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Mapping Blue Economy Potential Using Spatial Statistical Downscaling Model: Analysis of the Impact of Climate Change on Freshwater Fish Resources

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Abstract

Blue Economy is a sustainable economic concept that focuses on utilizing economic resources in marine, coastal and land ecosystems. Sustainable use of freshwater resources in the blue economy for inland waters supports economic growth with environmental balance. The Statistical Downscaling method is used to understand the impact of climate change on freshwater fish resources. To carry out mapping of the potential of the blue economy, it is carried out by statistical downscaling modeling with satellite variables with Integrated Nested Laplace Approximation parameter estimates. The response variable is satellite variables in the form of average rainfall. The modeling results show that Kalipuro District has the highest blue economy potential, while Kalibaru has the lowest. From the research results, that satellite data on average rainfall is a strong basis for printing statistical downscaling, increasing efficiency with open source digital data sources. Satellite data integration, maximizing analysis and comprehensive blue economy potential efficiency.

Keywords: blue economy; climate change; integrated nested laplace approximation (inla); spatial modeling; statistical downscaling

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INTRODUCTION

Blue Economy is a concept that aims to create a new paradigm that combines economic growth with the preservation of natural resources and environmental every protection. The sustainable utilization of ocean resources for economic advancement, enhanced livelihoods, and job creation while safeguarding marine ecosystem health is how the world bank defines the blue economy (Fudge et al., 2023). This term signifies a broad interest in the rapid growth of marine assets within oceanic limits, aiming to alleviate poverty, facilitate the shift towards sustainable economies, and aid in climate change mitigation (Barange et al., 2018). The emergence of the blue economy concept as a novel approach to promoting sustainable ocean development, in conjunction with the green economy, before and after the 2012 Rio+20 Conference on Sustainable Development, has been primarily supported by Small Island Developing States (SIDS) (Benzaken et al., 2024). This has raised awareness about the significance of coastal and ocean areal in sustainable development (Kullenberg, 2001). While there has been ongoing debate among policymakers and academics regarding the definition and extent of the blue economy, the growing interest in utilizing is as a framework for ocean governance and investment is attracting new stakeholders and shaping fresh avenues for development and financing, facilitating the advancement of multiple sustainable development goals (SDGs)(Sukiyono et al., 2024). In the context of Indonesia's 2045 vision to become a sovereign, advanced, jus and prosperous nation, blue economy focuses on regional excellence in the field of fisheries and the marine environment to achieve sustainable economic growth and community welfare. East Java Province, which is rich in marine resources, is one of the provinces in Indonesia with great maritime potential. Banyuwangi Regency, as part of East Java, has great potential in developing the marine and aquaculture sectors. High fisheries production in Banyuwangi, as noted in the Radar Banyuwangi 2022 report, reaches around 47.000 tons, with potential that is in line with the vision of local economic development and community welfare.

Previous research (Wijayanti & Ramlah, 2022) found that the concepts of blue economy and green economy had a positive impact on people's income in the Seribu islands. The study emphasizes community empowerment, income as the dependent variable, and includes the concepts of blue economy and green economy as moderating variables. Data collection was carried out using probability sampling and using multiple linier regression analysis (Wijayanti & Ramlah, 2022). Based on research conducted by Prayuda (2019) with the research method used being normative law or descriptive qualitative. The results obtained from research are that the Blue Economy concept and digitalization of aquaculture are expected to be able to increase food security, economic growth and comprehensive community empowerment. Efforts such as promoting the use of fish waste and sustainable marine development can advance the welfare of coastal communities (Prayuda et al., 2019). Based on research conducted by Adibrata (2022) using a qualitative descriptive approach to vannamei shrimp policy and cultivation. The research results show that the application of the blue economy concept for vannamei shrimp cultivation requires consistent government policies, sustainable marine development policies require political effectiveness and comprehensive water quality measurements. Cultivating vannamei shrimp in biofloc tarpaulin pond can increase economic benefits (Adibrata et al., 2022).

