ISSN 2354-9114 (online), ISSN 0024-9521 (print)
Indonesian Journal of Geography Vol 57, No.3 (2025): 537-545
DOI: 10.22146/ijg.102153 website: https://jurnal.ugm.ac.id/ijg

INDONESIAN JOURNAL OF GEOGRAPHY

RESEARCH ARTICLE

Integrating Support Vector Regression and Kriging in Spatial Interpolation of Statistical Seismicity Parameters

Dwi Agustin Nuriani Sirodj [1,2], Muhammad Nur Aidi [1*], Bagus Sartono [1], Utami Dyah Syafitri [1], Bayu Pranata [3]

[1]Department of Statistics and Data Science, School of Data Science, Mathematics, and Informatics, IPB University, Jl. Meranti Wing 22 Level 4 Kampus IPB Darmaga, Bogor 16680, Jawa Barat, Indonesia,
[2]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Islam Bandung, Jl. Ranggagading No.8, Tamansari, Kec. Bandung Wetan, Kota Bandung 40116, Jawa Barat, Indonesia,
[3]Earthquake and Tsunami Center, Agency for Meteorology, Climatology, and Geophysics (BMKG), Jl. Angkasa I, No.2 Kemayoran, Jakarta Pusat 10610, Indonesia

Received: 2024-12-03
Revised: 2025-04-29
Accepted: 2025-12-03
Published: 2025-12-22

Key words:
Earthquake; Support Vector Regression; Semivariogram; Spatial interpolation; IDW-Kriging

Correspondent email :
muhammadai@apps.ipb.ac.id

Abstract. Spatial interpolation methods, such as Inverse Distance Weighting (IDW) and kriging, are commonly used in various fields. In Kriging method, semivariogram fitting is an important step, where empirical data are used to derive a theoretical model. However, when the known theoretical semivariogram model does not provide a satisfactory fit, the bias in the estimated values is increased. To address this limitation, Support Vector Regression (SVR) can be used to model the empirical semivariogram with a machine-learning method. This method has been applied in ordinary kriging interpolation for semivariogram fitting to estimate parameters related to the potential occurrence of earthquake. Specifically, the calculated parameters, based on the Gutenberg-Richter law, include the seismic activity (*a*-value) and rock fragility (*b*-value) in the Sumatera region. The results showed that SVR can model the empirical semivariogram better than the theoretical. The integration of SVR-Ordinary Kriging provides the best performance compared to other methods, such as IDW, with the smallest RMSEP values for both the *b*-value and *a*-value measuring 0.1378 and 0.7423, respectively. Aceh and Mentawai Islands tend to show low *a* and *b* values, suggesting that these areas are more vulnerable to earthquake with large magnitudes.

1. Introduction

Spatial data research is an area that has experienced significant development in recent years. The main issue of spatial associations is frequently a concern in the modeling or predicting of a specific response. Another issue is the challenges faced in conducting measurements at all locations due to the continuous nature of the area. Consequently, estimation at points where measurements are not taken is essential. Interpolation method is used to estimate data at unsampled points. Spatial interpolation estimates values for unobserved locations based on observations at the observed (Pebesma & Bivand, 2023). The two spatial interpolation methods often used are kriging, which was introduced by Georges Matheron and Danie Kringe in 1963 (Matheron, 1963), and inverse distance weighting (IDW) (Shepard, 1968). IDW uses the principle of weights that are inversely proportional to the distance from the interpolated location (Pebesma & Bivand, 2023). Meanwhile, Kriging principle weighs the data measured by a stochastic model, considering the spatial variance represented by semivariogram (Matheron, 1963; Oliver & Webster, 2015).

Fitting semivariogram in kriging is important as it infers the theoretical semivariogram based on the empirical. The theoretical semivariogram that are popularly used are generalized linear, spherical, exponential, and Gaussian (Yakowitz & Szidarovszky, 1985). In some cases, a known theoretical semivariogram model does not provide a satisfactory estimate, thereby increasing the bias in the estimated value.

Semivariogram fitting was developed by (Shapiro & Botha, 1991), who added linear constraints related to smoothness, monotonicity, and convexity to the variogram function, which was previously known as the nonparametric method. Furthermore, this method is carried out using machine learning, namely the Support Vector Regression (SVR) algorithm (Han et al., 2016; Setiyoko et al., 2019) and Least Square Support Vector Machine (LS-SVM) (Huang et al., 2012), which provides better results. Therefore, integrating the SVR and kriging method in semivariogram fitting process will affect the calculation of weights on the estimated value. An advantage of SVR is computational complexity, which does not depend on the dimensions of the input space, and also has excellent generalization capabilities with high prediction accuracy (Awad & Khanna, 2015).

As an archipelago, Indonesia is very vulnerable to natural disasters such as earthquake. Based on earthquake disaster risk index in 2022 (Adi et al., 2023), 59% of cities/districts in Indonesia are included in the high-risk area. Sumatera Island is the most vulnerable area to earthquake, with several sources of threats, such as being located on active faults that are close to the subduction of the Indo-Australian plate and the Eurasian plate. Other threats include the Mentawai Fault System (MFS), the Sumatera Fault System (SFS), the existence of the Bukit Barisan Mountain, and active volcanoes that can cause volcanic earthquake (Kartikasari & Choiruddin, 2022; Metrikasari et al., 2021).

This study evaluates the performance of three spatial interpolation techniques —IDW, Kriging based on parametric semivariogram, and Kriging based on nonparametric semivariogram using SVR— in interpolating seismic activity parameters in Sumatera.

2. Methods

Secondary data from earthquake catalogs in Sumatera were used in this research. These data were obtained through the open-source website of The International Seismological Centre (ISC) Bulletin, and earthquake events from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) from January 1, 2000, to December 31, 2023. The data showed 2771 earthquake events with moment magnitude (Mw) > 5. According to (Irawan et al., 2020), earthquake with a scale of 5.0 - 5.9 will cause damage to a small area.

