Journal of Geospatial Science and Analytics

Journal homepage: https://ejournal.foundae.com/index.php/jgsa/index
e-ISSN: 3090-8086 | p-ISSN: 3090-532X

Climate impact on blue economy index: Bayesian spatio-temporal regression with statistical downscaling in Sumatera

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Article Info

Article history:

Received: January 01, 2025
Revised: February 10, 2025
Accepted: March 10, 2025

Keywords:

Bayesian inference
Blue economy index
INLA
Spatio-temporal regression
Statistical downscaling

DOI:
10.58524/jgsa.v1i1.9

Abstract

Climate change studies inherently involve spatial, temporal, and regional dimensions, while the blue economy's sustainability is significantly influenced by global climate factors. Sumatera, a key conservation region in Indonesia, faces challenges in managing its marine resources. Limited quantitative research at regency/city level led to the development of Blue Economy Index (BEI) as a measurement tool. This study constructs a BEI from 38 environmental, economic, and social indicators also identifies global climate variables affecting BEI significantly among five analyzed using best spatio-temporal statistical downscaling model with INLA approach. From 2019 to 2022, Medan City consistently achieved the highest BEI scores, while Subulussalam City recorded the lowest. The optimal model through WAIC, a nonparametric model with unstructured space-time interaction, revealed that skin temperature, sea level pressure, and precipitation significantly affect BEI. Unstructured spatial variation mainly influences BEI, while temporal trends show a decline in 2021 due to Covid-19, with dynamic spatial-temporal effects.

To cite this article: Athalia Christina, Ro'fah Nur Rachmawati, & Novi Hidayat Pusponegoro. (2025). Climate impact on blue economy index: Bayesian spatio-temporal regression with statistical downscaling in Sumatera. *Journal of Geospatial Science and Analytics*, 1(1), 13-34.

INTRODUCTION

Climate change studies obviously involve spatial, temporal and regional influences. The Global Climate Model (GCM) is often used to understand climate variations that occur in the world. However, GCMs still have limitations in simulating climate variables, especially regard to annual and seasonal variations. The coarse spatial resolution of GCMs is unable to simulate temperature, precipitation, clouds, aerosol processes, and climate in mountainous and coastal areas (Kundzewicz et al., 2018; Tefera et al., 2024).

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Therefore, statistical downscaling (SD) techniques are used to obtain climate information at regional scales, such as the Regional Climate model (RCM) by converting low-resolution GCM climate scales to high-resolution RCM climate scales (Djuraidah et al., 2021; Rachmawati et al., 2020). SD modeling to analyze the impact of climate change at the local scale using global data shows the complexity of the data used. The data complexity is in the form of a large amount of global climate data as predictor variables that need to involve dimensional reduction with principal component analysis (PCA) to overcome multicollinearity problems in the analysis (Hasan & Abdulazeez, 2021; Hediyati & Suartana, 2021). In addition, the complexity of large amounts of SD data involving geographic and time aspects or commonly referred to as spatio-temporal can be addressed using Bayesian inference with integrated nested Laplace approximation (INLA) (Maulina et al., 2019; Wang et al., 2018). Bayesian inference involving Laplace approximation is used to obtain accurate, convergent, and efficient estimates of model parameters (Morales-Otero et al., 2022).

The spatio-temporal model of SD with the INLA approach can have parametric and nonparametric structures when differentiated based on its temporal trend pattern. Then, the nonparametric model can be modified and developed by adding four types of spatio-temporal interaction components (Sani et al., 2023). In-depth spatio-temporal analysis of the model formed is an important foundation in designing effective strategies for the phenomenon under study. Therefore, the best model based on the Watanabe-Akaike Infomration Criterion (WAIC) value will be used as a reference in providing strategy recommendations to deal with the phenomenon under study (Opitz, 2017). The sustainability of blue economy's potential, which can be impacted by the global climate, is one of the fascinating topics being researched today. SD modeling can be utilized to comprehend how the worldwide climate affects the potential of blue economy.

In this study, the phenomenon of blue economy sustainability on the island of Sumatera at the regency/city level is the focus of research. This is based on the Indonesian Vision 2045 which states that economic transformation towards modern manufacturing and services that are competitive and provide high added value is needed to ensure welfare and social justice for all Indonesians (Kementerian PPN, 2023). The blue economy concept emphasizes community participation, resource efficiency, waste minimization, and multiple value-added income while maintaining environmental sustainability, especially the oceans (Nasution, 2022; Voyer et al., 2018).

With this economic concept, Indonesia has the advantage of being a maritime country. However, the declining maximum sustainable yield (MSY) value shows that Indonesia still has challenges in maintaining the sustainability of marine and fisheries potential (Nasution, 2022). As a follow-up to these problems, the Indonesian government has established conservation areas with a zoning approach to protect marine and fisheries potential. One of the conservation areas that has been established by the Indonesian government is the waters of Sumatera, which has a wealth of marine and fisheries resources (Akbar, 2022; Rusandi et al., 2021). However, the value of Indonesia's Blue Economy Index (IBEI) on the island of Sumatera at the provincial level is still below the national average (Kementerian PPN, 2023). This fact shows the importance of the relationship between blue economy potential at the regency/city level and marine economic performance at the provincial level. However, previous research on the blue economy index (BEI) at the regency/city level does not exist to date.

Based on previous literature studies, there is little quantitative research on the blue economy. This is especially true for a comprehensive approach that includes environmental, economic, and social dimensions to measure blue economy potential at the regency/city level. In addition, the Bayesian approach for spatio-temporal regression in SD modeling using INLA has also not been applied to examine the phenomenon of sustainability of blue economy potential. Therefore, this study aims to establish BEIs for 154 regencies/cities located on the island of Sumatera. In addition, the BEI that has been built will be used to identify global climate factors that have a significant effect on the phenomenon of blue economy sustainability in the period

2019 to 2022 through the best SD spatio-temporal regression model with the Bayesian INLA approach.

METHOD

To obtain global climate predictor variables specific to the island of Sumatera, SD uses GCM data. Determining the variables to be used as well as the domain (location and grid) is an important step to take with the aim of obtaining stable forecasting results. The SD method assumes that regional physiographic conditions and global climate conditions with low resolution can control regional climate with high resolution. Figure 1 shows the concept of statistical downscaling more clearly (Santri & Hanike, 2020).

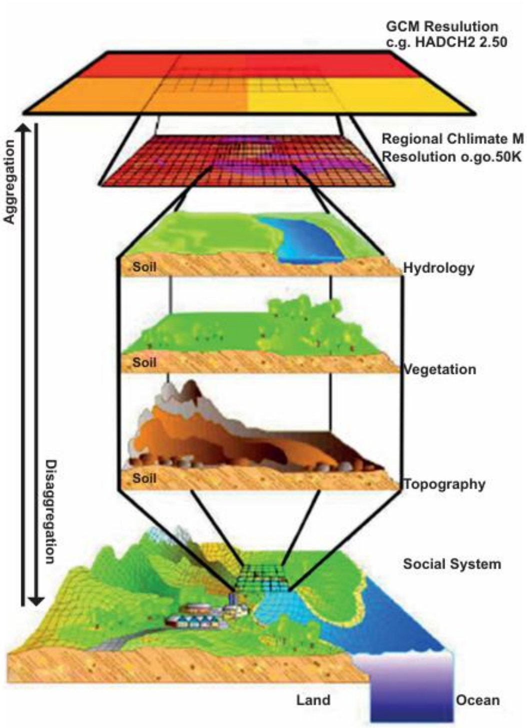


Figure 1. Statistical downscaling illustration

Based on the illustration in Figure 1, the concept of statistical downscaling has a general form as Equation (1).

$$y_t = f(X_{t\times g}) \quad (1)$$

Where y_t is the RCM local climate variable to be obtained, $X_{t\times g}$ is the GCM global climate variable to be possessed, also t and g denote the time and grid domain of the GCM, respectively.

This study used five statistical downscaling predictor variables, namely u-component of wind, v-component of wind, skin temperature, mean sea level pressure, and total precipitation. U-component of wind and v-component of wind in units of meters per second (m/s) are defined as the wind speed moving east and north respectively at a height of 10 meters above the earth's surface. Skin temperature in units of Kelvin (K) is defined as the temperature of the earth's surface in the uppermost layer that does not have the heat capacity to explain the surface energy balance and can immediately respond to changes in surface flux. To explain the atmospheric pressure adjusted to sea level height, the variable mean sea level pressure in Pascal (Pa) is used. Then, total precipitation in this study is defined as the total amount of water that falls to the earth's surface in the form of rain and snow measured in meters to explain the depth.

The five SD predictor variables were obtained from the Copernicus Climate Data Store with a dataset in the form of ERA5 hourly data on single levels from 1940 to present which has a spatial resolution of 0.25° × 0.25°. In accordance with the focus of this research limitation, namely the island of Sumatera, the specification of aggregate data or data with areal characteristics in this study has a total of 3185 grids formed from 49 latitudes and 65 longitudes. The data were taken in the time span from 2019 to 2022. More clearly, the descriptive analysis of the five SD variables can be seen in Table 1.

Then in accordance with the characteristics of SD data that are complex and prone to multicollinearity in regression analysis, dimensional reduction is carried out with principal component analysis (PCA) to overcome this. Based on Kaiser Criterion, scree plot, and cumulative proportion of variance, 3 out of 5 PCs or principal components are obtained which can explain 83% of the overall variation of the data. Each principal component explains how much variation in the overall data can be seen in Table 2. Then, the contribution of each SD predictor variable to the PC score can be seen in Table 3.