Statistical downscaling is a method used to transform global climate forecasts provided by Global Climate Models (GCMs) into regional or local scales (Eum et al., 2020). This technique involves the use of local climate observation data and accurate information about climate conditions at the regional or local level (Tefera et al., 2024). Based on varying empirical relationships between simulated and observed values, prior studies have demonstrated that statistical downscaling methods can effectively mitigate model biases, although the degree of success varies geographically and methodologically (Zhang et al., 2023). By employing statistical approaches such as regression, weather modeling, and other techniques, statistical downscaling aids in estimating climate changes that are more specific and relevant to a particular area. In statistical downscaling, domain of downscaling are independent variables with many dimensions where there are high probability of curses occurring dimensionality, spatial correlation between grids in the domain and multicollinearity between independent variables (Hadijati & Fitriyani, 2021). The larger the domain and the more variables used, the more complex the model will be. The method that can be used to solve high-dimensional problems is Principal Component Analysis (PCA) (Saha & Manickavasagan, 2021). PCA which was created by Peason in 1901 is a commonly employed method for reducing dimensions and extracting features, finding extensive use across various scientific and engineering applications as noted by Jolliffe (2002) (Yuan & Mancuso, 2023). The statement elucidates that Principal Component Analysis (PCA) serves as a prevalent technique or dimensionality reduction in data analysis across diverse domains.

However research on the development of a blue economy for the welfare of communities in coastal areas and around rivers, lakes, and swamps using statistical downscaling modeling still very rare to find. Therefore, this study aims to conduct statistical downscaling modeling of the blue economy potential in the Banyuwangi area, Indonesia.

METHOD

The response variable data used is the amounts of total fish total fish caught data in Banyuwangi Regency. The data used in this research consist of response data as the amounts of total fish caught in Banyuwangi Regency. The explanatory variables include data from the NOAA Physical Sciences Laboratory (NCEP/DOE Reanalysis II) satellite, measured in kg/m^s wit a spatial resolution of $2{,}5^0 \times 2{,}5^0$ in a global grid of 144×73. This data is monthly and covers the period from Januari 2022 to December 2022. The descriptive analysis is as **Table 1.** The variable of total fish catch is collected over a monthly periodic interval of 12 months. This data sourced from the BPS of Banyuwangi Regency.

Table 1. Descriptive Analysis

Variable	Min	Median	Mean	Max
JPI	9,9	36,7	45,79	255,5

Source : Data in this study

Based on **Figure 1**, the district the highest fish catch is located in the Kalipuro District. This could be to the likelihood of environmental conditions that support the presence of variety of fish species, such a ample food resources, diverse habitats suitable for fish, and a healthy marine ecosystem. Additionally, geographic factors, climate, and local fishing practices can also contribute to the high rate of fish catches in that area.