In the IDW method, the resulting predictions of earthquake are localized. The formula used to estimate the Z value at a given point $\boldsymbol{u}$ is as follows (Li, 2022):

$$Z^*(\boldsymbol{u})_{IDW} = \sum_{i=1}^{n} \lambda_i Z(\boldsymbol{u}_i) \quad (2.1)$$

$$\lambda_i = \frac{\left(\frac{1}{d_i^p}\right)}{\sum_{i=1}^{n}\left(\frac{1}{d_i^p}\right)};\ i = 1,2,\dots,n \quad (2.2)$$

Where $\boldsymbol{u}$ is the estimation point, $\boldsymbol{u}_i$ is the area of the sample points around the estimation point, and λ_i is the weight function, which is the inverse of the distance d_i between $\boldsymbol{u}_i$ $\boldsymbol{u}_i$ and $\boldsymbol{u}$. The value of p is the IDW power (IDP) or exponent value of a distance. The prediction model using the ordinary kriging method is as follows (Olea, 1999):

$$Z^*(u)_{OK} = \sum_{i=1}^{n} \lambda_i Z(u_i) \quad (2.3)$$

$$\sum_{i=1}^{n} \lambda_i = 1 \quad (2.4)$$

where u, u_i is a vector of areas for estimation and one of the closest data denoted by i; $Z^*(u)_{OK}$ is the estimated value at the location (u) through ordinary kriging method; λ_i is weight value at the i-th sample point; and n is the number of sample data. The weight value in ordinary kriging can be estimated through the following equation (Olea, 1999):

$$\boldsymbol{W} = \boldsymbol{\Gamma}^{-1}\boldsymbol{\Upsilon} \quad (2.5)$$

where:

$\boldsymbol{W} = (\lambda_1, \lambda_2, \dots, \lambda_n, \lambda)'$; $\boldsymbol{\Upsilon} = \big(\gamma(Z(u)_{OK} - Z(u_1)),$; $\gamma(Z(u)_{OK} - Z(u_2)), \dots, \gamma(Z(u)_{OK} - Z(u_n)), 1\big)'$ $\boldsymbol{\Gamma} =$

$$\begin{cases} \gamma\left(Z(u_i) - Z(u_j)\right), & i = 1,2,\dots,n,\ \ j = 1,2,\dots,n \\ 1, & i = n+1,\ \ j = 1,2,\dots,n \\ 1, & j = n+1,\ \ i = 1,2,\dots,n \\ 0, & i = n+1,\ \ j = n+1 \end{cases}$$

The estimator for semivariogram was obtained through the method of moments, and the results are as follows (Isaaks & Srivastava, 1989):

$$\gamma(h) = \frac{1}{2N_{(h)}} \sum_{i=1}^{N_{(h)}} [Z(u_i + h) - Z(u_i)]^2 \quad (2.6)$$

with $N_{(h)}$ is the number of pairs of observations separated by distance h; $Z(u_i + h)$ is the value of the variable at the location $u_i + h$; $Z(u_i)$ is the value of the variable at the location u_i, while the distance is calculated using the Euclidean distance.

The weight measurements using the IDW method were based only on the inverse distance, but the ordinary kriging method also considered the spatial variation represented by semivariogram plot. Theoretical semivariogram has limitations, as these models do not always adequately describe empirical semivariogram conditions. Therefore, a nonparametric method was developed based on the fitting process. (Huang et al., 2012) proposed the LS-SVM and the method was developed by (Han et al., 2016) using SVR for modeling empirical semivariogram with enhanced flexibility.

SVR is a development of a Support Vector Machine (SVM) with output variables as real or continuous values. The SVM model structure consists of input process variables, support vectors, kernel functions, and output variables (Han et al., 2016). The concept of SVR is based on the principle of structural risk minimization (SRM), which minimizes the upper bound of the expected risk. In SVR, the input variables in a lower-dimensional space are projected into a higher-dimensional space in order to convert nonlinear problems into linear models. This conversion is carried out using some nonlinear hyperspace functions.

Suppose a training data set $(x_1, y_1), \dots, (x_N, y_N) \epsilon R^m \times R$, where $x_i \epsilon R^m$ is the *i*-th data input variable and y_i is the output value. The SVR model can be formed through the following equation (Han et al., 2016):

$$y = f(x) = \sum_{i=1}^{N} w_i \partial_i(x) + b = w^T \partial(x) \quad (2.7)$$

where w is the weight vector on the hyperplane, $\partial_i(x)$ is the function that maps the input data into high-dimensional features, and b is a constant. The parameters in equation 2.7 can be obtained by minimizing the following risk function (L_r)(Han et al., 2016) :

$$L_r(w) = \frac{1}{2} w^T w + \lambda \sum_{i=1}^{N} |y_i - f(x)|_\varepsilon \quad (2.8)$$

where $|y_i - f(x)| = \begin{cases} 0, & if\ |y_i - f(x)| < \varepsilon \\ |y_i - f(x)| - \varepsilon, & others \end{cases}$

three main steps performed when integrating SVR in semivariogram fitting in the ordinary kriging method are as follows:

a) Calculating the empirical semivariogram.
b) Modeling the empirical semivariogram based on the SVR method where the parameters have been optimized.
c) Calculating weights for each observation point using SVR-based empirical semivariogram modeling results.

This research used the leave-one-out cross-validation (LOOCV) method, which is a special form of *k*-fold cross-validation where the number of folds equals the observations in a dataset (Li, 2022). The stages of LOOCV in kriging method are as follows:

a) Suppose $Z(x_i)$ is the *i*-th observation point data, $i = 1,2, \dots n$
b) Deleting one $Z(x_i)$ temporarily from the observation data set
c) Interpolation using kriging method on $(n-1)$ observation data is carried out to estimate $Z(x_i)$ that has been deleted in the initial stage.
d) Compare the estimated value of $\hat{Z}(x_i)$ with $Z(x_i)$ and calculate the estimation error with the following formula:

$$e_i = \hat{Z}(x_i) - Z(x_i) \quad (2.9)$$

Where e_i is predicted residual.

f) Repeat steps *a* to *d* for each i=1, 2,…,n
g) Calculate the performance measure of model goodness-of-fit.