Table 1. Descriptive analysis of SD predictor variables

Year	2019	2020	2021	2022
U-Component of Wind				
Min	-1.649	-1.002	-0.682	-0.289
Max	0.217	0.556	0.873	1.056
Mean	-0.250	-0.072	0.090	0.248
Std	0.358	0.263	0.255	0.277
V-Component of Wind				
Min	-0.237	-0.877	-0.686	-0.689
Max	1.203	0.419	0.671	0.815
Mean	0.186	0.004	-0.024	0.029
Std	0.248	0.169	0.214	0.266
Skin Temperature				
Min	291.676	291.651	291.285	291.180
Max	302.471	302.423	302.320	302.309
Mean	298.513	298.272	298.089	298.013
Std	2.306	2.182	2.242	2.247
Mean Sea Level Pressure				
Min	101037.145	100991.791	100983.293	100930.890
Max	101438.544	101389.763	101386.580	101340.251
Mean	101146.087	101094.317	101091.765	101044.255
Std	93.349	93.012	95.963	98.886
Total Precipitation				
Min	1.409	1.975	1.942	2.305
Max	49.559	68.081	58.974	69.204
Mean	12.073	14.801	13.748	14.497
Std	8.736	10.740	9.957	10.633

Table 2. Summary of PCs

	PC_1	PC_2	PC_3	PC_4	PC_5
Eigen Value	2.016	1.104	1.003	0.776	0.100
Variance Percentage	40.327	22.078	20.070	15.518	2.006
Cumulative Variance Percentage	40.327	62.406	82.475	97.994	100.000

The PC score will then be used as a fixed predictor variable in a Bayesian spatio-temporal statistical downscaling nonparametric regression model with unstructured space-time interactions to identify global climate factors that have a significant effect on the blue economic's potential sustainability in Sumatera'island. Sustainability of blue economy potential in this study is measured through the blue economy index (BEI) at regency/city level that has been compiled.

Table 3. Loading factor of PCs

	PC_1	PC_2	PC_3
U-Component of Wind	-0.367	0.514	0.064
V-Component of Wind	-0.041	-0.806	-0.200
Skin Temperature	0.681	0.021	0.054
Mean Sea Level Pressure	-0.633	-0.224	0.038
Total Precipitation	-0.002	0.191	-0.975

The preparation of the BEI adopts similar research to the Human Development Index (HDI) preparation method developed by the United Nations Development Program (UNDP) (Dasic et al., 2020; Harya, 2020). To produce a complete dataset, the preparation process begins with data imputation using the CART (Classification and Regression Trees) method. Furthermore, to adjust the scale between variables, the data was normalized using the min-max method. The BEI value is obtained by calculating the geometric mean of the index value of each dimension as formulated in Equation (2).

$$BEI = \sqrt{\left(\prod_{j=1}^{n} I_j\right)^{\frac{1}{n}}} \times 100 \quad (2)$$

The index of each dimension (I_j) in Equation (2) is calculated using the arithmetic mean of the corresponding indicators. The BEI consists of three main dimensions, namely environmental, economic, and social. Each dimension has a number of important indicators that show aspects of blue economic sustainability as presented in Table 4. A variety of sources provided the BEI indicator data, including Statistics of Ministry of Maritime Affairs and Fisheries/Statistik KKP (https://statistik.kkp.go.id/), Central Agency of Statistics/BPS (https://www.bps.go.id/), National Waste Management Information System/SIPSN (https://sipsn.menlhk.go.id/), and Satu Data Parekraf (https://satudata.kemenparekraf.go.id/). Then, the final results of the BEI calculation for the Sumatera region at the regency/city level are presented in Table 5.

Table 4. BEI of Sumatera constituent indicators

Dimensions	Variables
Environmental (8 variables)	Enlargement Cultivation Land Area of Tranquil Water Pool
	Hatchery Cultivation Land Area of of Fresh Water
	Total Waste Generated in a Year
	Total Waste Handled in a Year
	Total Waste Recycled in a Year
	Households' Percentage Distribution with PLN Electric Lighting Sources
	Households' Percentage Distribution with Non-PLN Electric Lighting Sources
	Households' Percentage Distribution with Non-Electric Lighting Sources
Economy (15 variables)	Sea Business Vessel Count
	Mainland Public Waters Business Vessel Count
	Small and Micro Fish Processing Facilities
	Fishery Households of Tranquil Water Pool Enlargement Aquaculture
	Fishery Households of Fresh Water Hatchery Aquaculture
	Fishery Households of Sea Capture
	Fishery Households of Mainland Public Waters Capture
	Fish Production Volume of Tranquil Water Pool Enlargement Aquaculture
	Fish Production Volume of Fresh Water Hatchery Aquaculture
	Fish Production Volume of Mainland Public Waters Capture
	Fish Production Value of Tranquil Water Pool Enlargement Aquaculture

Dimensions	Variables
	Fish Production Value of Fresh Water Hatchery Aquaculture Fish Production Value of Mainland Public Waters Capture Archipelago Tourist Trips by Origin Location Count Archipelago Tourist Trips by Destination Location Count
Social (15 variables)	Fishermen Count of Tranquil Water Pool Enlargement Aquaculture Fishermen Count of Fresh Water Hatchery Aquaculture Fishermen Count of Sea Capture Fishermen Count of Mainland Public Waters Capture Rate of Open Unemployment Rate of Labor Force Participation Poor Population Percentage PBI BPJS Health Insurance Population Persentage Non-PBI BPJS Health Insurance Population Persentage Jamkesmas Health Insurance Population Persentage Private Health Insurance Population Persentage Company Health Insurance Population Persentage Population Percentage of Access to Safe Drinking Water Sources High School Students Under the Ministry of Education and Culture Count Vocational School Students Under the Ministry of Education and Culture Count

Table 5. Descriptive analysis of BEI response variable

Year	2019	2020	2021	2022
Min	6.077	6.686	2.545	5.999
Max	33.938	39.020	31.520	33.648
Mean	13.286	14.576	9.223	13.777
Std	4.954	5.406	5.023	5.136

Bayesian spatio-temporal statistical downscaling nonparametric regression model with type 1 interaction or interaction between unstructured spatial and temporal patterns involves fixed variables and random variables as regression components. The fixed variables in this case are SD variables that have been converted to PC scores. Meanwhile, the random variables are the spatial, temporal, and unstructured spatio-temporal interaction components. The structured and unstructured spatial components are described in the BYM2 model written in Equation (3).

$$\frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i\right) \tag{3}$$

Where u_i and v_i are structured and unstructured spatial effects, τ_b is a precision parameter that describes the variance contribution of the sum of spatial random effects u_i and v_i, also ϕ is a mixing parameter that controls the variance contribution of random effects u_i. Meanwhile, the mixing parameter that controls the variance contribution of the random effect v_i is described by $1-\phi$ (Simkin et al., 2022).

Then, the structured temporal component is described in the random walk 2 (RW2) model. The RW2 model assumes that the second differences of all time effects follow a normal distribution with zero mean and are independent. The second difference in the model reflects the dependence of each value on its nearest neighbor and that neighbor's nearest neighbor (Nazia et al., 2022). Mathematically, the RW2 model can be described by Equation (4).

$$x_{i,t}|x_{i,t-1}, x_{i,t-2} \sim Normal(2x_{i,t-1} + x_{i,t-2}, \tau_x^{-1}) \tag{4}$$

The unstructured temporal component and the unstructured spatio-temporal interaction are assumed to follow a normal distribution with zero mean. The unstructured spatio-temporal interaction is defined as $R_\delta = R_v \otimes R_\phi = I \otimes I = I$ where R_v and R_ϕ are the structure matrices for the two components of the random effect. The two matrices can be assumed to be the identity matrix I because unstructured random effects mean that the random effects do not have a particular pattern or trend so there is no correlation with each other (Blangiardo & Cameletti, 2015).

The normal distribution is used because its flexible nature allows positive and negative deviations from the zero mean to have equal chances. This prevents bias in other parameter estimates and captures random fluctuations around the mean without indicating any systematic pattern. The approach can also facilitate the interpretation and implementation of the model within a Bayesian framework. Therefore, the linear predictor form for a spatio-temporal regression model with a nonparametric structure involving interaction components can be written in Equation (5).

$$\eta_{it} = \alpha + \sum_{m=1}^{M} b_m PC_m + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i\right) + \gamma_t + \phi_t + \delta_{it} \quad (5)$$

Where the right side of the regression form is a linear combination of predictors with α is a constant and the effect of the fixed predictor variables $PC_1, PC_2, PC_3, \ldots, PC_n$ is explained by the coefficients $b_1, b_2, b_3, \ldots, b_n$. Then, the spatial random variables in the BYM2 model are explained by $\frac{1}{\sqrt{\tau_b}}(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i)$, the structured and unstructured temporal random variables are explained by γ_t and ϕ_t, respectively, and δ_{it} explains the interaction component of the two random effects. Then to connect the linear combination of predictors with the mean of the response variable y, the link function η_{it} is used (Rachmawati & Pusponegoro, 2018). Based on the Kolmogorov Smirnov test, it is known that the BEI response variable follows a lognormal distribution with the form as in Equation (6).

$$y \sim Lognormal(\mu, \sigma^2) \quad (6)$$

To estimate the model parameters in Equation (5), the Bayesian inference method with the Integrated Nested Laplace Approximation (INLA) approach is used (Blangiardo & Cameletti, 2015; Rachmawati & Pusponegoro, 2018; Sani et al., 2023). In addition, Knorr-Held stated that in-depth analysis of the spatio-temporal interaction components in Equation (5) can be divided into four types. Of the four types of interactions, the phenomenon of global climate influence on the potential sustainability of the blue economy on the island of Sumatera can be explained more simply and realistically by a nonparametric model involving interactions between spatial and temporal unstructured (type 1) as the best model based on the Watanabe-Akaike Information Criterion (WAIC) value. WAIC considers the balance between the ability of the model to explain the data and the complexity of the model which can be written in Equation (7) (Sani et al., 2023).

$$WAIC = -2\sum_i E\left[\log\left(\pi(y|\theta)\right)\right] + 2\sum_i Var\left[\log\left(\pi(y|\theta)\right)\right] \quad (7)$$

Where the principal and second components of Equation (7) are the posterior log-likelihood mean and posterior log-likelihood variance, respectively.

