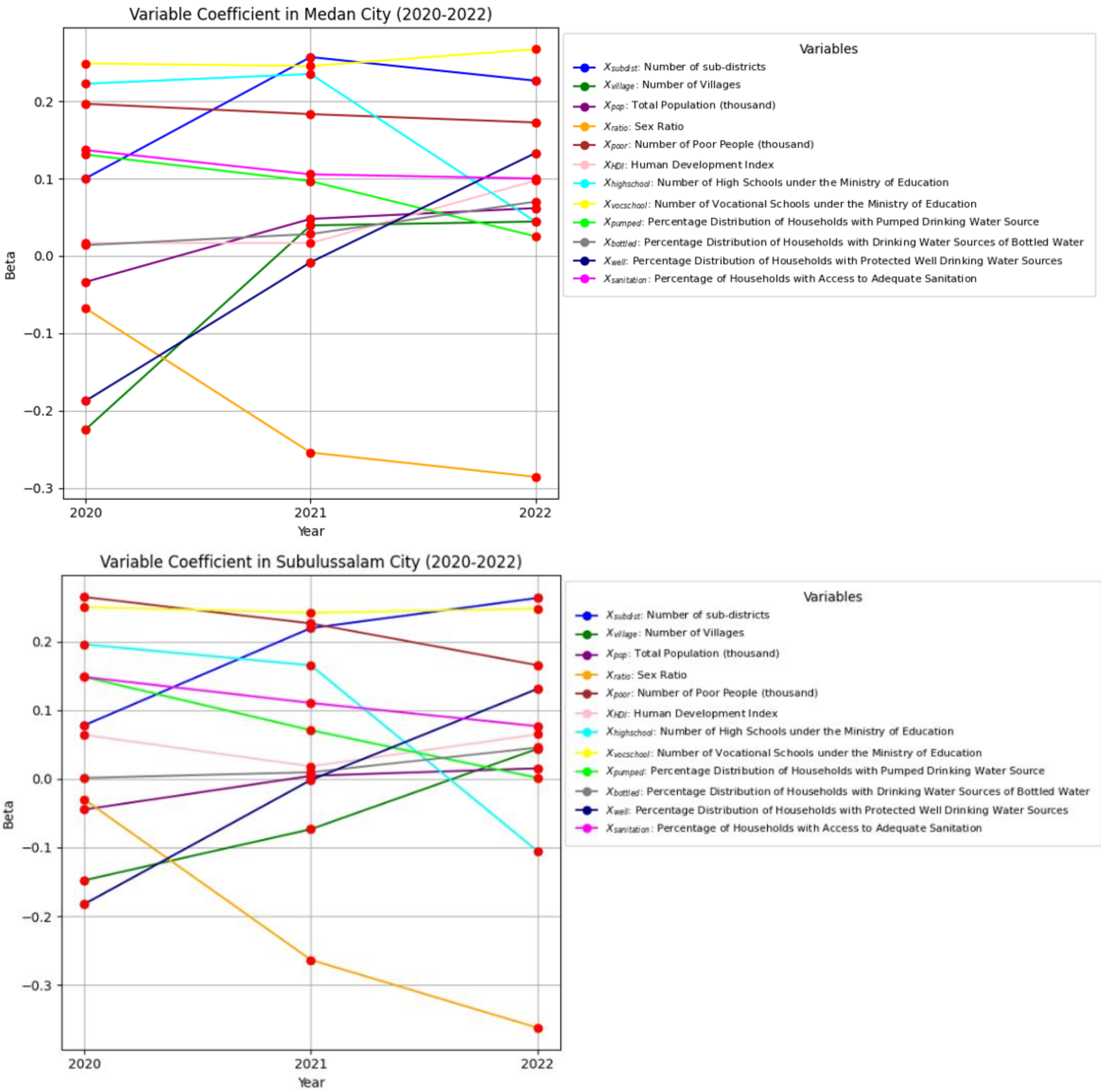


Figure 6. Temporal Trends of Medan City and Subulussalam City

c. Spatio-Temporal Analysis for Targeted Interventions: The spatio-temporal analysis in this research identifies regions with low blue economy potential as critical areas for intervention. By applying the MGTWR model, which simultaneously accounts for both spatial and temporal variations in blue economy dynamics, this study provides a more accurate understanding of the challenges faced by different regions in Sumatra. Unlike previous research, which often relied on static models or considered only spatial dimensions, this study shows how the factors influencing the blue economy evolve over time, enabling more targeted and effective interventions. Spatio-temporal analysis allows for the identification of more profound patterns and dynamic changes, offering a more accurate understanding of the factors influencing the blue economy in both spatial and temporal contexts (Christina et al., 2025). This research also emphasizes the importance of improving collaboration between neighboring regions to address shared challenges and significant factors affecting economic, social, and environmental conditions. This interconnected approach introduces a new perspective on blue economy development, which has previously been driven mostly by isolated local policies. Through cross-regional collaboration, synergies can be created to promote broader economic growth, especially in coastal and maritime areas where development opportunities are often interlinked. This aligns with the findings of Popoola & Olajuyigbe (2023), who emphasize the importance of regional cooperation in addressing shared challenges and strengthening inclusive, integrated blue economy policies. Comparing this finding with previous research, it is evident that the application of MGTWR adds depth and precision to spatial and temporal analysis, offering a new perspective on how economic policies can be more effectively directed to meet regional needs.

CONCLUSION

This research examines the BEI across various regions in Sumatra from 2020 to 2022, revealing significant regional disparities in the influence of social, economic, and environmental factors on BEI. Medan consistently ranked highest due to its advanced infrastructure, resource management, and strong maritime industry policies, while Subulussalam faces challenges in harnessing its maritime potential. Despite Medan's strong performance, Sumatra as a whole lags behind other regions in Indonesia, highlighting the need for policies that focus more on the blue economy. This study identifies Group LASSO and Elastic Net as effective methods for selecting key variables, such as education and gender ratio, that influence BEI. The MGTWR model with a Gaussian kernel was chosen for its ability to meet necessary assumptions, providing reliable results despite not having the highest R^2. The findings suggest the need for targeted interventions to boost the region's blue economy through sustainable investment, improved resource management, and comprehensive policy frameworks.

Future studies could explore additional factors such as marine resource sustainability, fisheries, and renewable ocean-based energy to further enhance the understanding of the blue economy. Expanding the model with multiscale approaches and global perspectives could provide a more comprehensive view of how spatial and temporal factors affect BEI. Additionally, using alternative variable selection methods could uncover other significant factors, further improving the accuracy and robustness of future models. Research focused on strengthening maritime infrastructure and aligning blue economy development with national defense and environmental sustainability goals would also be valuable for ensuring long-term economic and ecological resilience.

AUTHOR CONTRIBUTIONS

Each author of this article played an important role in the process of method conceptualization, simulation, and article writing.

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