(Li & Heap, 2008) proposed and briefly reviewed several error measures to evaluate the performance of methods. Root mean square error (RMSE) is the best measure because the method summarizes the average difference in observed units and predicted values.

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^{n} \left(\hat{Z}(x_i) - Z(x_i) \right)^2 \right]^{1/2} \quad (2.10)$$

Where n is the number of observations/samples, $Z(x_i)$ is the *i*-th observed value, and $\hat{Z}(x_i)$ is the *i*-th estimated value.

The distribution of earthquake magnitude can be explained by the Gutenberg-Richter law (Gutenberg & Richter, 1944) in the following equation:

$$\log N(M) = a - bM \quad (2.11)$$

Where $N(M)$ is the total occurrence of earthquake above magnitude *M*, a is a seismic constant that depends on the period, area, and activities of the observation area, and b is a measure of the size distribution of earthquake, which can provide information about the stress conditions in the Earth crust. The *a* and *b* parameters can be estimated through the maximum likelihood method with the magnitude distribution following an exponential distribution and formula:

$$\hat{b} = \frac{\log e}{(\bar{M} - m_0)} \quad (2.12)$$

where $\bar{M} = \frac{\sum_{i=1}^{n} M_i N_i}{\sum_{i=1}^{n} N_i}$ is the mean magnitude of earthquake data; M_i is the magnitude of the *i*-th data; N_i is a number of magnitudes of the *i*-th data; N is a number of earthquake data; m_0 is the magnitude of completeness of earthquake data. The estimated *a*-value can be obtained by Wekner's formula (Wahyuni et al., 2020) as follows:

$$\hat{a} = \log N(M \geq M_0) + \log(\hat{b} \ln 10) + m_0 \hat{b} \quad (2.13)$$

The type of magnitude obtained from the secondary data of earthquake catalogue in Sumatera varies for each event. Meanwhile, in the process of calculating the *a* and *b* values, the moment magnitude (M_w) is needed to obtain conversion of various types, such as Surface Wave (M_s), Bodywave (m_b), and Local Magnitude (M_L). The conversion equation of m_b and M_s into M_w followed the procedure in the research conducted by (Arimuko et al., 2023) while M_L does not need to be converted due to the representation of the moment magnitude.

The results of this research provide an overview of the performance evaluation of the three spatial interpolation methods using empirical data. Figure 1 describes the stages of analysis.

3. Result and Discussion

Data showed 2771 earthquake events in Sumatera from January 1, 2000, to December 31, 2023, which are visualized in Figure 2.

Figure 2 shows the distribution of earthquake events that spread in the southern region, as there are many active faults and subduction between the Eurasian plate and the Indo-Australian plate. There were five earthquake with magnitudes above 7 Mw, including Aceh on December 26, 2004, Nias on March 28, 2005, Bengkulu on September 12, 2007, Padang on September 30, 2009, and the Pagai Earthquake on October 25, 2010. The recorded data still requires a declustering