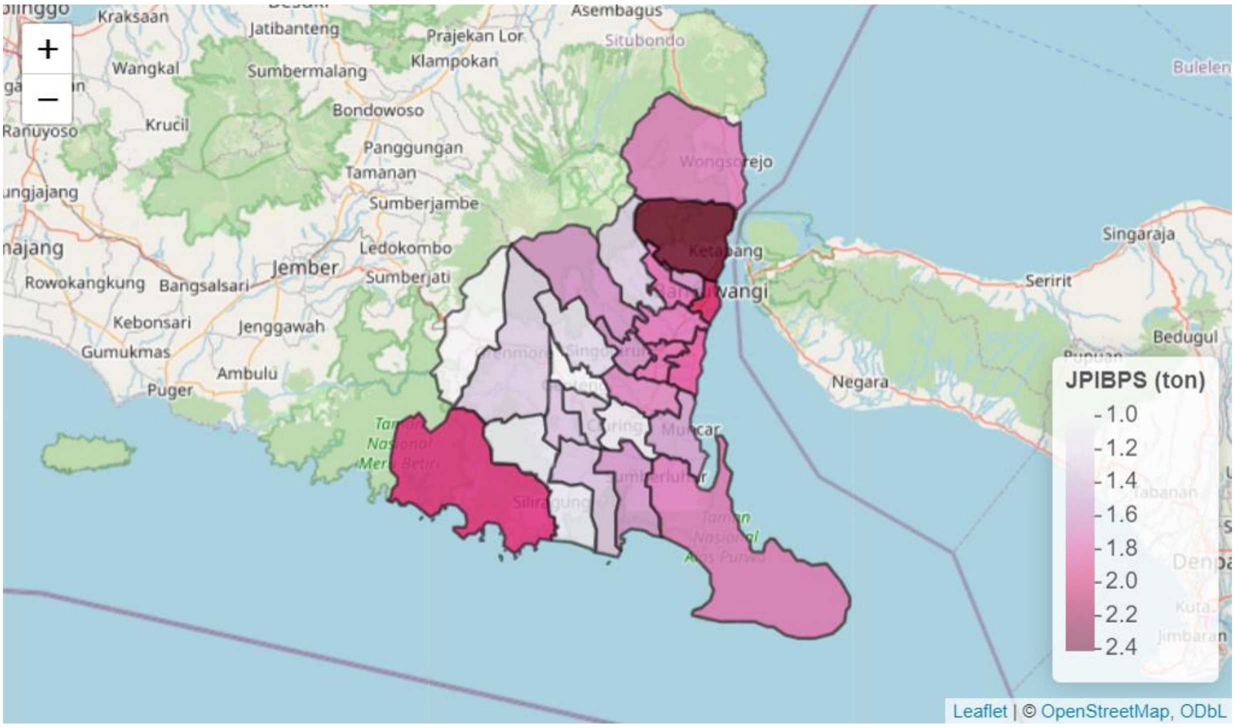

Figure 1. Number of Fish Caught

PCA amalgamates critical data from various features into a condensed set of principal components (PCs). Dimensionality reduction in PCA will produce several components, each component representing a variety of response value (Gandhi, 2015). **Table 1.** shows the proportion of variance of the main components. The selected principal components are expected to provide a cumulative percentage of variance between 80%-90%. Due to the cumulative proportion on PC2 reaching 98,8%, the variables utilized in this study are PC1 and PC2.

Table 2. Principal Component Analysis (PCA)

	PC1	PC2	PC3
Standard deviation	1,603	0,630	0,188
Variance Proportion	0,856	0,132	0,012
Cumulative Proportion	0,856	0,988	1,000

Source : Data in this study

Spatial Bayes regression models include fixed effects represented by independent variables $x_i, i = (1, \dots, n)$. The BYM stands for Besag, York, and Mollie model includes structured and unstructured components in spatial terms, allowing for the sharing of information on a global and local scale (Kim et al., 2023). In addition, this model also includes composed random effects of u_i which is a random effect with spatial structure and v_i which is a random effect which does not has a spatial structure.

$$\hat{y_i} = \beta_0 + \sum_{m=1}^{M} \beta_m x_{mi} + u_i + v_i \quad (1)$$

$\hat{y_i}$ is the number of fish caught in area i, β_0 in the formula represents the intercept, the coefficients β_m measure the effect of some covariates, $x = x_1, \dots, x_4$. The random effects are obtained from the autoregressive model conditional on the BYM2 specification. Simpson et al (2017) proposed a new parameterization of the BYM model called BYM2 (Riebler, Sørbye, Simpson, Rue, et al., 2016). BYM2 models using spatially structured component scales u_* and unstructured components spatial v_*.

$$b = \frac{1}{\sqrt{\tau_b}}(\sqrt{1-\emptyset}v_* + \sqrt{\emptyset}u_* \quad (2)$$

The precision parameter $\tau_b > 0$ controls u_* and v_*. Mixing parameters $0 \leq \emptyset \leq 1$ measures the proportion of marginal variance explained by structured effects u_*. Thus, the BYM2 model is the same as the single spatial model when $\emptyset = 1$, and an unstructured spatial model when $\emptyset = 0$.

So, the equation for spatial regression with parameter estimation using INLA is:

$$\hat{y_i} = \beta_0 + \sum_{m=1}^{M} \beta_m PC_{mi} + \frac{1}{\sqrt{\tau_b}}(\sqrt{1-\emptyset}v_* + \sqrt{\emptyset}u_* \quad (3)$$

u_* represents structured spatial random effects, while v_* represents unstructured spatial random effects (Blangiardo & cameletti, 2015).

