A LASSO–multiscale GTWR: quantifying the blue economy index and its influence on regional growth in the district city of Sumatra Island

Achi Rinaldi
(corresponding author)
Data Science, Universitas Islam Negeri Raden Intan Lampung, Indonesia
Email: achi@radenintan.ac.id

Ro'fah Nur Rachmawati
Statistics Department, School of Computer Science, Bina Nusantara University, Jakarta, Indonesia
Email: rofah.rachmawati@binus.ac.id

Muhamad Syazali
Department of Mathematics, Indonesia Defence University, Bogor, Indonesia
Email: muhamadsyazali@radenintan.ac.id

Achmad Abdurrazzaq
Department of Mathematics, Indonesia Defence University, Bogor, Indonesia
Email: achmad.abdurrazzaq@idu.ac.id

Muhammad Yusuf Al Habsy
The Indonesian Airforce, Indonesian Air Force Headquarters, Jakarta, Indonesia
Email: ysufalhabsy39@gmail.com

Keywords:
blue economy index,
LASSO,
Sumatra,
spatio-temporal regression,
multiscale GTWR

Indonesia's maritime position exhibits marked potential to advance a blue economy that promotes sustainable growth, social well-being and conserves marine ecosystem. Although quantitative blue economy studies are well developed internationally, similar data-driven approaches remain limited in the Indonesian context, particularly at district/city level. This study aims to construct a district-level blue economy index (BEI) and examine its relationship with regional economic performance across Sumatra using the multiscale geographically and temporally weighted regression (MGTWR) approach. The BEI integrates environmental, social and economic dimensions using 38 indicators across 154 districts and cities from 2019 to 2022. Variable selection is conducted using the least absolute shrinkage and selection operator (LASSO) method to alleviate multicollinearity. Results reveal notable spatial and temporal disparities: Medan City consistently exhibits the highest BEI, whereas Sawahlunto City records the lowest. The social and environmental dimensions show strong associations with economic outcomes, highlighting the importance of human capital, fisheries infrastructure and waste management in promoting inclusive blue growth. These findings provide empirical evidence for spatially adaptive policy interventions to strengthen Indonesia's district-level blue economy performance.

Introduction

A new paradigm, the 'blue economy', emphasises sustainable economic growth in the marine and fisheries sectors (Vaca Cabrero et al. 2024). This concept promotes responsible utilisation of the environment and opposes the overuse of resources. The goal of blue economy is to reduce the negative impacts of climate change and global warming on ecosystems and economies. Although various interpretations of the blue economy exist, two of the most influential frameworks come from the OECD and the European Union. The OECD (2016) conceptualises the ocean economy as a set of established and emerging industries that rely on ocean resources, emphasising innovation, productivity and long-term sustainability. Meanwhile, the EU defines it as all economic activities related to oceans, seas and coasts that contribute to sustainable development, job creation and ecological resilience (EC 2024). Building on these frameworks, this study defines it as the sustainable utilisation of marine and coastal resources through economic activities that generate long-term ecological, social and economic value. This definition aligns with Indonesia's maritime development agenda, which requires a balance among resource extraction, technological advancement and ecosystem protection. This condition presents an opportunity for Indonesia, as a maritime country, to promote the sustainable use of marine resources by considering socioeconomic impacts and ecosystem balance. In addition, the concept is in line with the Indonesia's Vision 2045, which focuses on new sources of economic exploration by utilising modern and competitive manufacturing and services to create high added value so that welfare and social justice for all Indonesians can be achieved (Yan–Sambodo 2023).

Recently, the concept of blue economy has attracted the attention of researchers, particularly with respect to environmental sustainability. Several studies have investigated the way blue economy can promote economic growth and environmental sustainability across regions. Kaczynski (2011) stated that the ability of the EU member states to innovate, cooperate, develop the right policies and coordinate well determines the future of the blue economy, which plays an important role in sustainable growth and development. In addition to these four factors, diversification strategies, accurate measurement, investment and sustainable management are the prerequisites for a blue economy to improve a country's economy (Alharthi–Hanif 2020, Kwiatkowski–Zaucha 2023, Phang et al. 2023). To address global challenges related to the blue economy, a multidisciplinary approach and global cooperation are essential. Such challenges can be successfully tackled with the commitment and focus of all parties on balancing economic growth and environmental sustainability (Martínez-Vázquez et al. 2021). In this regard, media plays an important role in increasing public understanding and supporting sustainable policies. To show that the green and blue economies play an important role in sustainable development, the balance of news coverage related to the two needs to be improved (Atmadi et al. 2024, Rasyid et al. 2022). These insights are excluded from cross-country comparisons, but they emphasise the methodological and conceptual gaps that remain unaddressed in Indonesia's context. Although Indonesian researchers have examined sectoral issues such as fisheries, coastal tourism and marine environmental valuation, an integrated and quantitative assessment framework is missing. Therefore, understanding the broader research landscape helps clarify why a standardised, data-driven blue economy measurement, particularly at the district/city level, is urgently required (Al Habsy–Syazali 2025, Christina et al. 2025).

In addition, Liang et al. (2022) and Phang et al. (2023) stated that cross-country and regional collaboration is necessary to achieve maritime sector sustainability by examining global trends and research directions of the blue economy. By knowing the global trends of the blue economy, a country is expected to avoid the blue economy 'trap' by ensuring that economic development does not only focus on short-term profits but also considers social welfare and long-term environmental sustainability (Wardhani et al. 2023, Al Habsy–Syazali 2025). Similarly, Pace et al. (2023) reported continuous innovation and research to be the key to the future of blue economy, as they would facilitate the achievement of environmental and social goals. This can help sustain marine ecosystems while creating inclusive economic growth. To achieve maritime sector sustainability, innovation and resource-based competitive advantage are the key strategies, as emphasised by Rianawati et al. (2024) in the context of blue economy development in Indonesia. This is true for Bangladesh as well, where blue economy can be a driving force for its economic development if the country overcomes challenges and capitalises on its strategic position in the Indo-Pacific region (Khan–Emon 2024). In China's coastal regions, a successful blue economy requires a holistic approach that combines technology, sustainable policies and strong economic networks to achieve long-term growth and resilience (Yu et al. 2024).

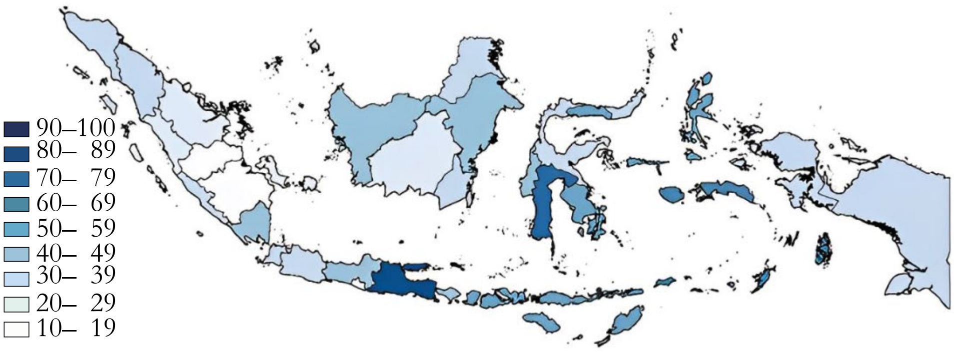
In addition to innovation and competitive advantage, collaboration-based governance also plays an important role in achieving sustainability in blue economy. Midlen (2024) emphasises that collaboration is essential to address environmental and economic challenges in coastal areas. Strategic planning and evidence-based policies are required to ensure that the blue economy can thrive as a long-term alternative, as emphasised by Alqattan (2024) in the context of Kuwait's economy. In the Middle East and North Africa (MENA) region, synergies between the maritime sector, clean energy and sustainable policies can bring long-term benefits (Elsherif 2024). This is true for Indonesia, which exhibits great potential in fisheries and marine sectors but faces challenges in maintaining its sustainability.

Indonesia, an archipelago with vast marine areas, is committed to maximising its marine potential to support the country's progress and resilience. The National Long-Term Development Plan (Rencana Pembangunan Jangka Panjang Nasional/RPJPN) 2005–2025 focuses on making Indonesia a sovereign, developed and resilient maritime nation by prioritising sustainable development (Bappenas 2004). The National Medium-Term Development Plan (Rencana Pembangunan Jangka Menengah Nasional/RPJMN) 2020–2024 elaborates on this goal and emphasises that achieving the sustainable development agenda requires effective marine management (Al Habsy et al. 2025, Kementerian Perencanaan Pembangunan Nasional 2004). The RPJMN 2020–2024 recognises that an ocean is a strategic asset that plays an important role in driving economic growth, improving people's welfare and maintaining environmental sustainability. Thus, integrated and sustainable marine management shall be a top priority for achieving the medium-term development goals.

Sumatra, the island with the second largest population in Indonesia, plays an important role in accelerating the nation's economic progress. According to the gross regional domestic product (GRDP), Sumatra's share of national GDP was 22.01% in 2023, placing it second after Java. With abundant marine resources, Sumatra offers strong prospects for the blue economy. Fisheries are one of the important industries that notably contributes to Sumatra's economy. In addition to fisheries, other sectors, such as marine mining, marine tourism and renewable energy, exhibit great potential for Indonesia's development. Sustainable use and management of marine resources are the important components of the blue economy development in Sumatra.

Figure 1

Indonesia blue economy index (IBEI) by 2022



Despite Sumatra's high blue economy potential, the provincial-level results of the Indonesia blue economy index (IBEI) show that the island's blue economy performance lags behind that of other Indonesian provinces. The IBEI value of each province in Sumatra remains below the national average of 40.43. East Java Province has the highest IBEI value (87.36), whereas Yogyakarta Special Region Province has the lowest (10.37). This suggests that Sumatra has enough space to improve its blue economy performance and optimally utilise its marine potential. Figure 1 presents the differences in the BEI values across provinces, indicating that Sumatra has untapped potential.

Although blue economy potential at the provincial level has been examined in several Indonesian studies, there lacks the presence of standardised and comprehensive measurement tools to assess blue economy performance at district/city level. Generally, existing studies focus on sectoral analyses, such as fisheries, coastal tourism or marine environmental valuation, rather than on the development of an integrated, multidimensional quantitative index. Although quantitative blue economy studies are well established internationally, particularly in Europe, similar quantitative and data-driven approaches are scarce in the Indonesian context. To date, no study has constructed a composite BEI at the district/city level or analysed its spatial and temporal dynamics using advanced econometric methods. However, the present study offers a unique contribution by quantitatively developing a BEI for all districts/cities and evaluating the spatio-temporal behaviour of each through regression modelling (La Torre et al. 2015). This approach enables a deeper understanding of the way localised blue economy potential contributes to the broader ocean economy within each province.