To obtain the research results, this study was supported by three software, namely Python, R-Studio, and QGIS (Quantum Geographic Information System). Python is used for preprocessing statistical downscaling data that has NetCDF4 format. R-Studio was used to perform BEI preparation and Bayesian spatio-temporal statistical downscaling modeling with the INLA approach. QGIS is used to visualize the distribution of BEIs on the island of Sumatera at the regency/city level as well as the spatial patterns and spatio-temporal interactions of BEIs based on the best model. Systematically, this research process can be explained by the algorithm below.

Algorithm. Bayesian nonparametric statistical downscaling with unstructured space-time interaction modeling.

Input: BEI constituent variable data $\boldsymbol{BEI_{in}}$, NetCDF4 global climate data $\boldsymbol{SD_{in}}$, assumption of parameters and hyperparameters
Output: BEI data $\boldsymbol{BEI_{out}}$, statistical downscaling data $\boldsymbol{SD_{out}}$, spatial posterior mean of u_i and v_i, temporal posterior mean of λ_t, space-time interaction posterior mean of δ_{it}, parameter estimation of α and b_m, also WAIC

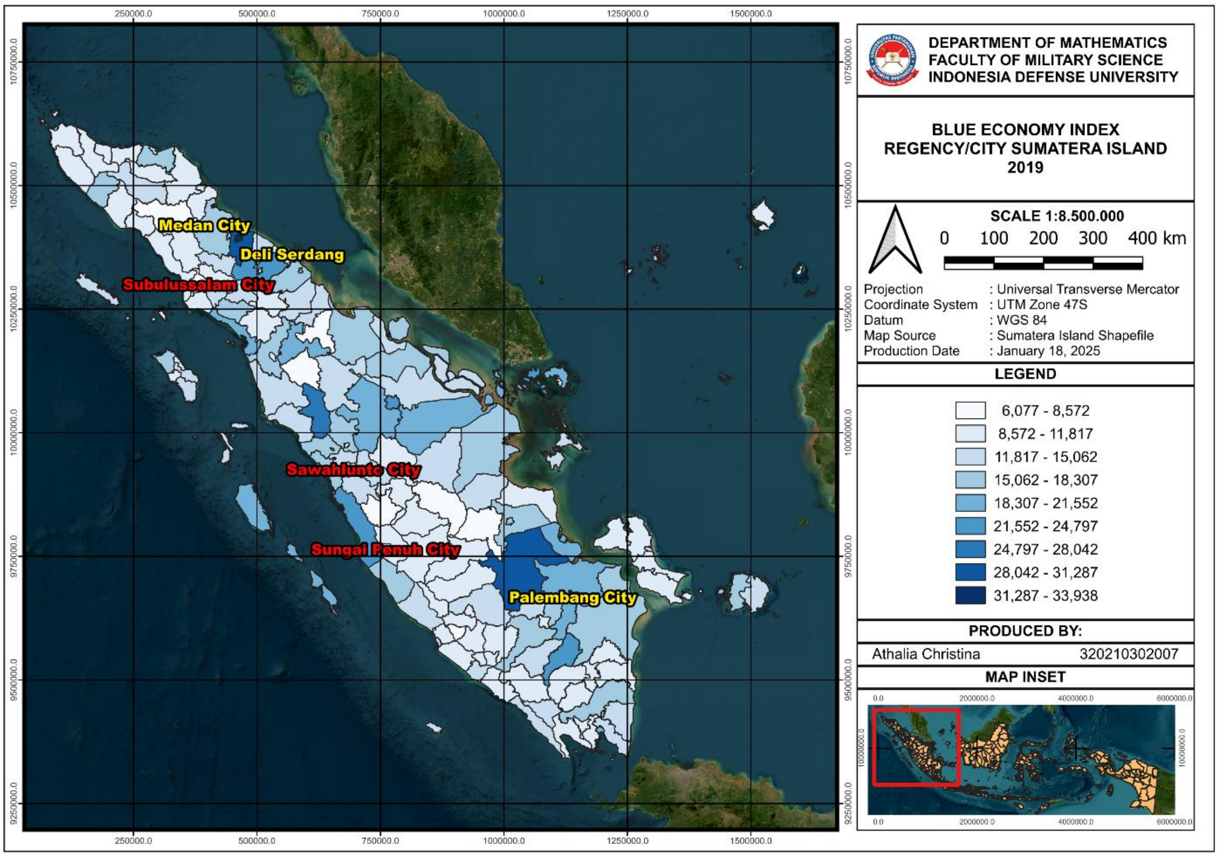
for $\boldsymbol{BEI_{in}}$ **do**
  If $\boldsymbol{BEI_{in(k)}}$ for $k = 1, 2, 3, \ldots, 38$ is NA, impute using CART method
  Normalize min-max $\boldsymbol{BEI_{in(k)}}$ for $k = 1, 2, 3, \ldots, 38$
  Compute I_j for $j = 1, 2, 3$ in Equation (2) using arithmetic mean method
  Compute $\boldsymbol{BEI}$ in Equation (2) using geometric mean method
end for
return: $\boldsymbol{BEI_{out}}$
Plot $\boldsymbol{BEI_{out}}$ distribution
for $\boldsymbol{SD_{in}}$ **do**
    Validate Sumatera island shapefile geometry
    Filter $\boldsymbol{SD_{in}}$ for Sumatera island
    Make geographic mask for each regency/city of Sumatera island
end for
for $\boldsymbol{SD_{in(p)}}$ **with** $\boldsymbol{p = 1, 2, 3, 4}$ **do**
  for $day = 1, 2, 3, \ldots, 365$ or 366 in 2019, 2021, 2022, and 2020 **do**
    Compute mean $\boldsymbol{SD_{in(p)}}$ for each regency/city
    for $year = 1, 2, 3, 4$ **do**
      Compute mean $\boldsymbol{SD_{in(p)}}$ for each regency/city
    end for
for $\boldsymbol{SD_{in(p)}}$ **with** $\boldsymbol{p = 5}$ **do**
  for $day = 1, 2, 3, \ldots, 365$ or 366 in 2019, 2021, 2022, and 2020 **do**
    Compute sum $\boldsymbol{SD_{in(p)}}$ for each regency/city
    for $year = 1, 2, 3, 4$ **do**
      Compute sum $\boldsymbol{SD_{in(p)}}$ for each regency/city
    end for
for $\boldsymbol{SD_{in(p)}}$ **with** $\boldsymbol{p = 1, 2, 3, 4, 5}$ **do**
  If $\boldsymbol{SD_{in(p)}}$ for $p = 1, 2, 3, 4, 5$ is NA, impute using average neighbor value
end for
return: $\boldsymbol{SD_{out}}$
for $\boldsymbol{BEI_{out}}$ **and** $\boldsymbol{SD_{out}}$ **do**
  Test $\boldsymbol{BEI_{out}}$ distribution using Kolmogorov-Smirnov method
  Reduce dimension $\boldsymbol{SD_{out}}$ using PCA method
  Compute u_i and v_i in Equation (3)
  Compute γ_t in Equation (4)
  Compute ϕ_t in Equation (5)
  Compute $\lambda_t = \gamma_t + \phi_t$
  Compute δ_{it} in Equation (5)
  Compute α, b_m for $m = 1, 2, 3$ in Equation (5)
end for
Plot spatial and space-time interaction random effect u_i, v_i, and δ_{it}
Compute WAIC
return: spatial, temporal, and space-time interaction posterior mean, parameter estimation, also WAIC