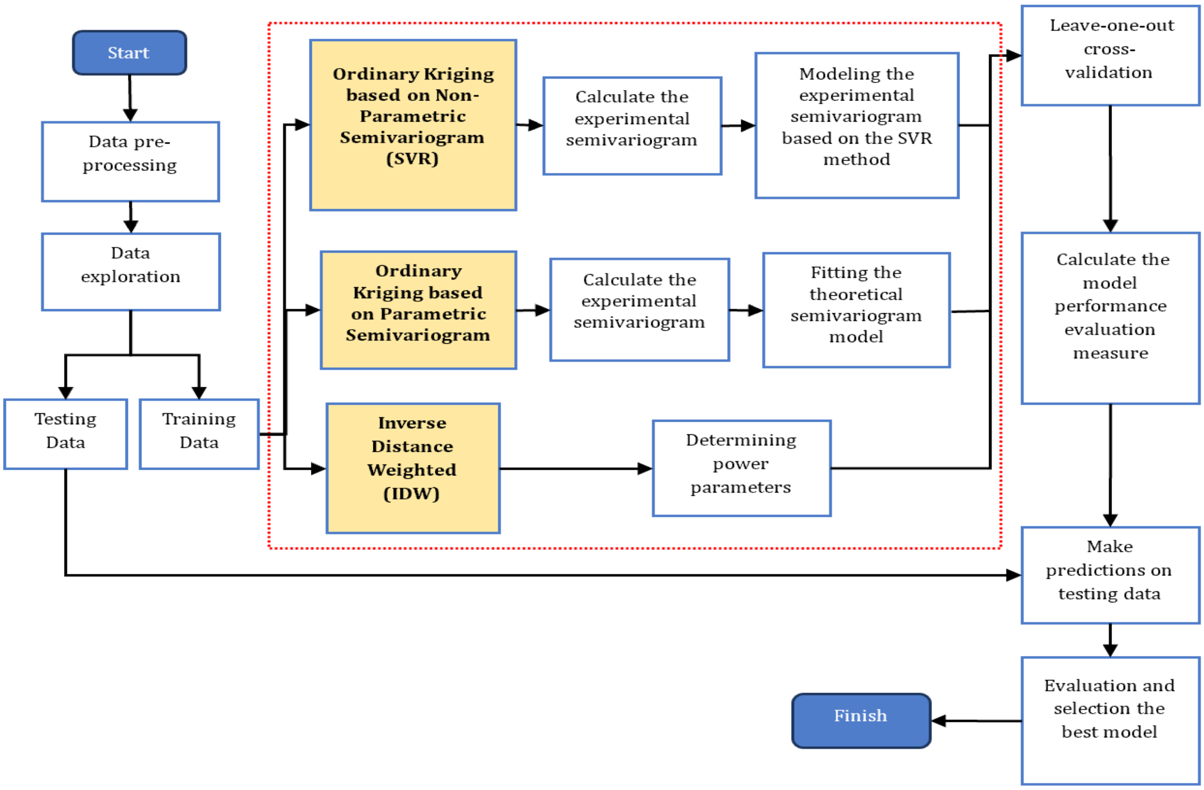

Figure 1. Research Flow Chart

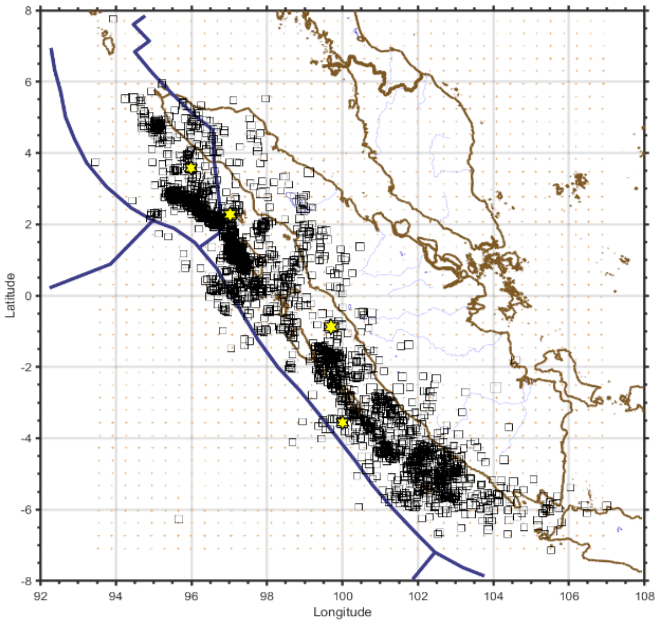

Figure 2. Map of Earthquake Occurrence in Sumatera for the period 2000-2023

process, which separates the main shock and aftershocks. The declustering process produced 1479 events with the largest magnitude of 7.9 Mw. The calculation of earthquake potential in an area is based on statistics of seismicity parameters as *a* and *b* values. This research divided Sumatera into research grids of $0.5^0 \times 0.5^0$. An overview of the number of earthquake events per research grid is shown in Figure 3.

Based on Figure 3, The Nias Islands have experienced high seismic activity over the past 23 years. This is illustrated by the color gradient on the map, where lighter colors in each grid indicate a higher number of earthquake events in the area. The data extraction results in 238 points that have *a* and *b* values were further analyzed to dwiscover the performance of the three interpolation methods. The data is divided into training and testing data with a proportion of 80:20. The training data was used to build interpolation model while the testing data predicted the *a* and *b* values at these areas. The distribution of points that become testing data is shown in Figure 4. The interpolation points are randomly distributed across the study area and are displayed as red dots. At these points, seismic parameter values are estimated based on the values from surrounding locations with known seismic data.

In the IDW spatial interpolation method, the determination of IDP is essential due to the effect on the