For analysing the factors that influence the response, understanding the spatial analysis of a region becomes essential, as demonstrated by Azzahra et al. (2024), who examined the spatial relationship to malaria spread. However, spatial analysis alone is insufficient and temporal analysis is required to determine the factors that influence over time. One innovative method for temporal and spatial analyses is multiscale geographically and temporally weighted regression (MGTWR) (Wu et al. 2019). This method uses the bandwidth value. MGTWR is a development of geographically and temporally weighted regression (GTWR). MGTWR bandwidth refers to the size of the neighbourhood scale used in local regression. The bandwidth used in MGTWR is more flexible than that in GTWR, which has a fixed value. The parameters of the MGTWR model are estimated using the least squares method, which facilitates the identification of significant spatial and temporal patterns. This method provides more flexibility for spatial and temporal analyses, particularly when examining phenomena affected by different spatial and temporal variables.

This study uses GRDP data at current prices as the response variable. The factors examined for their influence on economic growth are derived from the variables that are used to form BEI. However, the large number of predictor variables in regression analysis can lead to multicollinearityissues such as high correlations among variables. To overcome this issue, this study uses the least absolute shrinkage and selection operator (LASSO) method as a variable reduction method (Emmert-Streib–Dehmer 2019, Rahman et al. 2025). LASSO effectively identifies the most relevant variables and reduces multicollinearity by shrinking the coefficients of insignificant variables to zero. Thus, LASSO simplifies regression models and improves the accuracy of economic growth predictions.

Based on this context, the present study aims to accomplish the following two goals: (1) create Sumatra Island's BEI at the district/city level using 38 variables drawn from the environmental, economic and social dimensions and (2) use MGTWR modelling for each district/city on Sumatra Island from 2019 to 2022 to identify variables that markedly affect GDRP data at current prices. To ascertain the sustainability of the blue economy potential on the island of Sumatra year over year and to examine the relationship between regions in terms of blue economy potential and GDRP data at current prices, the model can detect both geographic and temporal patterns. The remainder of this paper is organised as follows: it begins with studies on MGTWR and its application to GRDP, followed by a description of the research methodology, and the analysis and discussion of the results. Finally, the paper presents conclusions, suggestions and recommendations.

Related studies on MGTWR and its application to GRDP

Gross regional domestic product

GRDP is an important measure for assessing the economic health of a region (Chen et al. 2022, Febriawan et al. 2023, Han et al. 2019). GRDP is divided into two types: current prices and constant prices (Alwasifah–Rahayu 2022, Aswanto 2023). Current GRDP measures the value of a region's total production at current prices, which is affected by price changes. By contrast, constant GRDP measures the value of production at base-year prices, showing actual economic growth without being influenced by price fluctuations. The two types of GRDP are complementary and important for understanding the economic performance of a region.

Results from previous studies

Table 1 summarises previous studies on the use of MGTWR methods in spatial and temporal data analysis and on factors affecting GRDP across various regions.

Table 1

Summary of previous studies

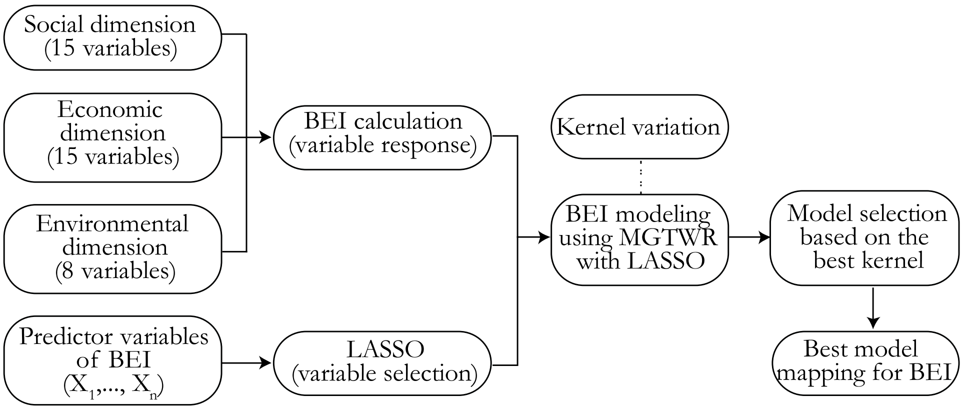
Author	Method	Dataset	Results
Wu et al. 2019	MGTWR	Shengchen variables: real transaction housing price (Y), property cost, distance to business centre and population density Kernel: Gaussian Time: 2010–2017	The results of this study indicate that factors, such as retail accessibility, land use patterns and the balance between employment and housing, markedly influence housing prices in Shenzhen.
Cheng et al. 2024	MGTWR	Hainan variables: hailing trips (Y), number of transport facilities, number of shopping facilities and number of food facilities Kernel: not explained Time: daily, May–October 2017	The best model used in this study is MGTWR. This model exhibits higher accuracy in fitting data.
Zhang et al. 2023	Remote sensing of night-time light	China Time: 2012–2021	Night-light growth is significantly correlated with gross domestic product (GDP) and population growth, indicating that regional economic development and population growth are the main causes of night-light changes.

Research method

This study follows a structured methodological workflow, beginning with the construction of a BEI on the basis of the following three key dimensions: social, economic and environmental. Once the BEI is obtained as the response variable, a set of potential predictor variables related to blue economy performance is compiled. Subsequently, these predictors are filtered using the LASSO method to identify the most relevant factors while addressing multicollinearity issues. Thereafter, the selected variables are incorporated into an MGTWR modelling framework, where several kernel functions, such as Gaussian, uniform and bi-square, are tested to capture spatial heterogeneity at multiple scales. This process concludes with the selection of the best-performing kernel and the mapping of model outcomes to illustrate the spatial distribution of the BEI. The complete methodological sequence is presented in Figure 2.

Figure 2

Methods workflow diagram of the study



Formation of the BEI

Indonesia's BEI

Blue economy is a macroeconomic concept that emphasises environmentally friendly innovation in the production of marine sector goods and services for social sustainability (Sarkar et al. 2022). This concept has been highlighted in international cooperation, including the Asia-Pacific Economic Cooperation (APEC) forum. The goal is to increase production, business transactions and employment in the marine sector as well as to equitably share the proceeds to improve people's welfare and preserve marine ecosystem (Fenichel et al. 2020). The concept is derived from the international sustainable development framework, which emphasises economic growth and community welfare while taking into account the stability of the marine environment (Niner et al. 2022).

With the assistance of ARISE Indonesia, the IBEI was developed in 2022 to function as a monitoring instrument for assessing the progress of blue economy implementation across regions in Indonesia. To support several aspects of the Sustainable Development Goals (SDGs), IBEI comprises three pillars (dimensions): environment, economy and social. The following describes the three pillars:

a) Environment pillar: this pillar addresses the quality of ocean and coastal ecosystems, which represent a sustainable ocean economy. A safe environment is crucial for promoting sustainable long-term economic growth.
b) Economic pillar: this pillar evaluates the contribution of the marine sector (fisheries and aquaculture, marine-based manufacturing and tourism) to Indonesia's economic growth.
c) Social pillar: this pillar emphasises inclusion by assessing the way marine sector can help Indonesians improve their quality of life. It focuses on two components of well-being: income and quality of life (health).

Missing value imputation

Filling in missing data in data analysis, especially in spatial data, is a crucial step (György et al. 2025, Mariani et al. 2024, Nugroho–Surendro 2024). A common method used for addressing this issue is classification and regression trees (CART), which builds a decision tree to predict missing data values based on group similarity (Carrizosa et al. 2021, Ozcan–Peker 2023). CART effectively handles missing data across various data types, such as numerical and categorical variables (Alam et al. 2021, Hamzah et al. 2021). It can handle complex data with multiple predictor variables and develop interpretable models without altering the original data distribution.

Data standardisation

Data standardisation is the process of transforming data into the same scale, which facilitates comparisons between variables and increases the accuracy of the analysis model (Ngoc et al. 2022, Ustun et al. 2019). Z-score is one of the commonly used standardisation methods (Anggoro–Supriyanti 2019, Pambudi et al. 2023). This method converts data into standardised values with a mean of 0 and a standard deviation of 1. The z-score can be calculated as follows:

$$z = \frac{x - \mu}{\sigma}, \tag{1}$$

where z is the z-score standardisation value, x is the value of the observation data and μ and σ are the mean and standard deviation of the data, respectively. Herein, z-scores are computed using a pooled multiyear reference (2019–2022 combined) rather than separately by year. This approach ensures that all variables are measured on a consistent scale across the entire time period, facilitating spatio-temporal comparisons and maintaining uniformity in the input data for the MGTWR model. Using pooled standardisation allows us to detect relative differences across districts and years without distorting the scale owing to year-specific fluctuations.

Preparation of the BEI

The calculation of the BEI follows the approach used by the United Nations Development Programme for calculating the human development index (HDI). HDI is composed of three dimensions: health, education and expenditure. Similarly, on the basis of the calculation conducted by IBEI, it is determined that the BEI calculation is divided into three dimensions: social, economic and environmental. To construct the BEI, the index value for each dimension is first calculated using the arithmetic mean method. Then, these dimension indices are aggregated using the geometric mean method. This process can be mathematically expressed as follows:

$$BEI = \sqrt[3]{I_{Environment} \times I_{Economic} \times I_{Social}} \times 100, \quad (2)$$

where $I_{Environment}$, $I_{Economic}$ and I_{Social} denote the standardised sub-indices for the environmental, economic and social dimensions, respectively. The geometric mean is used to integrate these three dimensions, and the result is multiplied by 100 to scale the BEI between 0 and 100.

Least absolute shrinkage selection operator (LASSO) method

LASSO is a method that selects the most relevant predictor variables in a regression model by reducing model complexity and improving prediction accuracy (Emmert-Streib–Dehmer 2019, Rahayu–Husein 2023, Yunus et al. 2020). This method imposes a penalty on the regression coefficients, driving some of them to zero via the L1 norm, thereby prioritising significant variables and diminisihing the impact of irrelevant ones. Parameter estimation β on LASSO is obtained as follows:

$$\hat{\beta} = argmin\left\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2\right\}, \quad (3)$$

where β denotes the regression coefficient, y_i is the response variable for the i-th observation and x_{ij} is the j-th predictor variable for the i-th observation.