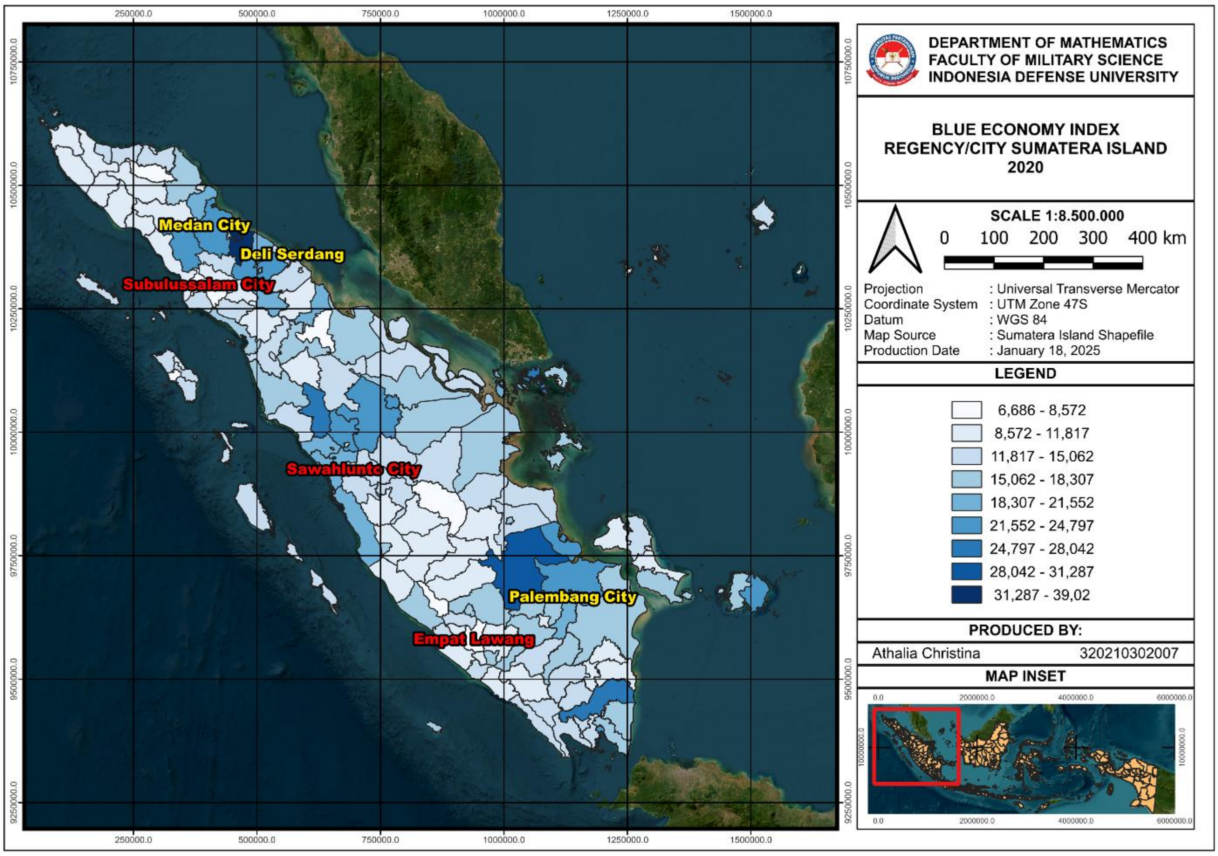
RESULTS AND DISCUSSIONS

Sumatera Island, with its vast marine resources, has a great opportunity to develop its blue economy potential in a sustainable manner. The BEI, which has been prepared using the UNDP method approach, is used to assess the environmental, economic and social performance of the marine sector as a whole so that the sustainability of blue economy potential can be measured comprehensively. The BEI results provide an overview of the regions with the highest and lowest scores. Regions with the highest scores indicate the success of the region in optimally managing the potential of the blue economy. Meanwhile, regions with the lowest scores indicate that there needs to be special attention in formulating and implementing strategic policies to improve the management of blue economy potential in the region. The BEI analysis can be used as a basis for evaluating gaps between regions, identifying barriers and challenges, and developing strategies for sustainable marine resource management. To provide a detailed picture of the condition of each regency/city, the distribution of BEI on the island of Sumatera is presented visually in Figure 2.

Based on the illustration in Figure 2, it can be seen that the BEI of Sumatera island at the regency/city level for four years ranged between 2 and 40. During this period, some of the regions that recorded the highest scores were Medan City, Palembang City, Deli Serdang, and Musi Banyuasin. In contrast, the regions with the lowest scores included Subulussalam City, Sawahlunto City, Sungai Penuh City, Empat Lawang, Pariaman City, Sabang City, and Lebong. Among these regions, Medan City and Subulussalam City were always among the three highest and lowest scoring regions during the time period.

The suboptimal potential of the marine economy in Subulussalam City is certainly influenced by several main factors. First, the city's limited access to public services due to its location in the highlands and remoteness from major economic centers. This is reflected in the low level of education and per capita expenditure in the region. Secondly, the lack of basic infrastructure, such as landfills, means that the community still dumps waste into the river, potentially damaging the quality of the aquatic environment. Third, fisheries is a non-base sector of the economy in Subulussalam City. Although it supports other sectors, it still does not function as the main economic support in the region. Holistically, these conditions hinder the growth of sustainable marine economic potential in the area (Indah & Jubaidah, 2021; Pasaribu et al., 2024; Riandy et al., 2023).

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FACULTY OF MILITARY SCIENCE
INDONESIA DEFENSE UNIVERSITY
BLUE ECONOMY INDEX
REGENCY/CITY SUMATERA ISLAND
2020
SCALE 1:8.500.000
0 100 200 300 400 km
Projection : Universal Transverse Mercator
Coordinate System : UTM Zone 47S
Datum : WGS 84
Map Source : Sumatera Island Shapefile
Production Date : January 18, 2025
LEGEND
6,686 - 8,572
8,572 - 11,817
11,817 - 15,062
15,062 - 18,307
18,307 - 21,552
21,552 - 24,797
24,797 - 28,042
28,042 - 31,287
31,287 - 39,02
PRODUCED BY:
Athalia Christina 320210302007
MAP INSET
Medan City
Deli Serdang
Subulussalam City
Sawahlunto City
Palembang City
Empat Lawang
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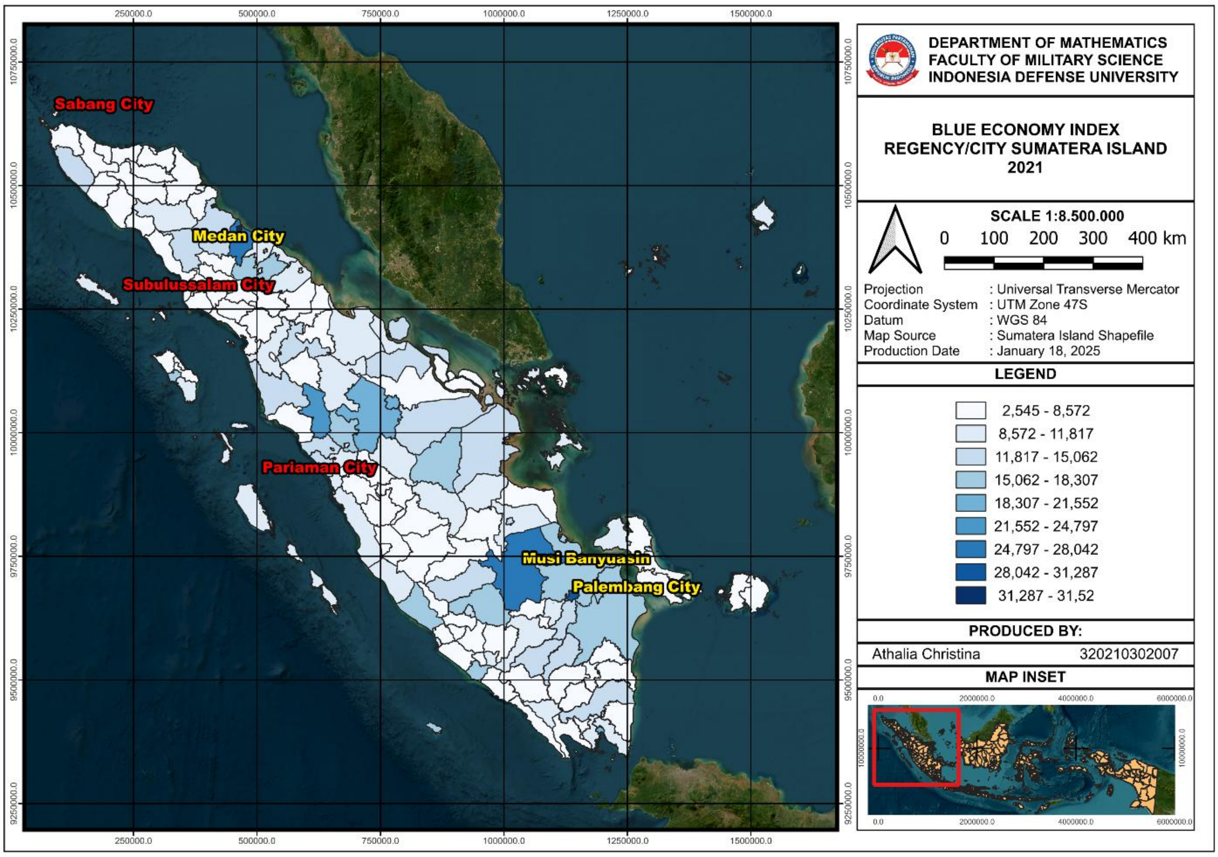
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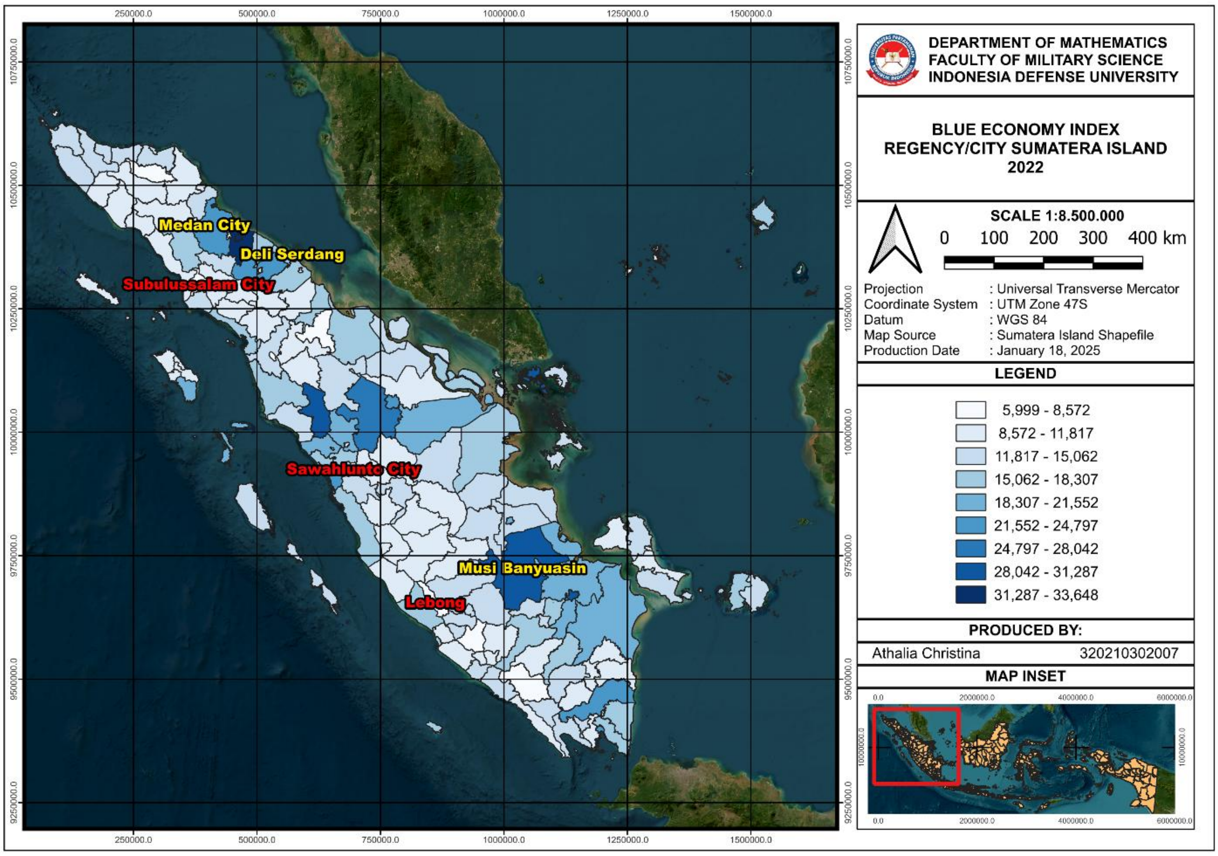