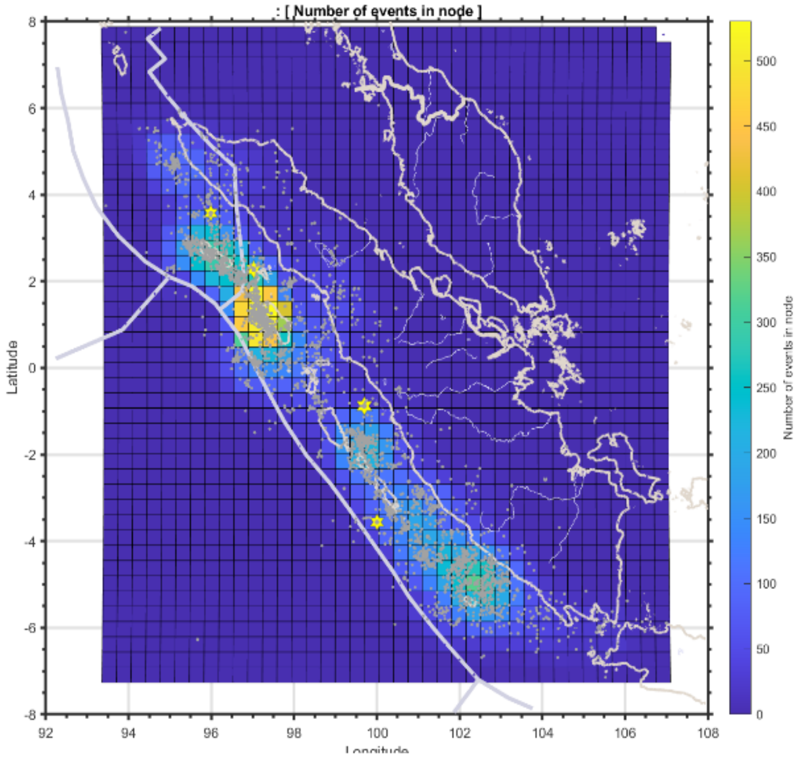

Figure 3. Number of Earthquake Events in Each Research Grid

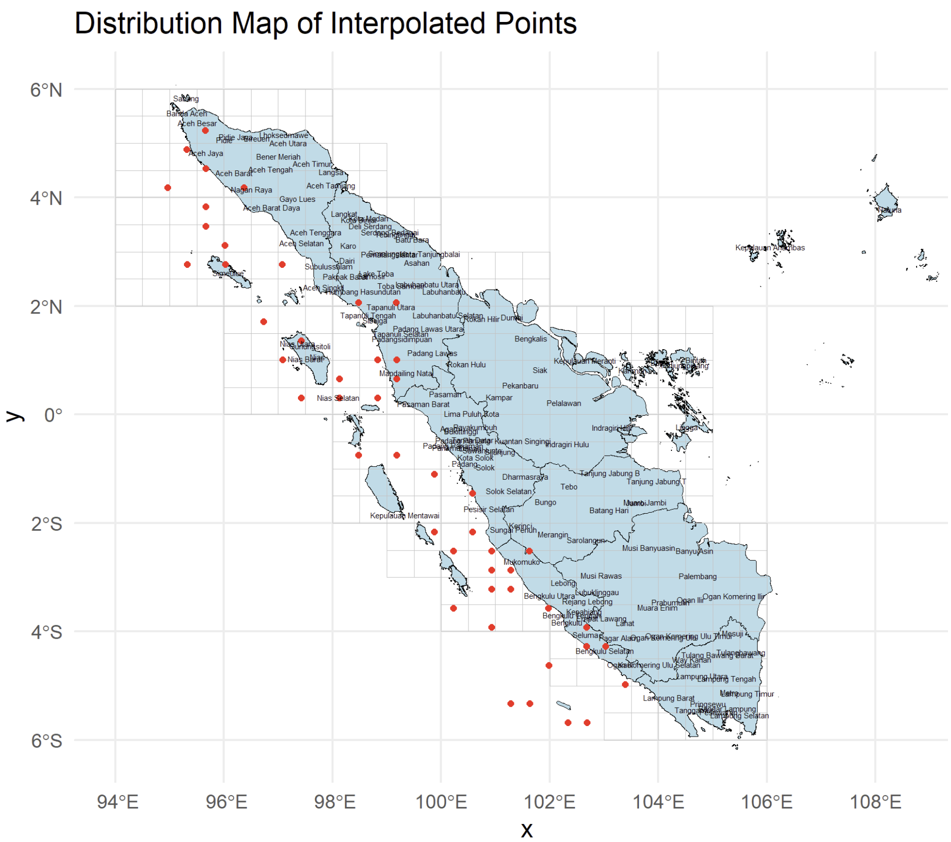

Figure 4. Distribution Map of Interpolated Points

calculation of weights on the predicted value. The optimal IDP was determined through LOOCV by examining the smallest RMSE value, as shown in Figure 5.

The result showed that the larger the IDP used, the smaller the resulting RMSE. At the *b* and *a* values, RMSE stabilizes when IDP is 4.4 and 5.0. The large IDP value shows that interpolation results through IDW are local. This implies that a greater distance between the sample data and interpolation point results in a smaller weight, and even tends not to affect the estimation process (Karaca et al., 2024). The predicted value at interpolation point will follow the pattern of values in the surroundings.

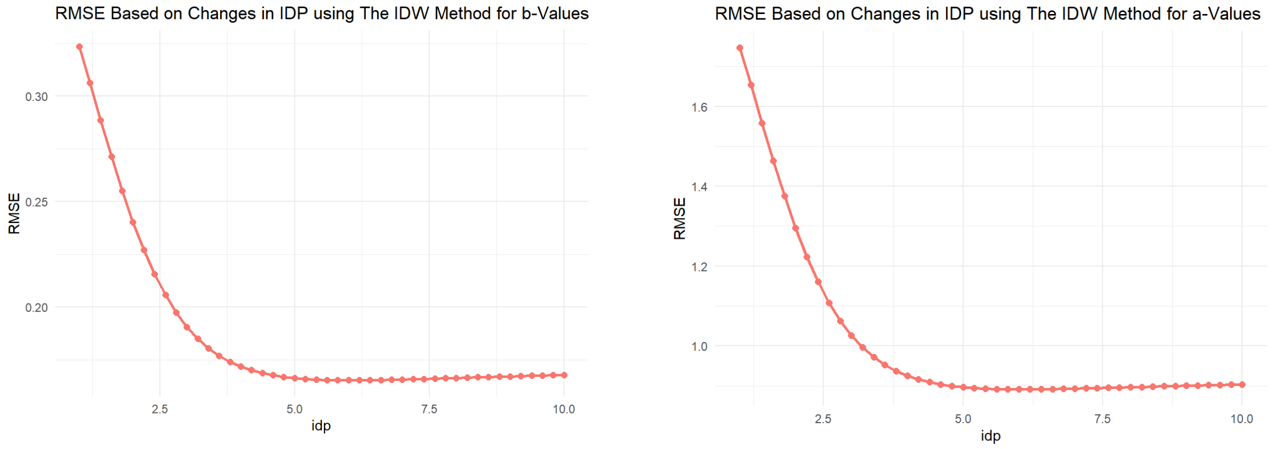

Figure 5. Power Parameters Selection in IDW

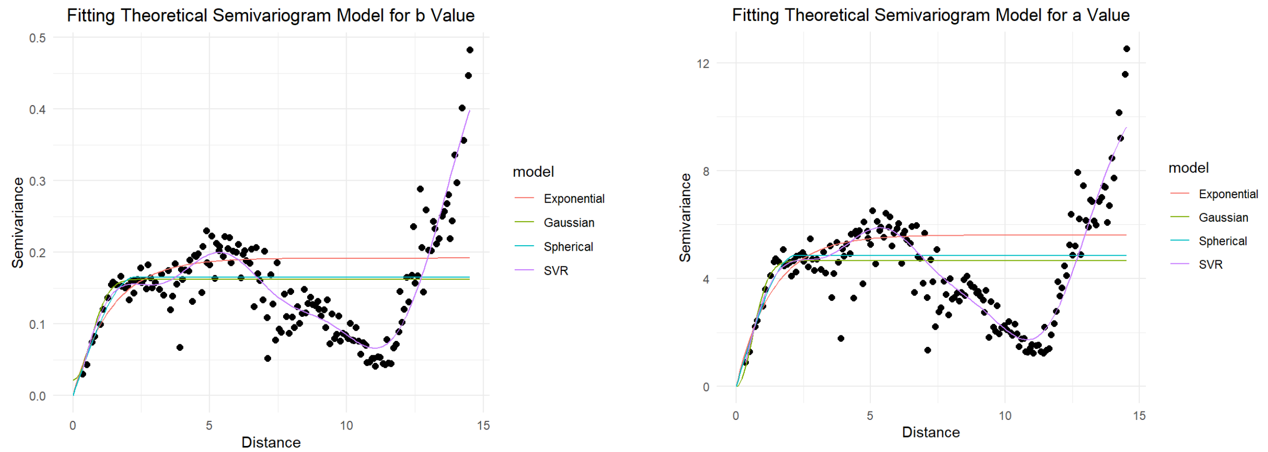

Figure 6. Fitting The Experimental Semivariogram

Table 1. RMSE of Fitting Semivariogram Model

Methods	Model	RMSE of b-Value	RMSE of a-Value
	Spherical	0.0746	2.0487
Parametric	**Exponential**	0.0806	2.2729
	Gaussian	**0.0737**	**2.0210**
Non-Parametric	**SVR**	**0.0297**	**0.8439**

In the ordinary kriging method, the weight calculation process considered spatial variation through the empirical semivariogram pattern. Empirical semivariogram modeling was carried out through two methods. First is a parametric method using common theoretical semivariogram, such as spherical, exponential, and Gaussian (Obroślak & Dorozhynskyy, 2017; Pyrcz & Deutsch, 2006). The second is a non-parametric method, which was carried out through modeling using the SVR machine-learning method. The process of fitting empirical semivariogram through the four models is shown in Figure 6.