RESULTS AND DISCUSSION

The resulting modeling on the number of fish catches specifially shows the details of the estimator values using the BYM2 model which are presented in **Table 3**. **Table 3** shows that the independent variable is the level of rainfall, resulting in 2 PCA which are used in the model calculations. PC1 and PC2 have a negative influence so that these independent variables can reduce the number of fish catches in Banyuwangi Regency.

Table 3. Statistical Downscaling Fixed Variable

	mean	sd	Credibility interval	
(Intercept)	1,523	160,698	$-313{,}630$	316,676
PC1	$-3{,}454 \times 10^{-7}$	31,623	$-62{,}017$	62,017
PC2	$-1{,}039 \times 10^{-7}$	31,623	$-62{,}017$	62,017

Source : Data in this study

The results of spatial modeling in the table above can be expressed in a regression equation, namely regression equation :

$$\hat{y}_i = \log(\rho_i) = 1{,}523 - 3{,}454 \times 10^{-7} PC_1 - 1{,}039 \times 10^{-7} PC_2 + \frac{1}{\sqrt{\tau_b}} (\sqrt{1-\emptyset} v_* + \sqrt{\emptyset} u_* \qquad (4)$$

The prior value for τ_b is expressed as 0,01. We define the prior for the mixing parameter $\emptyset$ as 2/3. Equation (4) employs a Bayesian spatial regression model with a log link function. This is done because the number of fish catches, which acts as the dependent variable, was normalized by taking the logarithm before antering the modeling process, hence it needs to be transformed back to its original value. Additionally, the explanatory Each addition of 1000 mm average rain will result in a decrease of 4,702 tons in the number of fish caught PC1. Every increase of 1000 mm in average rainfall will result in a decrease of 4,708 tons in the number of fish caught on PC2.

The spatial regression equation has spatial random effects that are modelled with using the BYM2 model, Simpson et al. (2017) proposed a new parametrization from a BYM model that uses spatially structured random components u_* and spatially unstructured random component v_* (Riebler, Sørbye, Simpson, & Rue, 2016). The variables u and v are random variables b. When the value of b is positif $b > 0$ the are has the highest potential to support the blue economy. Conversely, if the value of b is negative $b < 0$ the area has the lowest potential to support the blue economy in the region.

Table 4. Spatial Random Effect Value

No	Sub-district	Mean	Standard Deviation	Credibility Interval	
1	Kalipuro	0,883	0,052	0,777	0,988
2	Banyuwangi	0,503	0,052	0,399	0,609
3	Pesanggaran	0,420	0,052	0,316	0,526
4	Blimbingsari	0,271	0,052	0,166	0,377
5	Rogojampi	0,195	0,052	0,089	0,999
6	Glagah	0,191	0,052	0,086	0,297
7	Kabat	0,166	0,052	0,061	0,272
8	Tegaldlimo	0,140	0,052	0,035	0,246
9	Wongsorejo	0,122	0,052	0,017	0,227
10	Srono	0,106	0,052	0,001	0,212
11	Songgon	0,053	0,052	−0,052	0,159
12	Singojuruh	0,050	0,052	−0,055	0,155
13	Giri	0,043	0,052	−0,063	0,148
14	Purwoharjo	0,036	0,052	−0,070	0,141
15	Muncar	−0,005	0,052	−0,111	0,099
16	Bangorejo	−0,188	0,052	−0,293	−0,083
17	Tegalsari	−0,198	0,052	−0,303	−0,093
18	Glenmore	−0,239	0,052	−0,344	−0,134
19	Gambiran	−0,239	0,052	−0,344	−0,134
20	Licin	−0,240	0,052	−0,346	−0,135
21	Sempu	−0,297	0,052	−0,402	−0,191
22	Cluring	−0,363	0,052	−0,469	−0,258
23	Siliragung	−0,367	0,052	−0,472	−0,261
24	Genteng	−0,517	0,052	−0,623	−0,412
25	Kalibaru	−0,526	0,052	−0,631	−0,421