Figure 2. BEI distribution of Sumatera island at regency/city level

The success of Medan City in developing its marine economic potential is certainly supported by various strategic factors that strengthen its competitiveness (Hasibuan et al., 2024). Medan City as one of the three major metropolitan cities in Indonesia is not only the center of regional economy and trade but also has an important role on a national and international scale. In addition, the city also serves as the center of cultural, political, and economic activities that influence the dynamics of North Sumatera province. The 1,358-hectare mangrove area in the northern part of Medan City is also a valuable asset, especially the sustainable development of mangrove ecotourism in Belawan Sicanang has the potential to increase the income of coastal communities and attract tourists (Dian et al., 2024; Restu et al., 2024). Medan City has many opportunities to develop cultural and culinary tourism due to the fact that it is known as a multi-ethnic city with cultural and culinary diversity. With the combination of the region's potential in agriculture, fisheries, tourism, and marine ecotourism, Medan City has strong capital to continue driving the growth of its marine economy (Bonaraja Purba et al., 2024; Utama et al., 2022).

Based on previous research, the potential of the blue economy is also influenced by the global climate. This is because changes in ocean currents, ocean temperatures, and extreme weather patterns, as well as sea level rise, affect the survival of marine life, habitats and the communities that depend on them (Maeyangsari, 2023). However, understanding the dynamic relationship between climate factors and marine economic potential requires an appropriate approach. In this study, six spatio-temporal models were tested to determine the best approach to describe the complexity of the phenomenon based on available data. The analysis of each INLA-based model provides deep insights, both theoretically and practically, with the WAIC value used as the main benchmark to evaluate the performance of each model in understanding the complexity of the phenomenon.

As a first step in selecting the best model, a comparison of the mean values, standard deviations, 95% credibility intervals, and WAIC values as well as the form of regression equations of the six tested models are presented in Table 6 and Equations (8)-(13). Based on the calculation results, the nonparametric model with unstructured spatio-temporal interactions shows the lowest WAIC value, indicating that the model is not only able to capture relevant patterns from the data but also simple enough to avoid overly complex or impractical interpretations in real applications. In other words, the model can represent the phenomenon of the sustainability of blue economy potential on the island of Sumatera with more statistical plausibility while considering practical aspects and efficiency in modeling.

The results of the best model analysis show that the 2 principal components have a significant influence on the BEI, as indicated by the 95% credibility interval that does not include zero. Theoretically, this indicates that the PCs represent a combination of global climate variables that play an important role in explaining the variability of blue economy sustainability potential. Based on the loading factor values, there are 3 global climate variables that make dominant contributions to the significant PCs, specifically the variables of skin temperature and mean sea level pressure for PC_1 and total precipitation for PC_3.

Skin temperature, which has a significant effect on the potential for blue economic sustainability, supports the theory that sea surface temperature affects marine biological activities, such as the behavior, distribution, and habitat selection of marine species based on the temperature tolerance of each species (Freitas et al., 2021). One example is that as fish increase in size and age, they generally tend to favor and seek cooler and deeper waters. In addition, changes in skin temperature also affect ecosystem productivity, diet, and reproductive behavior of marine species due to thermal stratification. These impacts affect fish stock biomass and fisheries productivity, which determine the catch and profitability of the fisheries sector. Increasing surface temperatures make fisheries effort less efficient where more effort may be required to achieve the same catch (Porreca, 2021; Tanjung et al., 2025).

Table 6. Summary of models

Model	Fixed Effects	Mean	Std	95% Credibility Interval	Spatial Mixing Parameter (ϕ)	WAIC
Classic parametric	α	2.565	0.042	(2.483, 2.646)	0.301	3427.24
	PC_1	0.077	0.019	(0.041, 0.114)		
	PC_2	0.009	0.018	(-0.026, 0.044)		
	PC_3	-0.118	0.024	(-0.166, -0.071)		
	β	-0.044	0.014	(-0.072, -0.017)		
Dynamic nonparametric	α	2.454	0.125	(2.198, 2.709)	0.290	2973.69
	PC_1	0.050	0.018	(0.014, 0.085)		
	PC_2	0.023	0.014	(-0.004, 0.051)		
	PC_3	-0.084	0.023	(-0.129, -0.040)		
Unstructured space-time interaction	α	2.454	0.124	(2.201, 2.707)	0.290	2973.13
	PC_1	0.050	0.018	(0.014, 0.085)		
	PC_2	0.023	0.014	(-0.004, 0.051)		
	PC_3	-0.085	0.023	(-0.129, -0.040)		
Structured time interaction	α	1.370	338933.155	(-675953.206, (675954.810)	0.036	3121.65
	PC_1	-0.017	0.122	(-0.256, 0.223)		
	PC_2	-0.022	0.043	(-0.106, 0.061)		
	PC_3	0.098	0.104	(-0.106, 0.302)		
Structured space interaction	α	2.464	0.180	(2.108, 2.821)	0.264	2989.97
	PC_1	0.060	0.022	(0.017, 0.102)		
	PC_2	0.032	0.017	(0.000, 0.065)		
	PC_3	-0.076	0.024	(-0.123, -0.029)		
Structured space-time interaction	α	2.443	0.129	(2.178, 2.707)	0.362	3081.66
	PC_1	-0.074	0.045	(-0.163, 0.016)		
	PC_2	-0.059	0.037	(-0.131, 0.013)		
	PC_3	0.096	0.083	(-0.066, 0.261)		

Classic parametric	:	$\eta_{it} = \log(y) = 2.565 + 0.077PC_1 + 0.009PC_2 - 0.118PC_3 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i\right) + (-0.044 + \delta_i) \times t_j$	(8)
Dynamic nonparametric	:	$\eta_{it} = \log(y) = 2.454 + 0.050PC_1 + 0.023PC_2 - 0.084PC_3 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i\right) + \gamma_t + \phi_t$	(9)
Unstructured space-time interaction	:	$\eta_{it} = \log(y) = 2.454 + 0.050PC_1 + 0.023PC_2 - 0.085PC_3 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i\right) + \gamma_t + \phi_t + \delta_{it}$	(10)
Structured time interaction	:	$\eta_{it} = \log(y) = 1.370 - 0.017PC_1 - 0.022PC_2 + 0.098PC_3 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i\right) + \gamma_t + \phi_t + \delta_{it}$	(11)
Structured space interaction	:	$\eta_{it} = \log(y) = 2.464 + 0.060PC_1 + 0.032PC_2 - 0.076PC_3 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i\right) + \gamma_t + \phi_t + \delta_{it}$	(12)
Structured space-time interaction	:	$\eta_{it} = \log(y) = 2.443 - 0.074PC_1 - 0.059PC_2 + 0.096PC_3 + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}v_i + \sqrt{\phi}u_i\right) + \gamma_t + \phi_t + \delta_{it}$	(13)

The influence of skin temperature is inseparable from the role of mean sea level pressure (MSLP) which also determines marine conditions through its influence on oceanographic properties, sea level variations, and the distribution of biological ecosystems (Islek & Yuksel, 2023). The influence of MSLP on sea level variations can be recognized through the reverse barometer effect where lower atmospheric pressure causes sea level rise while higher pressure causes the opposite (Bâki Iz, 2018). Such fluctuations also impact marine biodiversity and nutrient distribution due to changes in wind patterns and ocean currents (Han et al., 2020). Thus, it can be concluded that significant changes in MSLP can cause instability in the marine environment including changes in species distribution patterns, fisheries productivity and biodiversity. Such instability would directly affect the potential sustainability of the blue economy, which relies heavily on the stability and productivity of marine ecosystems as the main source of income.