Research design and data collection techniques

This study uses a statistical analysis approach that focuses on spatio-temporal data and index calculations. Spatio-temporal data uniquely combine geographic location with time and allows us to visualise the way variables relate to each other in the context of space and time. These data generally consist of a dependent variable, an independent variable, a subject (e.g. the name of a place or person), geographical coordinates and a time range. This study focuses on 154 regencies/cities selected from 10 provinces located on the island of Sumatra during the 2019–2022 period.

By using these data, researchers can calculate the BEI and analyse the factors that influence the level of GRDP on the island of Sumatra at district/city level. The secondary data used in this study were sourced from Statistics Indonesia (BPS) [1], the Ministry of Tourism and Creative Economy [2], the National Waste Management Information System (SIPSN) [3] and the Ministry of Marine Affairs and Fisheries (KKP) of the Republic of Indonesia [4]. Following data collection, researchers preprocess the data using Python in Visual Studio Code. The variables used in this study are presented in Figure 3 and Table 2.

Some variables included in the BEI, such as the number of high school students, percentage of population with access to adequate drinking water, total annual waste recycling and percentage of poor population, are indirectly related to marine economic activities. However, these indicators capture the socio-economic and environmental foundations necessary for sustainable blue economy development. For instance, human capital, represented by education levels, supports innovation and skilled labour in fisheries, tourism and marine technology sectors. Access to clean water and effective waste management reflect the quality of coastal ecosystems, which directly affects fisheries, aquaculture and tourism productivity. Similarly, poverty levels indicate the capacity of local communities to participate in and benefit from blue economy activities. Therefore, the incorporation of these variables ensures that the index not only measures economic output but also captures the enabling conditions for sustainable and inclusive blue growth.

Figure 3

Blue economy index compilation pillars by district/city

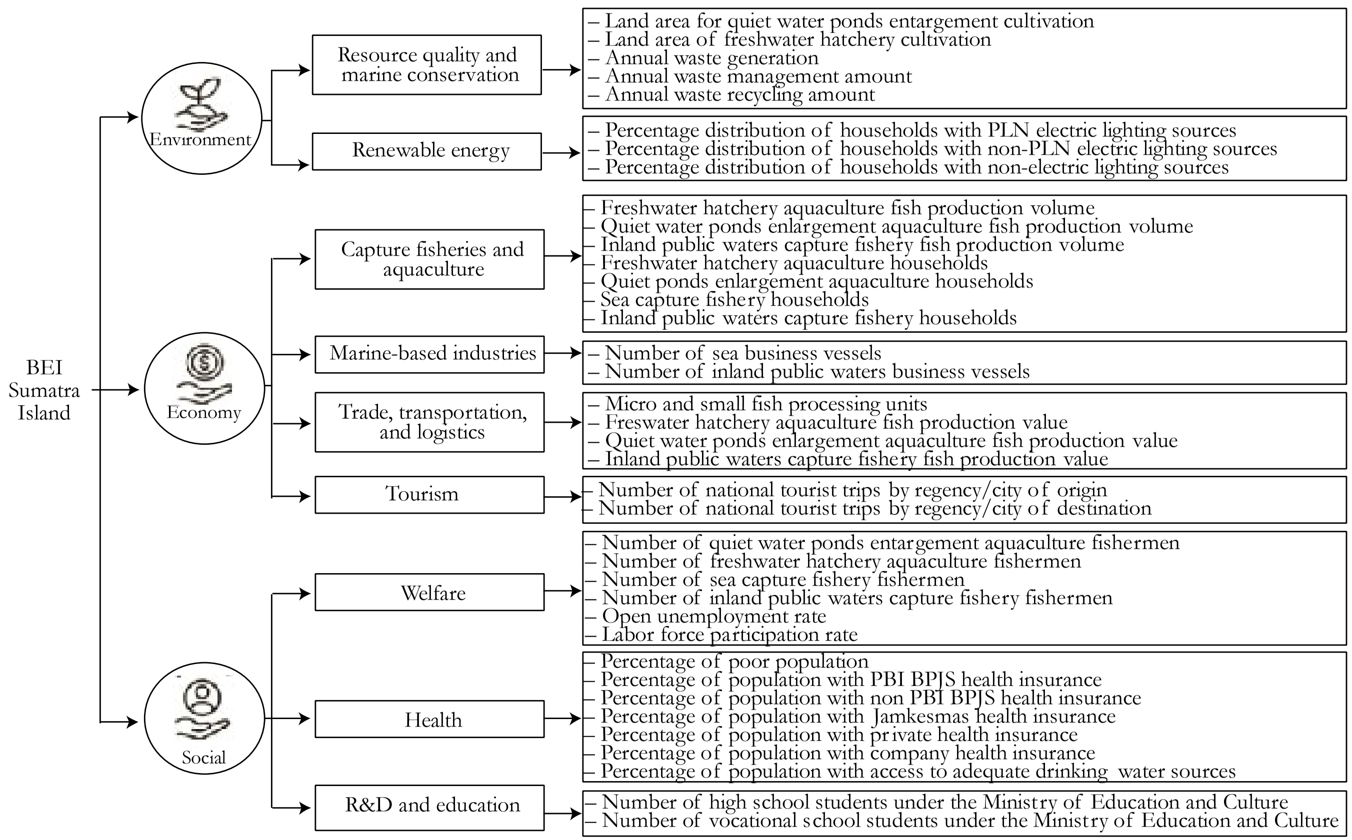


Table 2

Research variables

Variable	Definition
Response variable	
Y	District/city GRDP level
Predictor variable	
	Social
$X_{fishaqua}$	Number of stillwater pond aquaculture fishermen
$X_{marfish}$	Number of marine capture fishermen
$X_{fishpud}$	Number of public inland waters (PIW) capture fishermen
$X_{freshfish}$	Number of freshwater hatchery fishermen
X_{our}	Open unemployment rate
X_{labor}	Labour force participation rate
X_{poor}	Percentage of poor population
X_{PBI}	Percentage of the population with PBI BPJS health insurance
X_{NonPBI}	Percentage of the population with non-PBI BPJS health insurance
X_{jamkes}	Percentage of the population with Jamkesmas (*Jaminan Kesehatan Masyarakat*, Indonesia's national public health insurance programme)
$X_{private}$	Percentage of the population with private health insurance
$X_{company}$	Percentage of the population with company-based health insurance
$X_{drinking}$	Percentage of the population with access to adequate drinking water sources
X_{high}	Number of high school students under the Ministry of Education and Culture
X_{voc}	Number of vocational school students under the Ministry of Education and Culture
	Economic
X_{seaves}	Number of sea business vessels
X_{pudves}	Number of PIW business vessels
X_{micro}	Small micro fish processing unit (FPU)
$X_{fhquiet}$	Fishery households aquaculture cultivation of stillwater pond enlargement
$X_{fhmarin}$	Fishery households marine capture fisheries
X_{fhpud}	Fishery households PIW capture fisheries
$X_{fhfresh}$	Fishery households freshwater aquaculture hatcheries
$X_{volfresh}$	Volume of fish production of freshwater hatchery aquaculture
$X_{volquiet}$	Fish production volume of aquaculture fish production of stillwater pond enlargement
X_{volpud}	Volume of fish production in PIW capture fisheries
$X_{profresh}$	Value of fish production in freshwater hatchery aquaculture
$X_{proquiet}$	Fish production value of aquaculture in stillwater ponds
X_{propud}	PIW capture fisheries fish production value
X_{origin}	Number of archipelago tourist trips by district/city of origin
X_{arcdes}	Number of national tourist trips by destination district/city
	Environment
$X_{landquiet}$	Land area for cultivation of stillwater pond enlargement
$X_{landfresh}$	Land area for cultivation of freshwater hatcheries
X_{awg}	Total annual waste generation (tonnes)
X_{awm}	Total annual waste management (tonnes)
X_{awr}	Total annual waste recycling (tonnes)
X_{pln}	Percentage distribution of households with a source of electricity lighting by Perusahaan Listrik Negara (PLN)
X_{nonpln}	Percentage distribution of households with non-PLN electric lighting sources
$X_{nonelec}$	Percentage distribution of households with non-electric lighting sources

Multiscale geographically and temporally weighted regression: method, kernel function and inference

Parameter estimation in GTWR is performed using the weighted least squares method, which is modified to account for spatio-temporal weights (Huang et al. 2010, Liu–Dong 2021, Yasin et al. 2025). Given the matrix $W(u_i, v_i, t_i)$, the parameter estimates for each location of the GTWR model can be determined as follows:

$$\hat{\beta}(u_i, v_i, t_i) = (X^T W(u_i, v_i, t_i) X)^{-1} X^T W(u_i, v_i, t_i) Y, \tag{4}$$

where $\hat{\beta}(u_i, v_i, t_i)$ is the vector of estimated coefficients at location i, X is the matrix of predictors, Y is the response variable (GRDP) and $W(u_i, v_i, t_i)$ is a diagonal weight matrix based on spatial coordinates (u_i, v_i) and time t_i. The GTWR regression equation is given as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{j=1}^{p} \beta_k(u_i, v_i, t_i) x_{ij} + \varepsilon_i, \tag{5}$$

where y_i is the response variable at location i, $\beta_0(u_i, v_i, t_i)$ is the intercept at location i, $\beta_k(u_i, v_i, t_i)$ is the coefficient for predictor x_j at location i, x_{ij} is the value of predictor j at location i and ε_i is residual at location i. Spatial and temporal distances are defined using the Euclidean method as follows (Sifriyani et al. 2022):

$$\begin{cases} \left(d_{ij}^{s}\right)^2 = \left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2 \\ \left(d_{ij}^{T}\right)^2 = \left(t_i - t_j\right)^2 \\ \left(d_{ij}^{sT}\right)^2 = \phi^s \left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \phi^T \left[\left(t_i - t_j\right)^2\right], \end{cases} \tag{6}$$

where d_{ij}^{s} is the spatial distance between location i and j, d_{ij}^{T} is the temporal distance between location i and j, d_{ij}^{sT} is the combined spatio-temporal distance and weights ϕ^s and ϕ^T are the spatial and temporal balancing parameters. The kernel function is a spatial weighting element for each location. The kernel functions used in this study are presented in Table 3 (Al-Hasani et al. 2021).