Source : Data in this study

Table 4. shows that 14 sub-districts have a value of $b > 0$ in research on the number of fish catches. This suggest that there are 14 sub-district with a high potential to enhance the blue economy n Banyuwangi Regency. Based on the table, there is a credibility interval. Credibility interval $0{,}025 - 0{,}975$ refers to the range of values used to measure the lebel of confidence or belief in an estimation or parameter in statistical analysis (Hespanhol et al., 2019). This range covers 95% of the posterior distribution, meaning there is a 95% confidence that the true value of the parameter lies within that interval. Thus, the credibility in $0{,}025 - 0{,}975$ provides information on how confident we are in the parameter estimation conducted in statistical analysis. Sub-districts numbered 1-10 have a positive

credibility interval, indicating that these areas with 95% confidence can enhance the blue economy potential in Banyuwangi Regency. Sub-districts numbered 11-15 have a negative 0.025 value, suggesting that with 95% confidence, these sub-districts may have diverse effects or complex contributions. Sub-districts numbered 16-25 have both negative 0.025 and 0.975 values, indicating that with 95% confidence, these areas may have insignificant or inconsistent impacts in spatial analysis. Completely negative intervals imply that in the context of the model, these areas may not provide a strong or consistent contribution to the blue economy potential in their region. For a clearer picture, it can see from the thematic map presented below:

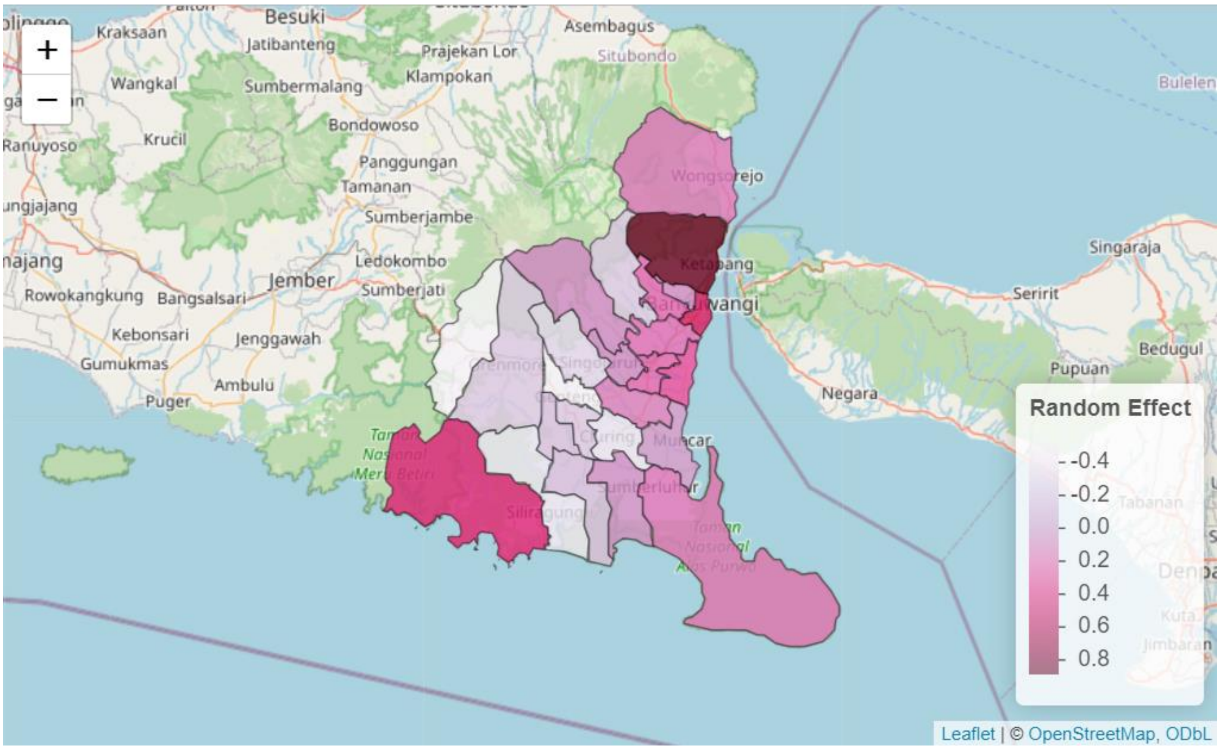

Figure 2. Random Effect

The image above provides an overview of the posterior map of the average values the number of fish catches obtained from using the BYM2 model shows that the proximity of an area can form a pattern it is divided into two. The first pattern was formed by Kalibaru district, Glenmore, Siliragung, Bangorejo, Gambiran, Tegalsari, Cluring, Genteng, empu, and Licin with a light red color. The second pattern is formed by sub-districts Purwoharjo, Tegaldlimo, Muncar, Srono, Blimbingsari, Rogojampi, Singojuruh, Songgon, Glagah, Giri, Kabat, Kalipuro, Wongsorejo, and Pesanggaran with color dark pink. Kalipuro district is a district with spatial random effects high, this can show that Kalipuro district can provide the greatest impact of increasing the potential of the blue economy. Kalibaru district is a sub-district with low spatial random effects, this shows that Kalibaru district can have a low impact of improvement towards increasing the potential of the blue economy. The error result of 3.64×10^{-4} for the statistical downscaling modeling indicates a very small error. A lower RMSE value signifies better prediction quality by the model. In this context, a low RMSE suggests a high level of agreement between the predicted values and the actual data. Therefore, the estimation results produced by this model closely resemble the true data. The error of the fitted value is related to the discrepancy between the observed data points and the values estimated by the model. This error may arise due to various factors such as model misspecification, unaccounted sources of variation, or inherent uncertainty in the data.

CONCLUSION

From research conducted on fish catch production in Banyuwangi using a statistical downscaling approach, model has an RMSE value of $3,64 \times 10^{-4}$. The results of this research are very interseting even though it only uses variables from satellite observations, is able to approximate the eactual data with a high degree of similarity. The conclusion of this research shows that the use of statistical downscaling methods in combination with INLA can provide promising results in predicting fish catch production in Banyuwangi. Statistical downscaling model has an ability to approximate actual data and can show great potential in practical applications. This indicates that satellite observations can be an efficient data source in statistical analysis, especially when local data are limited or incomplete. Thus, this research makes a significant contribution in expanding our understanding of the use if statistical methods in predicting fish catch production, as well as emphasizing the importance of further exploration regrading the potential use of data from satellites in the context of blue economy potential research.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest concerning the publication of this article. The authors also confirm that the data and the article are free of plagiarism.

REFERENCES

Adibrata, S., Lingga, R., & Nugraha, M. A. (2022). Penerapan blue economy dengan budidaya udang vaname (Litopenaeus vannamei). *Journal of Tropical Marine Science*, *5*(1), 45–54. https://doi.org/10.33019/jour.trop.mar.sci.v5i1.2964

Barange, Bahri, Beveridge, MCM, Cochrane, KL, Funge-Smith, Poulain, & eds. (2018). Impacts of climate change on fisheries and aquaculture: synthesis of current knowledge, adaptation and mitigation options. *Food and Agriculture of United Nations*.

Benzaken, D., Adam, J. P., Virdin, J., & Voyer, M. (2024). From concept to practice: Financing sustainable blue economy in lessons learnt from the Seychelles experience. *Marine Policy*, *163*. https://doi.org/10.1016/j.marpol.2024.106072

Blangiardo, M., & cameletti, M. (2015). *Spatial and Spatio-temporal Bayesian Models with R-INLA*.

Eum, H. Il, Gupta, A., & Dibike, Y. (2020). Effects of univariate and multivariate statistical downscaling methods on climatic and hydrologic indicators for Alberta, Canada. *Journal of Hydrology*, *588*. https://doi.org/10.1016/j.jhydrol.2020.125065

Fudge, M., Ogier, E., & Alexander, K. A. (2023). Marine and coastal places: Wellbeing in a blue economy. *Environmental Science and Policy*, *144*, 64–73. https://doi.org/10.1016/j.envsci.2023.03.002

Gandhi, V. (2015). Interfacing Brain and Machine. In *Brain-Computer Interfacing for Assistive Robotics* (pp. 7–63). Elsevier. https://doi.org/10.1016/b978-0-12-801543-8.00002-8

Hadijati, M., & Fitriyani, N. (n.d.). Prediction of Daily Rainfall in Dodokan Watershed Based on Statistical Downscaling Model: An Effort to Manage Watershed Ecosystems. In *Eastern Journal of Agricultural and Biological Sciences*. EJABS.