In addition to skin temperature and MSLP, rainfall also plays an important role in influencing ocean conditions. High levels of rainfall falling into the ocean suppress sea surface gravity waves, alter air-sea momentum fluxes, and increase near-surface currents that can affect ocean transportation mobility and water mixing processes. Not only that, extreme rainfall events also cause coastal erosion and the influx of sediments and pollutants into coastal waters, which results in a decrease in water quality so that ecosystems and marine life are also harmed (Piccolo, 2021). Increased submarine groundwater discharge, algal blooms and changes in the biogeochemical dynamics of marine ecosystems are also caused by heavy rainfall (Diego-Feliu et al., 2022). These effects impact species composition, salinity stratification and fisheries productivity, all of which contribute to the sustainability of the blue economy (Liu et al., 2024). Therefore, adjustments to management strategies that integrate the effects of skin temperature, MSLP and total precipitation are necessary to support the sustainability of the marine economy amidst the challenges of climate change.

In accordance with the ability of spatio-temporal regression that can consider spatial, temporal, and interaction patterns between the two, it is interesting to explore whether the BEI on the island of Sumatera has a certain spatial pattern. In this case, the spatial pattern of BEIs on the island of Sumatera reflects the interaction between various local and global factors in shaping the sustainability of the blue economy. Based on the results of the best spatio-temporal regression modeling, it is known that the spatial pattern of BEI on the island of Sumatera is more dominantly influenced by unstructured variations. This is evident from the ϕ value of 0.29 in Table 6, which means that the contribution of spatial relationships between regions tends to be small, while local factors, such as regional policies, infrastructure, and the unique characteristics of each regency/city have a greater influence on the BEI.

Figure 3 illustrates the spatial distribution of BEIs in Sumatera island in a structured manner. The colors on the map indicate the posterior mean value of the structured spatial random effect (u_i) which ranges from -0.622 to 1.024 where the value indicates the significance of the contribution of the structured spatial effect in each regency/city. Through this illustration, it can also be seen that the three regions with the highest BEI scores - Medan City, Deli Serdang, and Palembang City - have significant structured spatial contributions. Meanwhile, Subulussalam City and Sawahlunto City, which previously had the lowest BEI scores, showed the opposite.

Although there are color variations on the map, where red indicates areas with low structured spatial contribution and blue indicates areas with high structured spatial contribution, the distribution appears to be randomly scattered without a clear spatial pattern. This fact is in line with the modeling results, which show that unstructured variation has more influence on the spatial pattern of the Sumatera island BEI. However, Figure 3 still provides insight into the spatial contributions that may occur. This will be used for further analysis in planning sustainable development and management of Sumatera island's marine resources.

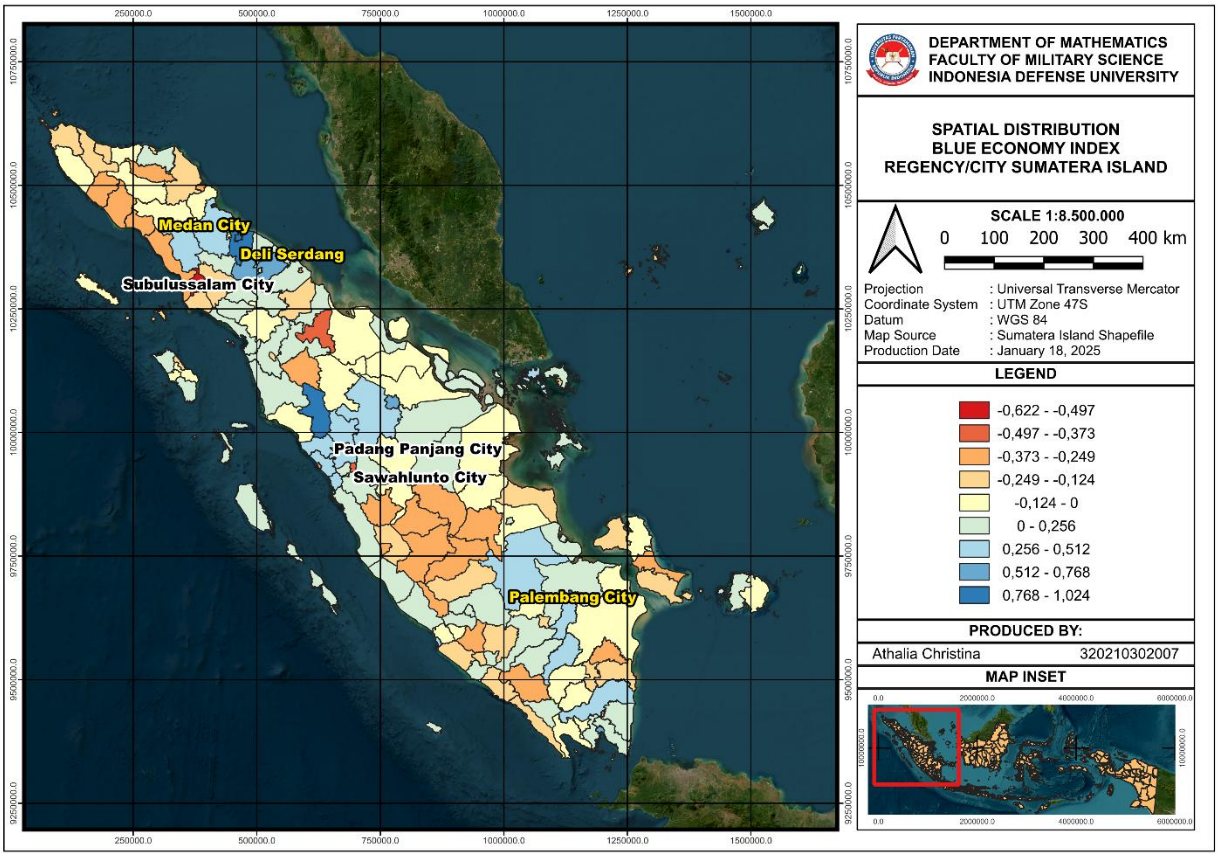


Figure 3. Spatial posterior mean of BEI in Sumatera island

Table 7. Temporal posterior mean of BEI in Sumatera island

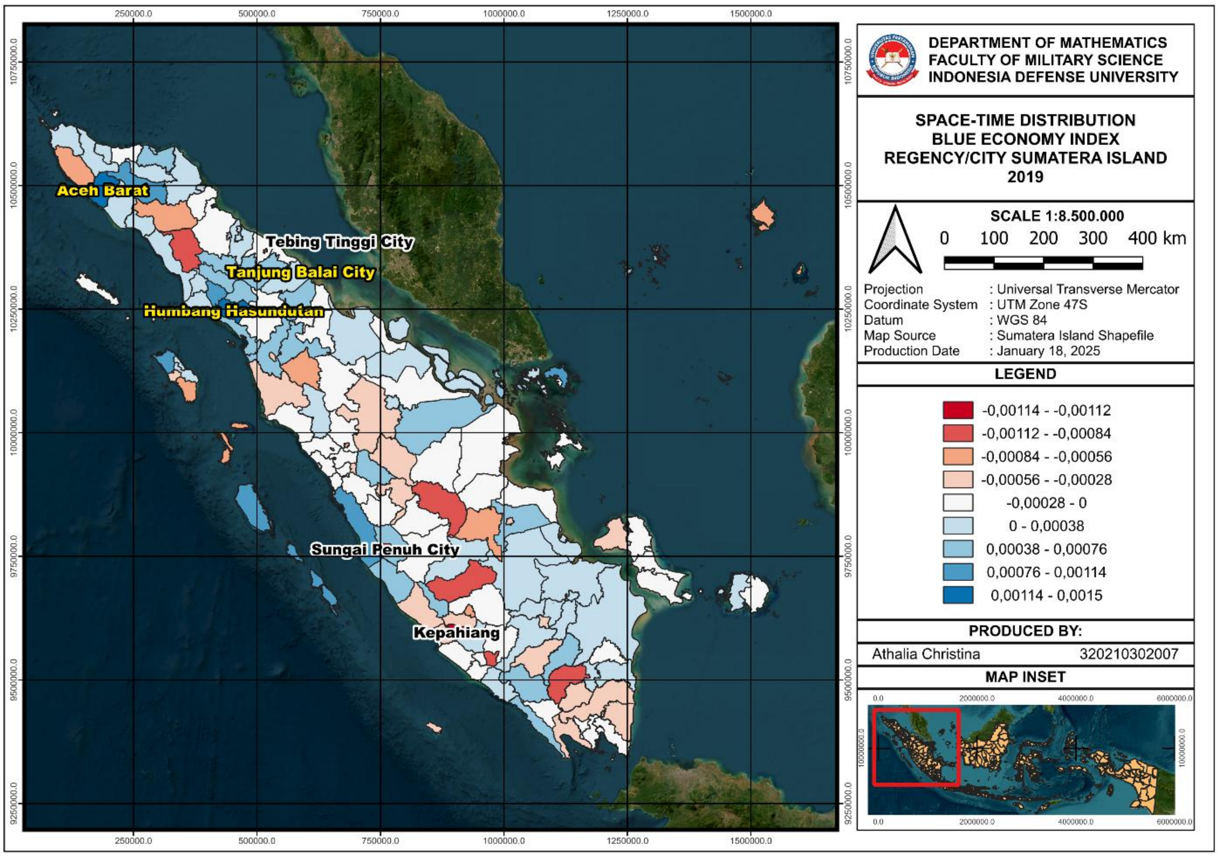
Year	2019	2020	2021	2022
$\boldsymbol{\lambda_t}$	0.099	0.155	-0.348	0.094