Table 3

Kernel functions

Function	Specifications	
Gaussian	$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{\lvert d_{ij}^{sT}\rvert}{b}\right)^2\right)$	(7)
Uniform	$w_{ij} = \begin{cases} \frac{1}{n_{ij}^{l}}, \text{where j is neighbour of i in order to l} \\ 0, \text{other} \end{cases}$	(8)
Bi-square	$w_{ij} = \begin{cases} \left(1 - \left(\frac{\lvert d_{ij}^{sT}\rvert}{b}\right)^2\right), \text{for } d_{ij} \leq b \\ 0, \text{for } d_{ij} > b \end{cases}$	(9)

MGTWR is an extension of GTWR that allows the identification of spatio-temporal relationship patterns with varying bandwidths for each variable (Liu et al. 2021). Bandwidth is a measure of neighbourhood scale, where the larger the bandwidth value, the more regions are used in the local regression. This method uses a weight function that varies according to spatial and temporal scales, allowing the identification of different patterns of relationships at different scales. The equation form of this method is as follows:

$$Y = \beta_{bwt_0s_0} + \beta_{bwt_1s_1} \otimes x_1 + \cdots + \beta_{bwt_ps_p} \otimes x_p \; + \; \varepsilon, \tag{10}$$

where ⊗ denotes the element-wise matrix multiplication and bwsp and bwtp are the spatial and temporal bandwidths, respectively.

MGTWR uses different bandwidths for each component of the model, allowing for more accurate modelling of spatio-temporal relationships and reducing bias in parameter estimation. The MGTWR model can be defined as follows:

$$y \; = \; f_{b_{w0}}(\beta_{0i}) + \sum_{j=1}^{k} f_{b_{wk}}(X_k) + \epsilon_i \, , i \; = \; 1, \ldots, n, \tag{11}$$

where $f_{b_{wk}} = b_{wk}(\beta_k)X_k$ represents a smoothing function or data borrowing scheme that selects kernel functions and computes weights and bandwidths. To estimate each f_{b_w} and calculate β_k, the following equation can be reconstructed:

$$f_{b_{wk}} \; = \; E(y - \sum_{p \neq k} f_{b_{wp}} - \varepsilon | X_k) = A_k(y - \sum_{p \neq k} f_{b_{wp}}). \tag{12}$$

After initialising each β for each predictor, the residuals of the GAM GTWR model for the back-fitting algorithm are defined as follows:

$$\hat{\varepsilon} \; = \; y - \sum_{j=1}^{k} \hat{f}_j. \tag{13}$$

Note that A_k is the hat matrix from the previously optimal model precision; thus, we get the following:

$$\hat{f}^{k+1} = A_k\left(\hat{f}^k + \hat{\varepsilon}\right). \tag{14}$$

At this stage, the score of change (SOC) is assessed to evaluate the discrepancies in predictions across iterations. SOC examines the residual sum of squares to determine the way model adjustments affect prediction accuracy over time, and it is expressed as follows:

$$SOC \; = \; \frac{RSS^{k+1} - RSS^k}{RSS^k}. \tag{15}$$

By incorporating SOC in the analysis, MGTWR can effectively adapt to changes in relationship patterns within the data, ensuring a robust assessment of spatio-temporal interactions. After convergence reaches, the final value of R_k can be computed to derive the overall hat matrix *S* for the model as follows:

$$S \; = \; \sum_k R_k, \tag{16}$$

where R_k is the partial hat matrix representing the contribution of the k-th predictor to the fitted values in the MGTWR model. In addition, R_k can be used to compute the effective number of parameters as follows:

$$ENP_k \; = \; tr(R_k) \tag{17}$$

$$ENP_{model} = \sum_k ENP_k. \tag{18}$$

Table 4 presents the algorithm behind MGTWR, outlining the key steps and computational process that enable it to explore complex interactions in spatio-temporal data through continuous adjustment mechanisms, resulting in a more flexible and accurate model.

Stages analysis

This study uses the MGTWR method with LASSO-selected variables and incorporated variations of kernel weighting functions to identify the best model for describing GRDP levels across all districts/cities of Sumatra Island. The BEI value is calculated at the district/city level throughout Sumatra. The stages of this study are outlined in the algorithm presented in Table 4.

Table 4

Estimation process of MGTWR

Step	Descriptions
1	Import data and merge Excel variable data with SHP data for each district/city on Sumatra
2	Pre-process the data and check for missing values
3	Fill missing values using the CART method
4	Perform data transformation as necessary
5	Calculate BEI for each district/city
6	Obtain BEI values at the district/city level
7	Select significant variables affecting GRDP using LASSO
8	Calibrate the MGTWR model to obtain initial values for $\hat{f}_k$, $\hat{\varepsilon}$ and R_k
9	Initialise $SOC \gg \eta$
10	Repeat until $SOC < \eta$
11	For each scale k:
12	Calibrate the univariate MGTWR model $(\hat{f}_k + \hat{\varepsilon}) \sim X_k$ to obtain $\hat{f}_k^*$ and $\hat{\varepsilon}^*$
13	Update $\hat{f}_k \leftarrow \hat{f}_k^*$ and $\hat{\varepsilon} \leftarrow \hat{\varepsilon}^*$
14	Compute R_k
15	End loop over scales
16	Compute new SOC^* and update $SOC \leftarrow SOC^*$
17	End loop until convergence
18	For each scale k:
19	Compute ENP_k
20	End loop over scales
21	Compute S (final statistics)
22	Compare models using R^2 and AIC to determine the best model
23	Conduct classical assumption tests: – normality test (Kolmogorov–Smirnov) – heteroscedasticity test (Breusch–Pagan) – multicollinearity test – autocorrelation (Durbin–Watson)
24	If the assumptions are not met, return to step 4 for data transformation
25	End

Results, analysis and discussion

Descriptive analysis

Table 5 presents a descriptive analysis of several variables that constitute the blue economy. The average values that continuously increase annually are those for the variables X_{high} (number of high school students) and X_{micro} (small micro fish processing unit [FPU]). The increase in the number of high school students in Sumatra is largely attributable to infrastructure projects led by the Sumatra government. Similarly, in case of FPUs, increasing demand and the increase in growth of labour and infrastructure facilities encourage activities aimed at improving production quality. To meet these demands, FPUs continue to invest, thereby positively influencing the economy of Sumatra. The dataset is first examined for missing values, as some variables have missing values. These missing values are imputed using the CART method. After imputation, the data are standardised.

Table 5

Descriptive analysis of variables

Variables	Statistic	2019	2020	2021	2022
$X_{marfish}$	Mean	3,787.162	4,037.961	3,687.805	3,815.39
	Standard deviation	7,147.625	6,250.314	6,083.615	5,474.098
$X_{fishpud}$	Mean	1,782.506	969.825	1,285.13	1,683.273
	Standard deviation	3,402.713	1,784.005	3,315.77	3,236.022
X_{seaves}	Mean	1,488.136	1,829.013	1,578.708	1,420.675
	Standard deviation	2,403.692	2,618.49	2,933.196	2,201.282
X_{micro}	Mean	100.799	100.916	102.474	105.474
	Standard deviation	177.124	177.137	177.364	135.902
X_{high}	Mean	9,063.981	9,130.37	9,176.565	9,266.688
	Standard deviation	8,249.73	8,207.914	8,287.362	8,403.693

BEI

On the basis of the results of the BEI dimensions presented in Table 6, the social pillar emerges as the most influential component. The dominance of the social pillar in the BEI calculation demonstrates the dependence of the population on fisheries and marine resources for their livelihoods. Despite vast maritime potential of Sumatra, its development remains suboptimal.

Table 6

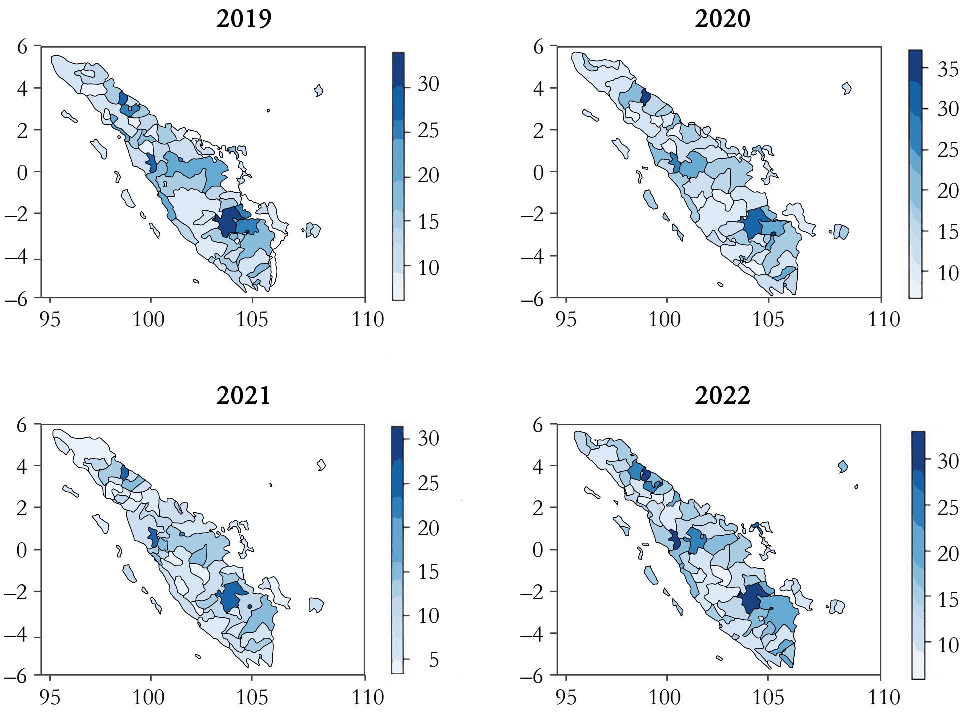
Overview of the dimensions of BEI in Sumatra

Pillars	Statistic	2019	2020	2021	2022
Environment	Mean	0.195	0.178	0.071	0.176
	Standard deviation	0.076	0.074	0.073	0.056
Economy	Mean	0.072	0.081	0.071	0.079
	Standard deviation	0.064	0.066	0.06	0.06
Social	Mean	0.219	0.232	0.226	0.234
	Standard deviation	0.055	0.052	0.053	0.052

On the basis of the compiled BEI results, the average BEI over 4 years is obtained. During the 4-year period, 2021 has recorded the lowest average BEI (9.21). In comparison, the average BEI was 13.5 in 2019, 14.17 in 2020 and 14.11 in 2022. To clearly illustrate the distribution of BEI values at district/city level, a visual map is presented in Figure 4.