The result showed that the empirical semivariogram data pattern is not linear and does not always increase monotonically. At a certain distance, the semivariance value tends to decrease. The empirical semivariogram modeling using SVR is visually better because the method follows the empirical semivariogram data pattern for both *a* and *b* values. Furthermore, the SVR modeling used in this research includes a Radial Basic Function kernel function with optimal hyperparameters are 0.2 epsilon (ε), 100 penalty constant (C), and 1 gamma. Radial Basic Function is a kernel used to solve problems in data with non-linear or complex relationships (Ding et al., 2021; Elen et al., 2022; Han et al., 2016).

Based on the result in Table 1, the parametric-based modeling of the Gaussian theoretical model has the smallest RMSE value of both *b* and *a* values, namely 0.0737 and 2.0210, respectively. However, compared to non-parametric-based modeling (specifically, SVR), the resulting RMSE for both values are significantly smaller, accounting for 0.0297 and 0.8439, respectively. This result showed that the SVR method is more effective than the theoretical Gaussian semivariogram model in modeling empirical semivariogram. The result is consistent with the report of (Han et al., 2016) that empirical semivariogram modeling based on SVR has a better ability without knowing the shape of the underlying model and more objectively reflecting spatial variation. Subsequently, the weights were calculated based on the two methods to evaluate the performance during ordinary kriging interpolation. The Root Mean Square Error of Prediction (RMSEP) measures the predictive error of IDW, Gaussian-Ordinary Kriging, and SVR-Ordinary Kriging in estimating the *b* and *a* values at interpolation point, as showed in Figure 5. The RMSEP results for the three models are shown in Table 2.

The data in Table 2 shows the smallest RMSEP value obtained by the SVR-Ordinary Kriging method for both the *b*-value and *a*-value, which are 0.1378 and 0.7423, respectively. This result shows that a more accurate empirical semivariogram model is associated with minimized prediction bias and increased accuracy of predicted results. Although the RMSEP value of the SVR ordinary kriging method is the smallest, the difference with the other two methods is quite close. The number of interpolated points was 48 points. According to (Al-Anazi & Gates, 2012), the performance of SVR remains consistently better for small sample sizes but depends on the

Table 2. RMSEP of All Models

Model	RMSEP of *b*-value	RMSEP of *a*-value
IDW	0.1446	0.7995
Gaussian-Ordinary Kriging	0.1382	0.8051
SVR-Ordinary Kriging	**0.1378**	**0.7423**