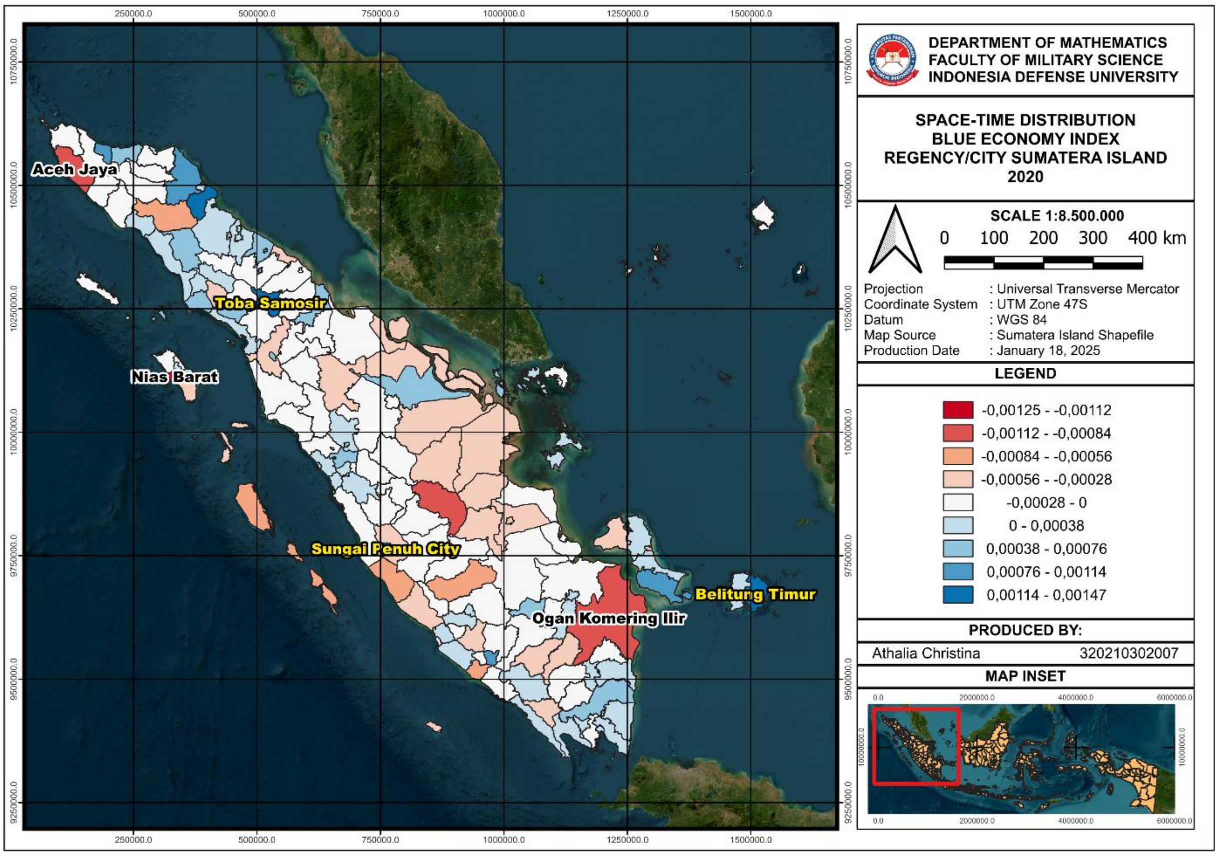
After identifying the spatial pattern of BEI on the island of Sumatera, this study also aims to investigate the temporal pattern of the phenomenon. This study investigates the temporal pattern of BEI on the island of Sumatera through a linear combination of structured (γ_t) and unstructured (ϕ_t) temporal effects expressed as $\lambda_t = \gamma_t + \phi_t$. To formulate marine resource management strategies to support the sustainability of blue economy potential based on data and time, understanding temporal trends is important. The temporal trends of the BEI of Sumatera island, obtained from the best regression model, are presented in Table 7.

Broadly speaking, the BEI on the island of Sumatera has decreased in 2021. The decline can be explained by various factors related to the Covid-19 pandemic (Sharma & Sharma, 2020). Reduced carbon dioxide emissions and cooler sea surface temperatures due to restrictions on global activities during the pandemic have allowed marine ecosystems to recover (Rangel-Buitrago et al., 2024). Despite the positive impacts of the pandemic, the pandemic has also had negative impacts. Increased plastic and microplastic pollution due to a surge in the use and disposal of poorly managed personal protective equipment (PPE) has affected the coastal and marine environment. Disruptions in marine sectors, such as fisheries and aquaculture, due to supply constraints, distribution, and bottlenecks in the global supply chain have led to a decline in blue economy output (Al Shehhi & Abdul Samad, 2021; Ihsan et al., 2022).

But as economic activity recovers and approaches to marine resource management change, the blue economy sector begins to rebound into 2022. Greater awareness of sustainability, innovations in business models, more proactive policy support and more in-depth research are driving the recovery of the blue economy's potential. A more holistic and adaptive approach to global challenges in managing the continuity of marine resources provides a positive impetus that brings the sector back to growth in the following year (Eugui et al., 2023; Ilma & Supriadi, 2022; Silvestri et al., 2024).

Furthermore, understanding the spatio-temporal interaction pattern is also an important step to take. The purpose of studying the relationship between the two random effects is to find out how time dynamics can affect the spatial distribution of BEI on the island of Sumatera or how geographical differences cause changes in the temporal pattern of the phenomenon. Visualization of the unstructured space-time interaction pattern will be presented in Figure 4.