Figure 4

Plot of BEI results



An interesting trend is observed in the analysis of the BEI of Sumatra Island from 2019 to 2022. Medan City, Palembang City, Musi Banyuasin, Deli Serdang and Pasaman are among the five regions with the highest BEI values. With the dominance of BEI in these regions, North Sumatra, South Sumatra and West Sumatra show strong potential for marine-based economic development. However, the case is different for the Bangka Belitung Islands, Riau Islands, Lampung and Riau regions. These four regions account for the districts or cities with the lowest BEI values over the 4-year period. From 2019 to 2022, the regions with the lowest BEI values from 2019 to 2022 include Sabang City, Solok City, Payakumbuh City, Padang Panjang City, Sungai Penuh City, Tebo, Empat Lawang, Pakpak Bharat, South Ogan Komering Ulu, Subulussalam City, West Aceh, Sawahlunto City, Humbang Hasundutan and Lebong. Sawahlunto City recorded the lowest BEI value among all regions in 2021 (3.37). The results of the BEI calculations for the entire region are presented in Appendix Table A1.

Variable selection

In the LASSO analysis, cross-validation (CV) is first performed to identify the optimal LASSO selection weights. The CV results are presented in Appendix Figure A1, which shows that the best mean square error value is 0.015, resulting in 20 selected variables that influence the GRDP level. The variables selected using the LASSO method are shown in Table 7.

Table 7

LASSO selection result variable

Dimensions	Variable
Social	$X_{marfish}$, $X_{fishpud}$, X_{jamkes}, $X_{company}$, X_{our}, X_{labor}, X_{poor}, X_{NonPBI} and X_{high}
Economic	X_{seaves}, X_{pudves}, X_{micro}, $X_{volquiet}$, X_{volpud} and X_{arcdes}
Environment	$X_{landquiet}$, X_{awg}, X_{awm}, X_{pln} and X_{nonpln}

Table 7 shows 20 variables from the economic, social and environmental dimensions that considerably affect the GRDP level. These variables are grouped into several subdimensions that constitute the BEI, namely fisheries, welfare, marine-based industry, trade, marine resource quality and marine conservation, tourism, health, renewable energy and education sub. The fisheries subdimension includes the volume of fish production from aquaculture enlargement of stillwater ponds and the volume of fish production from PIW capture fisheries. The welfare subdimension comprises the number of marine capture fishermen, the number of PIW capture fishermen, the open unemployment rate and the labour force participation rate. The marine-based industry subdimension includes the number of marine business vessels and PIWs. The trade subdimension includes small micro FPUs only. The marine resource quality and marine conservation subdimension includes the land area for stillwater pond enlargement cultivation, the amount of annual waste (tonnes) and the amount of annual waste handling (tonnes). The tourism subdimension is represented by the number of domestic tourist trips by destination district/city. The health subdimension includes the percentages of poor population and the population covered by health insurance schemes, such as non-PBI BPJS, Jamkesmas and company-based insurance. The renewable energy subdimension includes the percentage distribution of households with both electric and non-electric lighting sources. Meanwhile, the education subdimension is represented by the number of high school students under the Ministry of Education and Culture. Table 7 shows that the social dimension exerts the most dominant significant influence.

Classical assumption test of the MGTWR–LASSO model

The normality test shows that the p-value is less than the significance level of 0.05 (Table 8), indicating that the residual values between the observed and prediction data are not normally distributed (Figure 5). Although slight deviations from normality are observed at the tails, the residual distribution in the central region is reasonably symmetric, indicating that the model fit is adequate for predictive purposes. Moreover, the predicted values closely follow the trend and variability of the observed data. This similarity in patterns suggests that the model provides an acceptable fit despite the violation of the normality assumption.

Figure 5

Diagnostic plots of the fitted model

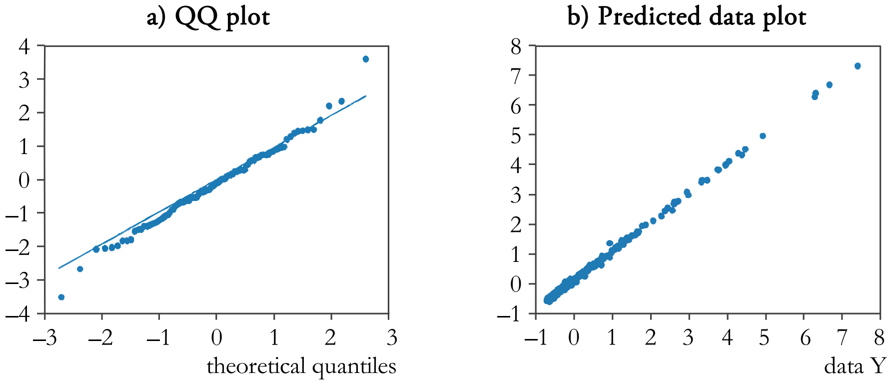


Table 8

Model assumption test

Test	LASSO
Normality test (Kolmogorov–Smirnov)	6.577×10^{-116} *
Heteroscedasticity test (Breusch–Pagan)	0.712*
Moran's I	0.001 (0.157)*
Autocorrelation test (Durbin–Watson)	0.005 (0.706)*
Temporal heterogeneity test	Boxplot on Figure 5

* p-value.

The Breusch–Pagan test for heteroscedasticity yields a p-value of 0.712, which is >0.05 significance level, indicating constant residuals. Furthermore, the Moran's I test is positive, suggesting a clustered spatial pattern. A Durbin–Watson result of 0.706 reveals autocorrelation among the residuals. However, Durbin–Watson indicates first-order or global autocorrelation, while GTWR is a local-scale model. Therefore, some degree of residual autocorrelation can remain even when the model adequately captures local spatio-temporal patterns. The maximum value of the boxplot that varies each year and the presence of some outliers indicate that spatial analysis alone is not sufficient for this study (Figure 6). Thus, spatio-temporal analyses are required.

Figure 6

Temporal heterogeneity of GRDP

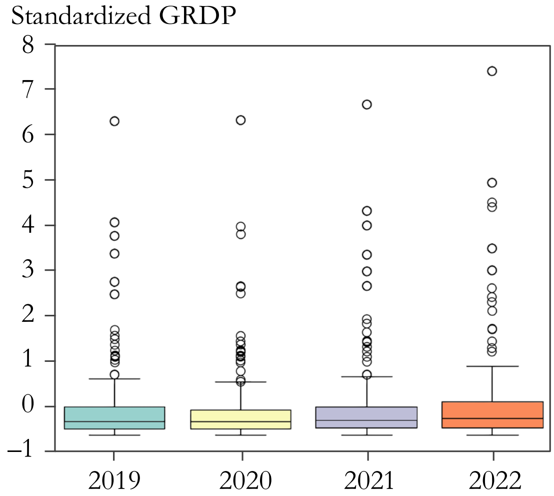


Table 9

VIF values of LASSO variables

Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF
$X_{marfish}$	3.439	$X_{landquiet}$	1.064	X_{awg}	5.934	X_{jamkes}	1.047
$X_{fishpud}$	5.559	$X_{volquiet}$	1.240	X_{awm}	5.233	$X_{private}$	1.468
X_{seaves}	3.356	X_{volpud}	1.351	X_{arcdes}	2.255	X_{pln}	1.044
X_{pudves}	5.563	X_{our}	1.891	X_{poor}	1.480	X_{nonpln}	1.311
X_{micro}	1.273	X_{labor}	1.455	X_{NonPBI}	1.780	X_{high}	3.136

Table 9 indicates that some predictor variables exhibit moderately high variance inflation factor (VIF) values (e.g. >5), suggesting potential correlations among predictors. However, as the model uses LASSO regularisation, multicollinearity is reduced through coefficient shrinkage. Therefore, the model remains interpretable and reliable for inference.

Selection of the best model

Diagnostic test

In this section, models using different kernel functions are compared to identify the best one for representing the GRDP level of each district/city on Sumatra Island. Table 10 presents the R^2 and Akaike information criterion (AIC) values for each model.

Table 10

Model comparison

Model	MGTWR–LASSO	
	R^2	AIC
Gaussian	0.995	−917.575
Uniform	0.820	735.386
Bi-square	0.999	−1,530.517

According to Table 10, the best model is the MGTWR–LASSO model with the bi-square function, achieving the largest R^2 and the smallest AIC values. Its R^2 value (0.999) indicates that the variables in this model explain 99.9% of the overall GRDP data.

Bandwidth and significant variables

After obtaining the best model, further analysis is conducted to identify the variables that affect each region using a two-way t-test. The hypotheses are formulated as follows:

$H_0\colon \beta_k = 0, k = 1,2,3 \ldots, p$ (k is not significant)

$H_1\colon \beta_k \neq 0, k = 1,2,3 \ldots, p$ (k is significant)

Of the 20 variables, all are observed to considerably affect GRDP, with the affected areas varying each year. The model employs a flexible bandwidth value for each variable, making parameter estimation more efficient than other methods, such as GTWR. Table 11 presents the bandwidth value and summary of the regression coefficient values on the basis of the values obtained from the best model.

Table 11

Significant variables and their optimal bandwidths

Variable	Bw	Variable	Bw	Variable	Bw	Variable	Bw
$X_{marfish}$	2.4	$X_{landquiet}$	2.0	X_{awg}	6.3	X_{jamkes}	2.0
$X_{fishpud}$	6.3	$X_{volquiet}$	8.0	X_{awm}	4.4	$X_{private}$	0.3
X_{seaves}	2.4	X_{volpud}	6.3	X_{arcdes}	6.2	X_{pln}	6.6
X_{pudves}	2.6	X_{our}	6.4	X_{poor}	2.4	X_{nonpln}	6.4
X_{micro}	1.0	X_{labor}	3.7	X_{NonPBI}	2.2	X_{high}	1.0

From the best model, regression coefficients are obtained, allowing an efficient mapping of GRDP levels on the basis of the significant variables in each region. The region with the highest GRDP level from 2019 to 2022 is Medan City. Economic and trade centres are concentrated mainly in the North Sumatra region. For example, PT Toba Surimi Industries, a major processed fish company in Medan, considerably affects the local economy. Its high production capacity generates employment both directly and indirectly, thereby increasing the income and welfare for workers and contributing to the economic growth of the city. Accordingly, this study presents an example of the best regression model that maps the Medan City area in 2019–2022 based on the MGTWR–LASSO model with a bi-square kernel.

$$y_{medancity2019} = -0.175 + 0.053\, X_{marfish} + 0.046\, X_{fishpud} - 0.036\, X_{our} -0.024\, X_{awg} + 0.022\, X_{awm} - 0.095\, X_{poor} + 0{,}668\, X_{high} \quad (19)$$

$$y_{medancity2020} = -0.175 + 0.051\, X_{marfish} + 0.046\, X_{fishpud} - 0.036\, X_{our} -0.024\, X_{awg} + 0.025\, X_{awm} - 0.095\, X_{poor} - 0.05\, X_{jamkes} + 0.647\, X_{high} \quad (20)$$

$$y_{medancity2021} = -0.175 + 0.048\, X_{marfish} + 0.046\, X_{fishpud} - 0.036\, X_{our} -0.024\, X_{awg} + 0.028\, X_{awm} - 0.095\, X_{poor} + 0.644\, X_{high} \quad (21)$$

$$y_{medancity2022} = -0.175 + 0.045\, X_{marfish} + 0.046\, X_{fishpud} - 0.036\, X_{our} -0.024\, X_{awg} + 0.03\, X_{awm} - 0.095\, X_{poor} + 0.65\, X_{high} \quad (22)$$

According to equations 19–22, Medan City exhibits different regression models each year. In the 2019, 2021 and 2022 regression models, Medan City was positively influenced by the following variables: the number of marine capture fishermen, the number of PIW capture fishermen, the amount of annual waste handling and the number of high school students under the Ministry of Education and Culture. By contrast, the variables that negatively affect GRDP at current prices in the Medan City include the open unemployment rate, the annual amount of waste generation and the percentage of the poor population. In 2020, the Medan City was negatively influenced by an additional variable: the percentage of the population exhibiting Jamkesmas health insurance.