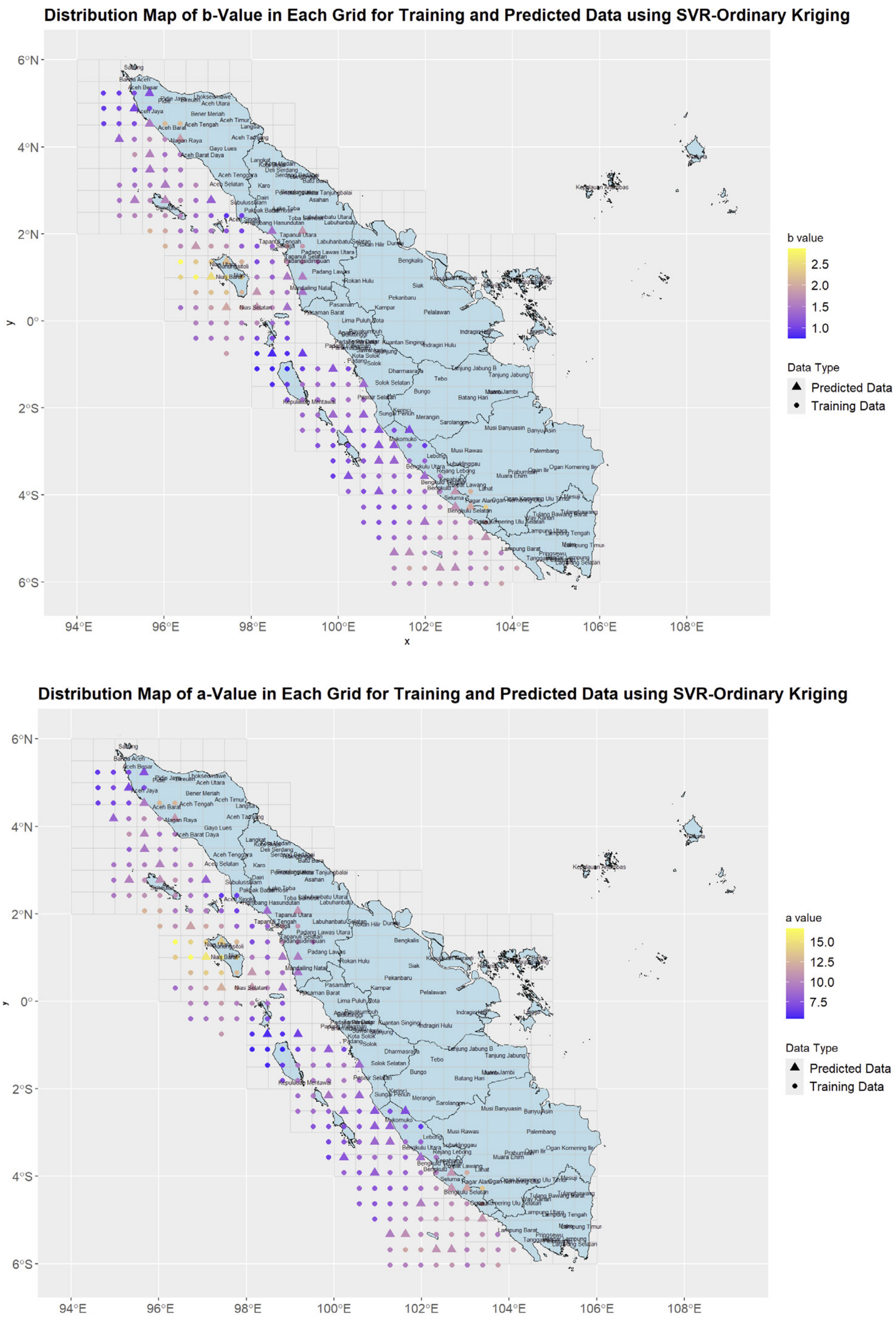

Figure 7. Distribution Map of Interpolated Data

type of kernel and loss functions used. The SVR method with the Radial Basic Function kernel also performs best for small, complex, non-stationary, and non-linear data (Kurnia et al., 2024). Based on Figure 7, the distribution of the *b* and *a* values at the interpolated point was concluded to follow the pattern of surrounding values, as shown by the similarity of colours around the area.

Figure 7 shows a map of *b* and *a* values distribution on the grid that can be calculated. The color intensity shows the *b* and *a*, as dark and light shades represent low and high values, respectively. Based on this representation, the Aceh and Mentawai Islands tend to show low *a* (seismic activity) and *b* values (rock fragility), suggesting that these areas are more vulnerable to earthquake with large magnitudes. This is consistent with the result of (Arimuko et al., 2023), who applied spatial segmentation to the Sumatra Fault Zone based on the spatial variation of the *b*-value. The results showed that the lowest and highest *b*-values were observed in northern and central Sumatera, respectively. The existence of the Aceh Fault can also lead to seismic hazards in the densely populated areas along the fault line, including the city of Banda Aceh (Marliyani et al., 2024). (Pailoplee, 2017) conducted a seismic hazard estimation along the Sumatra-Andaman subduction zone, and the results showed that the southern segment of the northwest and west coasts of Sumatra is a high-hazard area. The high hazard in this area was due to short recurrence intervals of 6-12 and 10-30 years for magnitude 6.0 and 7.0 Mw earthquake, respectively, compared to other areas. In addition, the Mentawai megathrust subduction zone makes the Mentawai islands one of the priority areas with a high risk of tsunamis in Indonesia (Mardiatno et al., 2017).

4. Conclusion

In conclusion, the empirical semivariogram fitting process in the ordinary kriging method was essential in the weight calculation process. The SVR method modelled the empirical semivariogram better than the theoretical. SVR-Ordinary Kriging integration provided the best performance compared to other methods with the smallest RMSEP for both *b* and *a* values, namely 0.1378 and 0.7423, respectively. Based on the distribution map, the area around Aceh and the Mentawai Islands had low *b* and *a* values, showing the potential for earthquake with large magnitudes. The findings demonstrate that SVR-Ordinary Kriging outperforms the parametric semivariogram model in capturing spatial variability, resulting in more accurate predictions at unobserved locations. This highlights the potential of machine learning, particularly SVR, to address the limitations of traditional Kriging methods, which rely heavily on theoretical semivariogram models, and to enhance the accuracy of spatial interpolation of seismic parameters.

Acknowledgment

The authors are grateful to the Directorate General of Higher Education, Research, and Technology of The Ministry of Education, Culture, Research, and Technology for funding this research through the 2024 Doctoral Research Scheme by Contract Number: 027/E5/PG.02.00.PL/2024 dated June 11, 2024.

References

Adi, A. W., Shalih, O., Shabrina, F. Z., Rizqi, A., Putra, A. S., Karimah, R., Eveline, F., Alfian, A., Syauqi, Septian, R. T., Widiastomo, Y., Bagaskoro, Y., Dewi, A. N., Rahmawati, I., Seniarwan, Suryaningrum, H. A., Purnamasiwi, D. I., & Puspasari, T. J. (2023). *IRBI : Indeks Risiko Bencana Indonesia Tahun 2022* (1st ed.). Badan Nasional Penanggulangan Bencana. https://inarisk.bnpb.go.id/IRBI-2022/mobile/index.html#p=1

Al-Anazi, A. F., & Gates, I. D. (2012). Support vector regression to predict porosity and permeability: Effect of sample size. *Computers & Geosciences*, *39*, 64–76. https://doi.org/10.1016/J.CAGEO.2011.06.011

Arimuko, A., Rohadi, S., & Rahman, A. S. (2023). Seismotectonic Studies to Determine the Recurrence of Earthquakes Mw > 7 Using a Statistical Approach and Plate Motion in the Megathrust Western Part of Java. *Geotechnical and Geological Engineering*, *41*(2), 1397–1406. https://doi.org/10.1007/S10706-022-02342-Z/METRICS

Awad, M., & Khanna, R. (2015). Support Vector Regression. *Efficient Learning Machines*, 67–80. https://doi.org/10.1007/978-1-4302-5990-9_4

Ding, X., Liu, J., Yang, F., & Cao, J. (2021). Random radial basis function kernel-based support vector machine. *Journal of the Franklin Institute*, *358*(18), 10121–10140. https://doi.org/10.1016/J.JFRANKLIN.2021.10.005

Elen, A., Baş, S., & Közkurt, C. (2022). An Adaptive Gaussian Kernel for Support Vector Machine. *Arabian Journal for Science and Engineering*, *47*(8), 10579–10588. https://doi.org/10.1007/S13369-022-06654-3/METRICS

Gutenberg, B., & Richter, C. F. (1944). Frequency of earthquakes in California. *Bulletin of the Seismological Society of America*, *34*(4), 185–188. https://doi.org/10.1785/BSSA0340040185

Han, C., Wang, J., Zheng, M., Wang, E., Xia, J., Li, G. S., & Choe, S. (2016). New variogram modeling method using MGGP and SVR. *Earth Science Informatics*, *9*(2), 197–213. https://doi.org/10.1007/S12145-016-0251-9/TABLES/8