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INDONESIA DEFENSE UNIVERSITY
SPACE-TIME DISTRIBUTION
BLUE ECONOMY INDEX
REGENCY/CITY SUMATERA ISLAND
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Coordinate System : UTM Zone 47S
Datum : WGS 84
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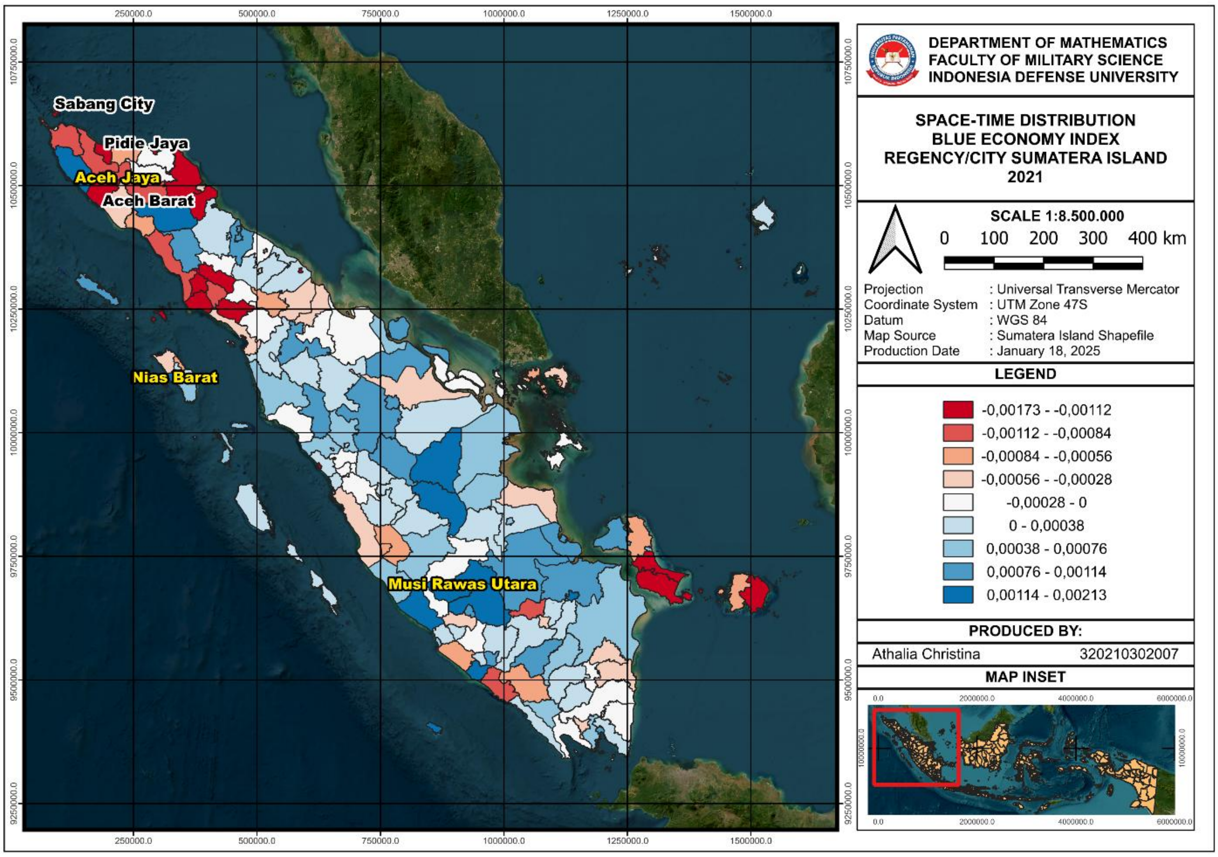
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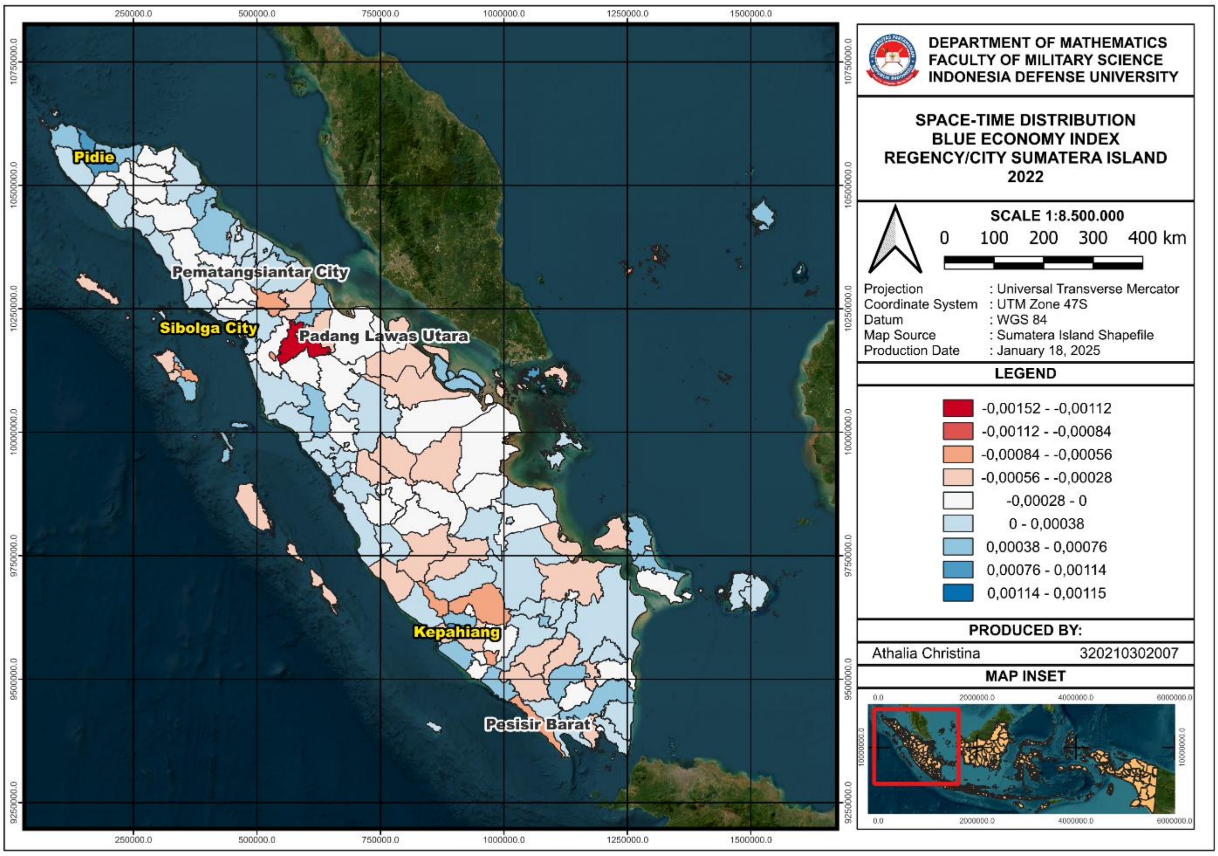

Figure 4. Space-time interaction posterior mean of BEI in Sumatera island

Regions with the highest and lowest mean posterior values differ every year, as shown by the yellow and black text in Figure 4. This indicates a dynamic interaction between local, spatial and temporal components. In general, areas with positive mean posterior values indicate contributions or interactions that support an increase in blue economy potential, while areas with negative mean posterior values indicate contributions or interactions that result in a decrease in blue economy potential. This pattern suggests that spatio-temporal interactions play an important role in determining the dynamics of the blue economy on the island of Sumatera. Regions with high mean posterior values (more than zero) tend to have relative advantages that promote blue economy growth, while regions with low mean posterior values (less than zero) tend to face greater challenges in managing and utilizing their potential.

To maintain the sustainability of the blue economy potential, especially on the island of Sumatera, practical studies can be made based on the theoretical studies above. Practically, some strategies that can be developed to maintain the sustainability of the blue economy are as follows.

a. Ecosystem-based management for climate change mitigation.

Improving critical habitats such as mangroves, coral reefs and seagrass beds can help protect marine ecosystems from the impacts of climate change. In addition, the use of global climate data, such as sea surface temperature, mean sea level pressure and total precipitation can also help model ecosystem changes and design adaptive policies.

b. Adaptation to sustainable fisheries and aquaculture.

Ecosystem-based management of fish stocks by considering the dynamics of the marine environment and encouraging diversification of catch types and development of environmentally friendly aquaculture can reduce pressure on natural fish stocks.

c. Technological innovation and monitoring systems.

Use of advanced technologies, such as ocean sensors, remote sensing and GIS to monitor changes in the marine environment. Implementation of real-time monitoring systems to predict climate change impacts and evaluate the effectiveness of sustainability strategies.

d. Strengthening adaptive and collaborative policies.
Development of spatio-temporal data-based policies to manage risks and optimize marine resource allocation. Implementation of cross-sector and inter-regional cooperation on technology and resources to support the blue economy.

e. Local capacity building and awareness.
Increased community awareness of the impacts of climate change through education and campaigns, as well as training to coastal communities to protect marine ecosystems through environmentally friendly and sustainable blue economy practices.

f. Economic diversification and regional resilience.
Investments in infrastructure, market access and business innovation, such as eco-friendly aquaculture and ecotourism to increase resilience to climate change impacts and global challenges.

g. Region-specific focused policy development.
Formulation and development of management policies tailored to the specific conditions of each region with the aim of addressing local challenges and sustainably harnessing the potential of the blue economy.

By integrating these practical strategies, a more targeted and locally responsive approach can be achieved to ensure the sustainability of Sumatera's blue economy potential. Through adaptive management, the use of advanced technology, and increased community capacity and awareness, we can sustainably optimize the potential of marine resources, maintain ecosystems, and build resilience to climate change.

CONCLUSION

Blue economy index (BEI) was established to measure the potential of blue economy at regency and city level, especially in Indonesia as an archipelago and maritime country that has great potential in implementing the concept of marine economy. The results of BEI research on the island of Sumatera showed that Medan City and Subulussalam City consistently obtained the highest and lowest BEI scores in the period 2019 to 2022. Blue economy potential in a region can be influenced by global climate factors. Bayesian nonparametric statistical downscaling model with unstructured space-time interaction as the best model based on the WAIC value shows that skin temperature, sea level pressure, and precipitation have a significant impact on BEI in Sumatera island. Spatial analysis shows that BEI is more dominantly influenced by local factors that vary in an unstructured manner, such as regional policies and infrastructure. Meanwhile, temporal analysis shows that BEI decreased in 2021 due to the Covid-19 pandemic and recovered in 2022. Then, the spatio-temporal interaction analysis shows that there are annual dynamics in areas that have advantages in promoting blue economy growth and areas that face challenges in its management. To maintain the sustainability of blue economy potential in Sumatera Island, the recommended strategies based on the results of this study include climate change mitigation, fisheries sector adaptation, technological innovation, policy strengthening, also capacity building and economic resilience tailored to the unique characteristics of each region.

As a continuity, some suggestions for further research aimed at broadening and deepening the understanding of the phenomenon of the sustainability of blue economic potential include: (1) The use of other global climate indicators that have not been investigated for their influence on blue economy potential in this study, such as ocean heat content, ocean pH, dissolved oxygen content, ocean acidification, and ocean color and phytoplankton populations; (2) The use of alternative modeling methods to improve understanding of blue economy potential locally, such as multiscale geographically and temporally weighted regression (MGTWR); (3) Use of additional evaluation metrics to ensure model accuracy and error rates, such as R-squared and root mean-square error (RMSE); and (4) Research on other regions in Indonesia, such as the islands of Sulawesi, Kalimantan, and Java. Thus, the overall goal of sustaining Indonesia's blue economy potential can be achieved.

AUTHOR CONTRIBUTIONS

AC and RNR designed the study. AC worked on almost all technical details, such as data collection and processing, as well as writing the research article. RNR and NHP verified the analysis methods and oversaw the findings. All authors provided critical feedback and helped shape the research, analysis, and manuscript.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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