After obtaining the bandwidth value and significance of the variables, a partial test is conducted using a two-way t-test to determine the significance of the variables in each region. The two-way t-test allows us to determine whether the variable has a statistically significant influence on the dependent variable. The grouping of variables is shown in Figure 7. Different colours indicate different groups of significant variables in each region.

Based on the visualisation, the discussion focuses on the groups of significant variables in the two regions of Sumatra Island with the highest and the lowest BEI values. The two regions with the highest BEI values are Medan City and Palembang City, whereas the two regions with the lowest BEI values are Sawahlunto City and Subulussalam City.

a) District or city with the highest BEI value in 2019–2022:
  – Medan City (year 2020: 37.166): On the basis of the visuals in Figure 7, it can be concluded that in 2019, 2021 and 2022, Medan City is affected by the same variables, namely, the number of marine capture fishermen, the number of PIW capture fishermen, the open unemployment rate, the amount of annual waste generation, the amount of annual waste handling, the percentage of the poor population and the number of high school students under the Ministry of Education and Culture. These variables remained influential in 2021, with the addition of one more significant variable, namely, the percentage of the population covered by Jamkesmas

health insurance. These significant variables are consistent with the fact that Medan City exhibits the potential to become a new metropolitan city, a centre of government, a national tourism site and an economic driver city.

- Palembang city (year 2020: 36.988): On the basis ofthe visuals in Figure 7, it can be concluded that in 2019 and 2020, Palembang City was influenced by the following variables: the number of PIW capture fishermen, the volume of aquaculture fish production of enlarged stillwater ponds, the level of open unemployment, the number of trips of domestic tourists by district or city of destination, the percentage of the poor population and the percentage of the population with non-PBI BPJS health insurance. Meanwhile, in 2021–2022, Palembang City was influenced by the number of PIW capture fishermen, the volume of aquaculture fish production in stillwater ponds, the open unemployment rate, the amount of annual waste handling (tonnes), the percentage of the poor population and the percentage of the population with non-PBI BPJS health insurance. The variables with a considerable effect are consistent with the fact that Palembang City can develop both small and medium-sized industries.

b) District or city with the lowest BEI value:
   - Subulussalam City (year 2021: 3.549): On the basis ofthe visuals in Figure 7, it can be concluded that most variables with a significant effect on the ADHB GRDP of Subulussalam City remained consistent over the 4-year period. The variables that consistently exhibited a significant effect on Subulussalam City throughout the 4 years were the number of PIW capture fishermen, FPUs, the production volume of fish enlargement in stillwater ponds, open unemployment rate, annual amount of waste generation, annual amount of waste handling, percentage of poor population, percentage of population with non-PBI BPJS health insurance and number of high school students under the Ministry of Education and Culture. The number of marine capture fishermen and the area of stillwater pond cultivation exhibited a significant effect but only in the first 2 years, i.e. 2019 and 2020. Meanwhile, the number of boats was significant only in 2022. These significant variables are consistent with the fact that economic growth in Subulussalam City is strongly influenced by the availability of infrastructure. Thus, it can be concluded that the presence of FPUs considerably affects the economic growth in Subulussalam City.
   - Sawahlunto City (year 2021: 3.374): On the basis of the visuals in Figure 7, it can be concluded that most variables with a significant effect on GRDP at current prices in Sawahlunto City remained consistent over the 4-year period. The variables that remained significant in Subulussalam City throughout the 4 years were the number of PIW capture fishermen, FPUs, the production volume of fish enlargement in stillwater ponds, the open

unemployment rate, the percentage of the population with non-PBI BPJS and company-based health insurance and the number of high school students under the Ministry of Education and Culture. In addition, some variables were significant only in certain years, such as the number of national tourist trips by destination district/city, which only exhibited a significant effect in 2019 and 2020 and the annual amount of waste handling, which only exhibited a significant effect in 2021 and 2022. Meanwhile, the percentage of the population with Jamkesmas-type health insurance was significant only in 2022. These significant variables are consistent with the fact that local economic activities in Sawahlunto City are largely supported by local own-source revenues.

c) Temporal trends:
Furthermore, to determine the temporal trend of significant variables in the four regions, the coefficient of each significant variable from 2019 to 2022 is used. The coefficient explains the extent of influence of the variable on GRDP at current prices. The temporal trends are shown in Figure 8.

On the basis of the visuals in Figure 8, the temporal trends of the significant variables in each region exhibit different conditions. The first example is the effect of the number of high school students under the Ministry of Education and Culture. In Subulussalam City, this effect increased in 2020 but decreased in 2021 and 2022. Meanwhile, the effect of the number of senior high school students in Sawahlunto City and Medan City decreased in 2020 and then gradually increased in the following years.

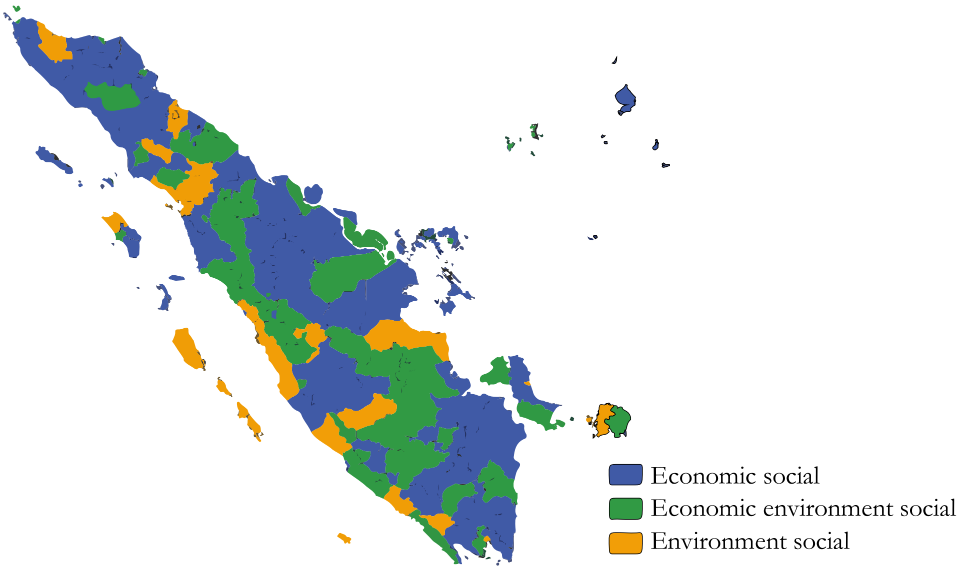
The second example is the influence of FPUs. FPUs in Subulussalam City showed an increasing influence over the 4-year period. By contrast, in Sawahlunto City, this effect decreased. The third example is the effect of the annual amount of waste handling. In Sawahlunto City and Palembang City, the temporal trend of this effect demonstrated a consistent increase.

The other three variables are the land area of stillwater pond enlargement, the number of domestic tourist trips by destination district/city and the percentage of the population with health insurance. These three variables considerably affected only certain cities. The land area of stillwater pond enlargement cultivation, which was significant only in Subulussalam City, consistently showed a decreasing influence over the 4-year period. The number of domestic tourist trips by destination district/city, which considerably affected only Palembang City, exhibited a consistent upwards trend, indicating an increasing effect over time. Meanwhile, the percentage of the population with Jamkesmas health insurance, which considerably affected only Medan City, decreased its influence in 2020 and then gradually increased in the following years. The inconsistent influence of these significant variables over the 4 years can largely be attributed to the impact of the Covid-19 pandemic.