Hespanhol, L., Vallio, C. S., Costa, L. M., & Saragiotto, B. T. (2019). Understanding and interpreting confidence and credible intervals around effect estimates. In *Brazilian Journal of Physical Therapy* (Vol. 23, Issue 4, pp. 290–301). Revista Brasileira de Fisioterapia. https://doi.org/10.1016/j.bjpt.2018.12.006

Kim, J., Yoo, D., Hong, K., & Chun, B. C. (2023). Health behaviors and the risk of COVID-19 incidence: A Bayesian hierarchical spatial analysis. *Journal of Infection and Public Health*, *16*(2), 190–195. https://doi.org/10.1016/j.jiph.2022.12.013

Kullenberg, G. (2001). Contributions of marine and coastal area research and observations towards sustainable development of large coastal cities. In *Ocean & Coastal Management* (Vol. 44).

Prayuda, R., Sary, D. V., & Riau, U. I. (2019). Strategi Indonesia dalam Implementasi Konsep Blue Economy terhadap Pemberdayaan Masyarakat Pesisir di Era Masyarakat Ekonomi ASEAN. *Indonesian Journal of International Relations*, *3*(2), 46–64.

Riebler, A., Sørbye, S. H., Simpson, D., & Rue, H. (2016). An intuitive Bayesian spatial model for disease mapping that accounts for scaling. *Mathematics and Statistic*. http://arxiv.org/abs/1601.01180

Riebler, A., Sørbye, S. H., Simpson, D., Rue, H., Lawson, A. B., Lee, D., & MacNab, Y. (2016). An intuitive Bayesian spatial model for disease mapping that accounts for scaling. *Statistical Methods in Medical Research*, *25*(4), 1145–1165. https://doi.org/10.1177/0962280216660421

Saha, D., & Manickavasagan, A. (2021). Machine learning techniques for analysis of hyperspectral images to determine quality of food products: A review. In *Current Research in Food Science* (Vol. 4, pp. 28–44). Elsevier B.V. https://doi.org/10.1016/j.crfs.2021.01.002

Sukiyono, K., Romdhon, M. M., Mulyasari, G., Yuliarso, M. Z., Nabiu, M., Trisusilo, A., Reflis, Napitupulu, D. M., Nugroho, Y., Puspitasari, M. S., Sugiardi, S., Arifudin, & Masliani. (2024). Smallholder palm oil and sustainable development goals (SDGs) achievement: An empirical analysis. *Sustainable Futures*, *8*. https://doi.org/10.1016/j.sftr.2024.100233

Tefera, G. W., Ray, R. L., & Wootten, A. M. (2024). Evaluation of statistical downscaling techniques and projection of climate extremes in central Texas, USA. *Weather and Climate Extremes*, *43*. https://doi.org/10.1016/j.wace.2023.100637

Wijayanti, A., & Ramlah, R. (2022). Pengaruh Concept Blue Economy Dan Green Economy Terhadap Perekonomian Masyarakat Kepulauan Seribu. *Owner*, *6*(3), 1732–1743. https://doi.org/10.33395/owner.v6i3.906

Yuan, D., & Mancuso, N. (2023). SuSiE PCA: A scalable Bayesian variable selection technique for principal component analysis. *IScience*, *26*(11). https://doi.org/10.1016/j.isci.2023.108181

Zhang, M., Guo, Z. Y., Dong, G. T., & Tan, J. G. (2023). Projected heat wave increasing trends over China based on combined dynamical and multiple statistical downscaling methods. *Advances in Climate Change Research*, *14*(5), 758–767. https://doi.org/10.1016/j.accre.2023.09.001