Huang, Z., Wang, H., & Zhang, R. (2012). An Improved Kriging Interpolation Technique Based on SVM and Its Recovery Experiment in Oceanic Missing Data. *American Journal of Computational Mathematics*, *2012*(01), 56–60. https://doi.org/10.4236/AJCM.2012.21007

Irawan, L., Hasibuan, L. H., & Fauzi, F. (2020). Analisa Prediksi Efek Kerusakan Gempa Dari Magnitudo (Skala Richter) dengan Metode Algoritma ID3 menggunakan Aplikasi Data Mining Orange. *Jurnal Teknologi Informasi: Jurnal Keilmuan Dan Aplikasi Bidang Teknik Informatika*, *14*(2), 189–201. https://doi.org/10.47111/JTI.V14I2.1079

Isaaks, H. B., & Srivastava, R. M. (1989). *An Introduction to Applied Geostatistics*. 561. https://books.google.com/books/about/Applied_Geostatistics.html?id=vC2dcXFLI3YC

Karaca, O., Erol, B., & Erol, S. (2024). Assessments of Gravity Data Gridding Using Various Interpolation Approaches for High-Resolution Geoid Computations. *Geosciences 2024, Vol. 14, Page 85*, *14*(3), 85. https://doi.org/10.3390/GEOSCIENCES14030085

Kartikasari, Y. M., & Choiruddin, A. (2022). Analisis Risiko Gempabumi di Sumatera dengan Cauchy Cluster Process. *Inferensi*, *5*(2), 123–134. https://doi.org/10.12962/J27213862.V5I2.12307

Kurnia, I., Sadik, K., & Silvianti, P. (2024). *Perbandingan Performa SVR, Random Forest dan ARIMA pada Analisis Data Deret Waktu (Studi Kasus Kemiskinan di Tingkat Kabupaten/Kota)* [Institut Pertanian Bogor]. http://repository.ipb.ac.id/handle/123456789/134850

Li, J. (2022). Spatial Predictive Modelling with R. *Spatial Predictive Modelling with R*, 1–383. https://doi.org/10.1201/9781003091776/SPATIAL-PREDICTIVE-MODELING-JIN-LI

Li, J., & Heap, A. D. (2008). *A Review of Spatial Interpolation Methods for Environmental Scientists*. Australia: Geosience Australia. https://www.researchgate.net/publication/246546630

Mardiatno, D., Malawani, M. N., Annisa, D. N., & Wacano, D. (2017). Review on Tsunami Risk Reduction in Indonesia Based on Coastal and Settlement Typology. *Indonesian Journal of Geography*, *49*(2), 186–194. https://doi.org/10.22146/IJG.28406

Marliyani, G. I., Klinger, Y., Hady, A. K., Setianto, A., Helmi, H., Kurniawan, T., Kambali, R. A. P., Sugito, Z., Jihad, A., Setiawan, Y., Rusdin, A. A., Rohadi, S., Triyono, R., & Karnawati, D. (2024). Exploring Aceh Fault Zone for Slip Rates and Paleoseismic Trenching Potential along Sumatran Fault. *Indonesian Journal of Geography*, *56*(1), 138–147. https://doi.org/10.22146/IJG.93456

Matheron, G. (1963). Principles of geostatistics. *Economic Geology*, *58*(8), 1246–1266. https://doi.org/10.2113/GSECONGEO.58.8.1246

Metrikasari, R., Metrikasari, R., & Choiruddin, A. (2021). Pemodelan Risiko Gempa Bumi di Pulau Sumatera Menggunakan Model Inhomogeneous Neyman-Scott Cox Process. *Jurnal Sains Dan Seni ITS*, *9*(2), D102–D107. https://doi.org/10.12962/j23373520.v9i2.52318

Obroślak, R., & Dorozhynskyy, O. (2017). Selection of a semivariogram model in the study of spatial distribution of soil moisture. *Journal of Water and Land Development; 2017; No 35*, *7*(35), 161–166. https://doi.org/10.1515/jwld-2017-0080

Olea, R. A. (1999). Geostatistics for Engineers and Earth Scientists. In *Geostatistics for Engineers and Earth Scientists*. Springer Science Business Media New York. https://doi.org/10.1007/978-1-4615-5001-3

Oliver, M. A., & Webster, R. (2015). *Basic Steps in Geostatistics: The Variogram and Kriging*. Cham, Switzerland: Springer International Publishing. https://doi.org/10.1007/978-3-319-15865-5

Pailoplee, S. (2017). Probabilities of Earthquake Occurrences along the Sumatra-Andaman Subduction Zone. *Open Geosciences*, *9*(1), 53–60. https://doi.org/10.1515/GEO-2017-0004/MACHINEREADABLECITATION/RIS

Pebesma, E., & Bivand, R. (2023). Spatial Data Science: With Applications in R. *Spatial Data Science: With Applications in R*, 1–300. https://doi.org/10.1201/9780429459016/SPATIAL-DATA-SCIENCE-EDZER-PEBESMA-ROGER-BIVAND

Pyrcz, M. J., & Deutsch, C. V. (2006). Semivariogram models based on geometric offsets. *Mathematical Geology*, *38*(4), 475–488. https://doi.org/10.1007/S11004-005-9025-5/METRICS

Setiyoko, A., Arymurthy, A. M., Basaruddin, T., & Arief, R. (2019). Semivariogram fitting based on SVM and GPR for DEM interpolation. *IOP Conference Series: Earth and Environmental Science*, *311*(1), 012076. https://doi.org/10.1088/1755-1315/311/1/012076

Shapiro, A., & Botha, J. D. (1991). Variogram fitting with a general class of conditionally nonnegative definite functions. *Computational Statistics & Data Analysis*, *11*(1), 87–96. https://doi.org/10.1016/0167-9473(91)90055-7

Shepard, D. (1968). A two-dimensional interpolation function for irregularly-spaced data. *Proceedings of the 1968 23rd ACM National Conference, ACM 1968*, 517–524. https://doi.org/10.1145/800186.810616

Yakowitz, S. J., & Szidarovszky, F. (1985). A comparison of kriging with nonparametric regression methods. *Journal of Multivariate Analysis*, *16*(1), 21–53. https://doi.org/10.1016/0047-259X(85)90050-8