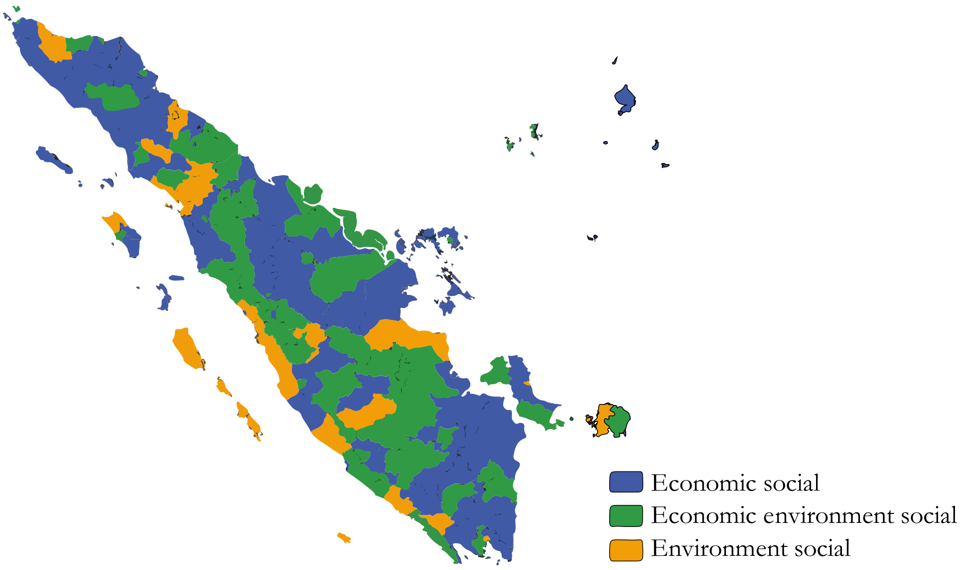
Figure 7

Group of significant variables of regencies/cities on Sumatra Island

2019



2020



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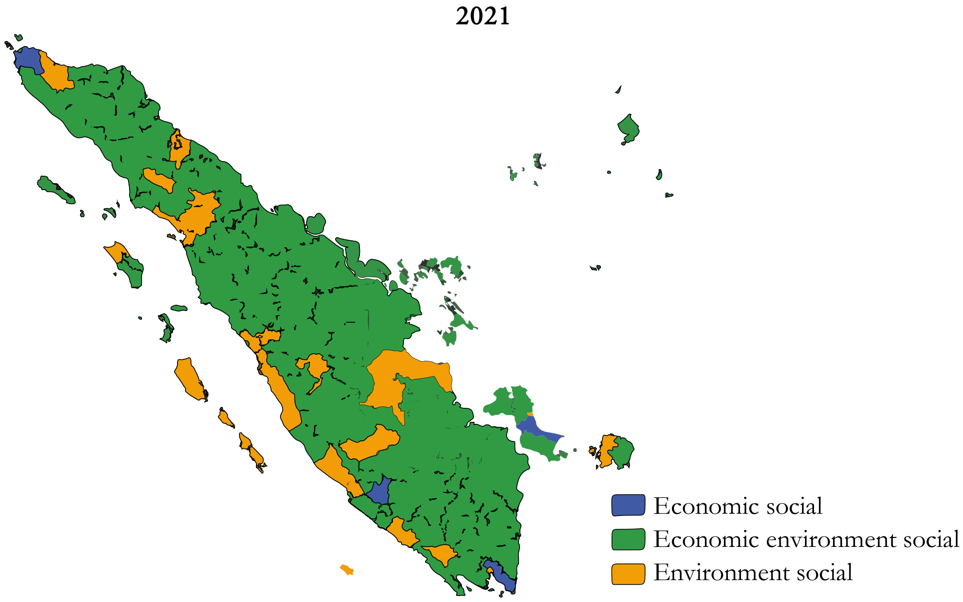

2021
Economic social
Economic environment social
Environment social

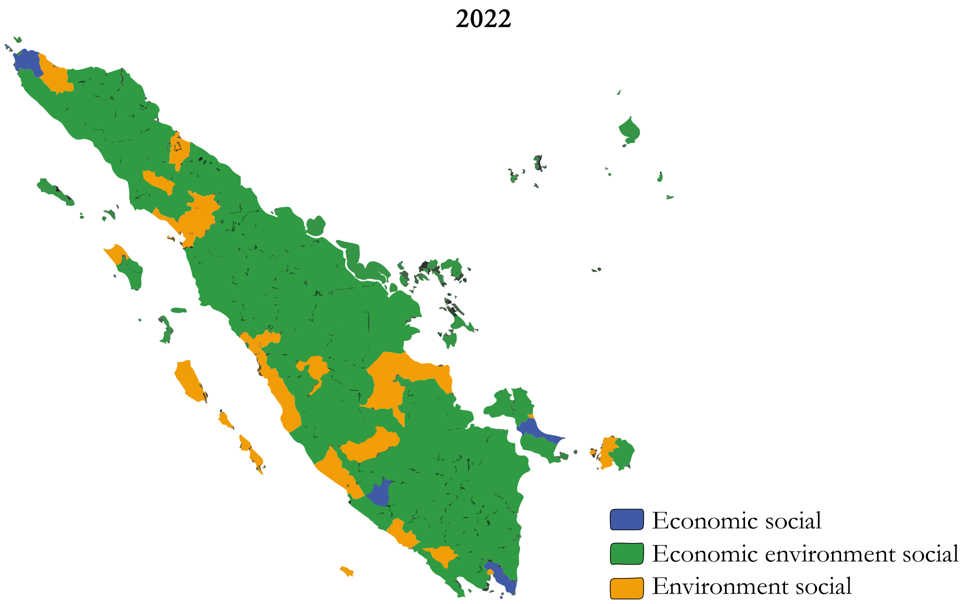
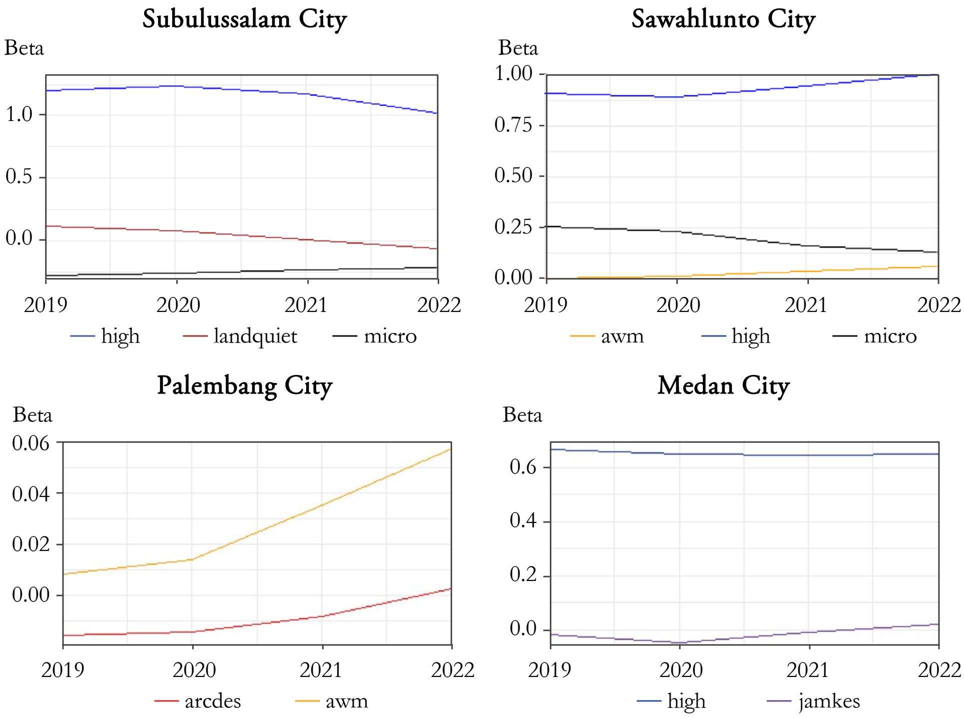

2022
Economic social
Economic environment social
Environment social

Figure 8

Temporal trends of significant variables



Conclusions and recommendations

On the basis of the discussion in the previous section, the BEI value for each district were obtained and the factors that influenced GRDP were modelled using blue economy variables. The results revealed that the social dimension largely contributed in the construction of the index when compared with the environmental and economic dimensions. Over the 4-year period from 2019 to 2022, Medan City and Sawahlunto City recorded the highest and the lowest BEI values, respectively. In particular, the factors that influenced the level of GRDP, as identified through LASSO variable selection, included the number of fishermen, number of boats, small micro FPUs, cultivation land area, fish production volume, open unemployment rate, labour force participation, waste management, tourist visits, percentage of poor people, health insurance coverage, lighting sources and education. The best model obtained in this study was the MGTWR–LASSO model with a bi-square kernel, with an R^2 value of 0.999 and an AIC value of −1,530.517. Spatio-temporal analysis revealed that most areas exhibited different groups of significant variables each year, although adjacent areas shared the same significant variables.

On the basis of the BEI results, social aspects contributed the most to the index. Therefore, economic growth could be promoted through strategies focused on the social dimension (Yan–Sambodo 2023). Examples of such strategies included providing social assistance, improving access to education and health to achieve equitable economic growth and implementing labour training programmes to improve the quality of human resources. The economic growth of the Medan City and Sawahlunto City, the regions with the highest and lowest BEI values, respectively, was markedly influenced by indicators across the environmental, economic and social dimensions. Fisheries activities, waste management, the number of poor people, health insurance coverage and education played a major role in the economy of both the regions. Furthermore, the economy of Sawahlunto City was influenced by FPUs and tourism. To maximize the potential of the blue economy in driving economic growth in Sumatra Island, particularly in the two regions, these aspects should be further developed.

The results of the significant variables affecting the BEI in this study aligned with the government policies such as, the medium- to long-term strategy of the Indonesian Ministry of Maritime Affairs and Fisheries, aiming to expand marine conservation areas, promoting sustainable aquaculture and curbing plastic pollution in the sea through a circular economy and coastal community participation [5]. Implementing this strategy could maximise the potential of the sea in a sustainable manner. Marine waste management had been enforced through government regulations designed to reduce pollution in marine ecosystems, thereby improving water quality and fisheries productivity (Leonardo et al. 2024). The government had set a poverty-reduction target that relies on social assistance and income-enhancing empowerment initiatives, particularly within coastal communities (Leonardo et al. 2024). Finally, the government made efforts to improve its access and quality of education at all levels, recognising healthy human resources as capital for a sustainable economy (Pemerintah Indonesia 2024).

On the basis of the spatio-temporal analysis results, areas that required more attention, namely those exhibiting low BEI values, could be identified. The MGTWR results reveal that certain social, economic and environmental variables in adjacent districts exhibited similar patterns. Strengthening collaboration between these regions could optimise shared resource management and enhance the overall impact on economic growth, as interventions targeting one district could positively influence neighbouring districts with similar variable patterns. These significant variables could indicate the existence of common factors that represent the dependency of the same environmental, economic and social conditions between regions. Through this common dependency, economic growth in one region was expected to influence economic growth in other regions, especially those in close proximity. Thus, strategies to boost the economy could be effectively and efficiently applied to regions that shared significant variables. Using this strategy, community welfare could be achieved through economic growth that could be felt by all levels of society.

On the basis of the current findings, future studies could enhance the MGTWR model when combined with LASSO by exploring various kernel functions beyond the bi-square kernel, such as mixed or adaptive kernels, to further optimise spatial weighting across diverse regions. In addition, investigating the effects of unilateral approaches or mixed-effects models could deepen our understanding of the regional economic dependencies in relation to the blue economy, potentially capturing more nuanced variations across districts (Liu et al. 2017, Nuramaliyah et al. 2019). In terms of explanatory variables, future studies could consider incorporating additional environmental indicators, such as mangrove coverage, which have demonstrated significant ecological and economic value in supporting coastal resilience and fishery productivity (Prasetyo 2023, Ridzuan et al. 2022). Expanding the model with these variables could offer a more comprehensive view of the factors influencing GRDP, especially in coastal regions where mangroves and other coastal resources played crucial roles in sustaining local economies. This extended model could provide valuable insights into policy development by highlighting the most impactful variables for sustainable economic growth across different dimensions.

Appendix

Table A1

BEI calculation results for the entire region

Kabupaten/Kota	2019	2020	2021	2022
Kota Medan	33.938	37.166	31.446	32.927
Kota Palembang	32.447	36.988	29.895	29.592
Musi Banyuasin	32.007	29.053	26.185	30.720
Deli Serdang	29.968	36.463	25.194	32.042
Pasaman	27.694	27.620	24.196	31.336
Kota Pekanbaru	22.855	23.800	20.821	21.804
Kota Bandar Lampung	24.605	24.789	19.143	21.932
Kota Bengkulu	14.327	15.535	19.109	22.008
Kota Banda Aceh	13.036	13.093	18.537	16.612
Padang Pariaman	17.861	18.911	17.074	18.047
Lima Puluh Kota	18.100	22.669	16.941	19.220
Simalungun	23.434	15.877	16.292	22.991
Batu Bara	14.214	13.025	15.964	16.649
Ogan Komering Ilir	18.428	16.495	15.563	20.237
Ogan Komering Ulu Timur	17.160	17.910	15.193	17.703
Indragiri Hulu	14.951	14.832	14.402	13.965
Kota Jambi	15.483	15.908	14.260	19.871
Muaro Jambi	15.739	12.477	13.835	15.073
Agam	17.099	19.139	13.788	18.515
Lampung Utara	10.304	11.859	13.289	11.277
Indragiri Hilir	20.677	16.250	13.048	15.156
Langkat	17.279	21.319	12.998	23.737
Kota Padang	17.831	20.638	12.980	21.875
Kampar	19.621	23.455	12.965	24.296
Kota Dumai	9.811	12.657	12.953	12.494
Aceh Tenggara	11.143	20.864	12.888	15.773
Lampung Tengah	17.270	21.912	12.812	21.810
Musi Rawas Utara	8.922	13.095	12.322	12.587
Pelalawan	21.333	17.566	12.163	18.087
Kota Batam	22.804	24.093	11.692	30.784
Banyuasin	25.609	21.872	11.297	20.028
Humbang Hasundutan	12.604	12.376	11.261	7.219
Kepulauan Mentawai	12.113	17.995	11.160	16.316
Muara Enim	15.626	16.740	11.106	16.641
Padang Lawas Utara	18.856	13.885	11.051	9.412
Ogan Ilir	19.313	20.640	10.862	20.258
Musi Rawas	14.655	16.560	10.768	13.577
Belitung Timur	13.537	17.423	10.648	11.502
Kepulauan Anambas	12.030	11.825	10.636	9.395
Lampung Barat	12.783	13.448	10.615	14.790
Gayo Lues	7.936	11.739	10.613	12.698
Rokan Hulu	13.436	14.380	10.588	13.933
Tanah Datar	14.959	16.369	10.397	14.251

(Table continues on the next page.)

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Kabupaten/Kota	2019	2020	2021	2022
Muko Muko	13.357	10.453	10.341	12.272
Mandailing Natal	12.475	19.042	10.292	15.796
Lingga	14.139	15.882	10.266	13.969
Simeulue	12.453	12.889	10.216	9.651
Batanghari	8.551	10.054	10.016	12.555
Rokan Hilir	16.058	15.948	9.867	15.851
Ogan Komering Ulu Selatan	16.095	7.574	9.845	9.417
Mesuji	9.774	10.099	9.840	10.697
Sarolangun	10.483	11.321	9.819	10.045
Serdang Bedagai	13.859	18.661	9.744	18.592
Asahan	15.926	17.067	9.741	15.342
Bengkulu Utara	13.216	15.444	9.658	16.673
Lampung Selatan	14.233	16.964	9.590	20.559
Bangka Barat	13.257	11.113	9.480	10.962
Tanjung Jabung Barat	13.886	12.112	9.433	12.123
Nias	10.588	13.731	9.422	10.011
Tapanuli Selatan	15.274	14.327	9.312	12.644
Pasaman Barat	11.879	14.443	9.261	15.234
Bengkalis	11.787	14.381	9.219	13.633
Pesisir Selatan	21.057	18.450	9.109	17.631
Padang Lawas	7.657	8.479	9.028	7.980
Bengkulu Selatan	14.780	14.194	8.939	16.498
Nias Selatan	12.355	12.860	8.925	16.486
Karimun	13.215	18.360	8.863	13.932
Belitung	16.838	14.999	8.722	14.704
Rejang Lebong	10.791	15.508	8.594	16.274
Kepulauan Meranti	13.583	15.290	8.568	16.447
Tapanuli Tengah	20.002	13.605	8.553	15.723
Aceh Jaya	10.145	10.998	8.481	13.732
Dharmasraya	10.324	12.605	8.467	12.211
Kepahiang	8.730	10.858	8.367	15.967
Kuantan Singingi	14.901	13.539	8.293	10.875
Labuhanbatu	13.930	18.769	8.253	19.095
Bintan	14.693	15.758	8.218	14.380
Kota Tebing Tinggi	13.268	12.487	8.157	12.442
Way Kanan	9.688	18.256	8.150	14.313
Lampung Timur	12.597	16.440	8.018	16.274
Ogan Komering Ulu	11.947	12.626	7.918	11.645
Solok	15.693	13.565	7.907	13.935
Merangin	9.067	10.465	7.800	9.015
Karo	10.136	12.129	7.718	11.962
Pakpak Bharat	19.313	7.693	7.654	13.962
Tanggamus	10.600	14.287	7.573	13.896
Siak	12.334	12.298	7.557	11.621
Nias Utara	12.259	13.569	7.377	12.062
Empat Lawang	9.104	7.811	7.371	9.872
Nias Barat	9.398	11.488	7.346	11.055

(Table continues on the next page.)

(Continued.)

Kabupaten/Kota	2019	2020	2021	2022
Pesisir Barat	14.526	12.477	7.268	10.521
Kota Metro	8.797	11.544	7.135	11.805
Bengkulu Tengah	9.381	11.480	7.073	9.201
Aceh Selatan	10.346	11.157	7.054	9.669
Tulang Bawang	10.642	11.582	6.986	11.361
Labuhanbatu Selatan	8.595	9.063	6.933	8.466
Bungo	9.527	10.484	6.927	10.225
Samosir	12.258	12.498	6.911	10.690
Solok Selatan	8.074	8.810	6.801	8.503
Kota Lubuk Linggau	10.692	10.841	6.777	13.440
Tanjung Jabung Timur	10.494	12.029	6.703	13.403
Penukal Abab Lematang Ilir	18.483	11.294	6.670	16.849
Kota Binjai	20.122	11.731	6.630	13.993
Kota Sibolga	10.645	9.766	6.578	12.708
Lahat	9.889	10.041	6.322	9.052
Pringsewu	11.082	13.354	6.269	15.915
Tapanuli Utara	11.031	11.813	6.221	10.868
Bangka	10.773	12.584	6.175	13.904
Aceh Utara	15.046	13.247	6.049	15.401
Pesawaran	14.979	13.541	6.036	11.469
Natuna	12.550	15.125	5.985	18.657
Tulang Bawang Barat	9.460	11.591	5.979	8.697
Kota Prabumulih	9.562	10.500	5.960	10.569
Kota Pangkal Pinang	13.252	12.415	5.954	11.503
Aceh Barat Daya	9.125	10.452	5.908	9.210
Aceh Besar	10.965	10.786	5.896	12.946
Aceh Tamiang	16.426	11.316	5.890	16.221
Kota Tanjung Balai	16.489	14.245	5.877	9.522
Kota Tanjung Pinang	10.626	10.795	5.836	13.481
Seluma	9.240	10.687	5.802	11.421
Pidie	11.181	17.021	5.654	15.786
Kota Pagar Alam	14.847	19.661	5.633	10.069
Kerinci	8.923	9.782	5.618	10.979
Kaur	10.524	10.417	5.586	12.390
Labuhanbatu Utara	13.210	10.996	5.493	9.295
Toba Samosir	11.102	11.367	5.489	9.383
Kota Lhokseumawe	11.862	12.364	5.465	13.105
Kota Pematangsiantar	12.557	12.376	5.381	11.006
Nagan Raya	10.392	9.683	5.363	9.772
Kota Payakumbuh	7.075	8.955	5.279	10.293
Kota Solok	7.166	10.109	5.185	7.495
Sijunjung	16.360	13.189	5.147	10.600
Bireuen	10.867	13.318	5.106	12.776
Aceh Timur	13.041	10.779	5.022	15.096
Bangka Selatan	10.769	11.089	4.930	11.866
Lebong	9.488	8.272	4.925	6.328
Kota Padang Sidempuan	8.682	8.077	4.918	11.220

(Table continues on the next page.)

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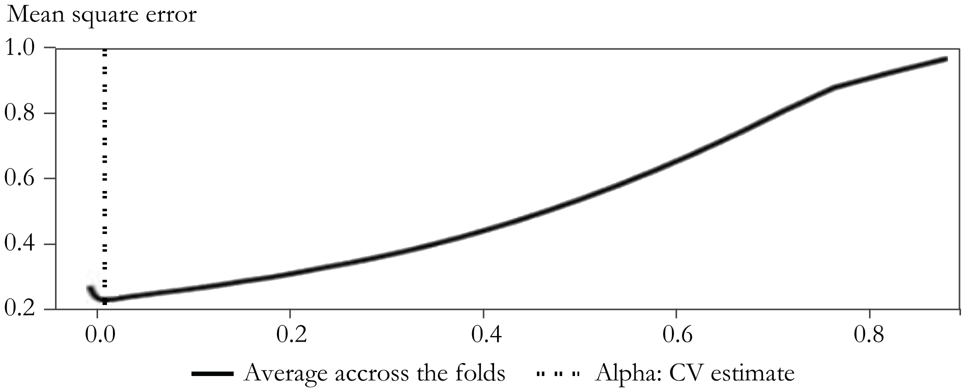
Kabupaten/Kota	2019	2020	2021	2022
Kota Bukittinggi	10.797	11.931	4.808	12.472
Bangka Tengah	9.085	10.462	4.497	11.138
Kota Sungai Penuh	6.040	10.156	4.494	8.201
Kota Pariaman	9.190	12.561	4.357	9.717
Kota Gunungsitoli	11.077	10.760	4.353	9.335
Kota Langsa	8.754	10.307	4.344	22.079
Aceh Singkil	10.623	11.021	4.337	12.173
Kota Padang Panjang	6.959	13.337	4.325	7.519
Bener Meriah	8.557	9.906	4.308	8.132
Aceh Tengah	13.763	10.477	4.305	10.299
Pidie Jaya	13.719	10.609	4.166	8.589
Dairi	11.190	10.982	4.017	8.875
Tebo	7.597	7.930	3.998	7.510
Kota Sabang	7.213	9.041	3.974	11.245
Aceh Barat	9.365	10.290	3.696	9.687
Kota Subulussalam	7.343	6.632	3.549	6.007
Kota Sawahlunto	8.294	11.248	3.374	14.305

Figure A1

CV LASSO



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