Mercator, Fortaleza, v. 25, e25007, 2026 ISSN:1984-2201

EVALUATION OF SPATIAL INTERPOLATION METHODS FOR SOCIOECONOMIC VARIABLES

https://doi.org/10.4215/rm2026.e25007

Melo, S.N. [a*] - Nascimento, E. [b]

(a) PHD in Geography

ORCID: https://orcid.org/0000-0003-3363-5208. **LATTES:** https://lattes.cnpq.br/9875457749739729.

(b) PHD in Geography

ORCID: https://orcid.org/0000-0002-3697-5200. **LATTES:** https://lattes.cnpq.br/4129536624525275.

Article history:
Received 02 December, 2025
Accepted 28 December, 2025
Published 10 April, 2026

(*) CORRESPONDING AUTHOR

Address: UEMA. Cidade Universitária Paulo VI, Tirirical, Zip Code: 65055970, São Luís (MA), Brazil. Phone: (+55 98) 3245-6141

E-mail: silasmelo@professor.uema.br

ARTICLE

Abstract

In Cartography, interpolation methods are used to identify the spatial arrangement of a variable by estimating unknown values based on sample points. Although they are increasingly used in social and human sciences, in general, in these fields of knowledge, there is no concern regarding the use of the ideal interpolator. Considering this research question, this paper presents an evaluation of the three most used methods for the spatial interpolation of socioeconomic variables: Inverse Distance Weighting (IDW), Thin Plate Spline (TPS) and Kriging. The performances of the three methods for interpolating a real socioeconomic variable (average land prices per square meter in a Brazilian city) are compared to the respective results for a physical variable (hypsometry by quoted points). The evaluation of the interpolators was performed based on visual analysis of the spatialization, and with cross-validation statistics using two error metrics (Mean Absolute Error and Root Mean Squared Error). In general, the results indicate that the socioeconomic variable was interpolated more efficiently by the Kriging method, while the IDW and Spline interpolators performed better for the physical variable.

Keywords: Socioeconomic Variables, Spatial Interpolation, Inverse Distance Weighting, Thin Plate Spline, Kriging.

Resumo / Resumen

AVALIAÇÃO DE MÉTODOS DE INTERPOLAÇÃO ESPACIAL PARA VARIÁVEIS SOCIOECONÔMICAS

Em Cartografia, os métodos de interpolação são utilizados para identificar o arranjo espacial de uma variável, por meio da estimação de valores desconhecidos com base em pontos amostrais. Apesar de serem cada vez mais utilizados nas ciências sociais e humanas, em geral, nesses campos do conhecimento, não há uma preocupação quanto ao uso do interpolador ideal. Tendo em vista essa questão de pesquisa, o presente trabalho apresenta uma avaliação dos três métodos mais utilizados para a interpolação espacial de variáveis socioeconômicas: Inverso da Distância Ponderada (IDW), Thin Plate Spline (TPS) e Krigagem. São comparadas as performances dos três métodos para a interpolação de uma variável socioeconômica real (preços médios de terrenos por metro quadro em uma cidade brasileira) aos respectivos resultados para uma variável física (hipsometria por pontos cotados). A avaliação dos interpoladores foi realizada com base em análise visual da espacialização, e com estatísticas de validação cruzada utilizando duas métricas de erro (Erro Médio Absoluto e Erro Quadrático Médio). De modo geral, os resultados indicam que a variável socioeconômica foi interpolada de maneira mais eficiente pelo método de Krigagem, enquanto que os interpoladores IDW e Spline apresentaram melhor desempenho para a variável física.

Palavras-chave: Variáveis socioeconômicas, Interpolação espacial, Inverso da Distância Ponderada, Thin Plate Spline, Krigagem.

EVALUACIÓN DE MÉTODOS DE INTERPOLACIÓN ESPACIAL PARA VARIABLES SOCIOECONÓMICAS

En Cartografía, los métodos de interpolación se utilizan para identificar la distribución espacial de una variable, mediante la estimación de valores desconocidos a partir de puntos muestrales. Aunque su uso es cada vez más frecuente en las ciencias sociales y humanas, en general, en estos campos no existe una preocupación por emplear el interpolador ideal. Ante esta problemática, el presente trabajo evalúa los tres métodos más utilizados para la interpolación espacial de variables socioeconómicas: Inverso de la Distancia Ponderada (IDW), Thin Plate Spline (TPS) y Kriging. Se comparó el desempeño de los tres métodos en la interpolación de una variable socioeconómica real (precios medios de terrenos por metro cuadrado en una ciudad brasileña) con los resultados obtenidos para una variable física (hipsometría por puntos cotados). La evaluación se basó em análisis visual de la espacialización y validación cruzada con dos métricas de error (Error Medio Absoluto y Error Cuadrático Medio). Los resultados indican que la variable socioeconómica se interpoló con mayor eficiencia mediante Kriging, mientras que IDW y Spline mostraron mejor desempeño para la variable física.

Palabras-clave: Variables Socioeconómicas, Interpolación Espacial, Inverso de la Distancia Ponderada, Thin Plate Spline, Kriging.

INTRODUCTION

In a broad definition, interpolation is the process of constructing a new set of data from previously known discrete point values. In Cartography, it becomes a powerful tool, as from sampling and data collection of some points referring to a geographic variable, it is possible to employ an interpolator and, from it, identify the spatial arrangement of the referred variable (Stein, 2012). In other words, spatial interpolation methods are used to estimate values of a variable in unsampled locations based on known points. The literature shows that they are widely used in research in natural sciences, in areas such as geology (Liu et al., 2021), climatology (Farias et al., 2017), pedology (Silva et al., 2010), bathymetry (Ferreira et al., 2013), topography (Barbosa et al., 2008), agronomy (Corá et al., 2004), among others.

Although some studies use spatial interpolation methods for research on social and human phenomena, such as diseases, social risks, crime, and income inequality (Folharini et al., 2023; Nascimento et al., 2020; Ramos & Melo, 2022; Silva et al., 2020), in general there is no concern about the quality of the use of the ideal interpolator. That is, there is a research gap regarding the application of spatial interpolation methods for social, demographic, and economic variables. Do interpolators applied to physical variables perform the same when used for socioeconomic variables in the same area? If not, what would be the main directional differences?

In order to provide answers to these research questions, the present study analyzes the three most used methods for the spatial interpolation of socioeconomic data (Inverse Distance Weighting, Spline, and Kriging), comparing their performances in predicting values of a real socioeconomic variable (land prices) with the respective results for a physical variable (quoted points) in the same area. Furthermore, based on the principle of scientific reproducibility, the research also presents a script developed in the R language, which allows the replication of this experiment for any set of spatial data.

The text, henceforth, is organized into three parts. In the first of these, below, a characterization of the interpolation methods used in the research is carried out based on specialized literature. The text is completed, next, with the methodological approach and the research results, followed by the final considerations.

SPATIAL INTERPOLATORS

The methods of spatial interpolation are quite numerous and varied. But in general, they can be differentiated into two groups, according to the mathematical mechanism of interpolation: the so-called deterministic methods, which use predefined mathematical functions for value estimation, and the stochastic methods, which consider the existing spatial dependence between the data (Stein, 2012). These methods differ in how they handle data variability and in the consideration of the uncertainty associated with spatial estimates. In the present study, three interpolators widely used in the literature for their applicability in different spatial contexts were selected. Two of them are deterministic, the Inverse Distance Weighting (IDW) and the Thin Plate Spline (TPS); and one is stochastic, Kriging.

The IDW interpolator estimates values based on the weighting of the distances between the unknown point and the known neighboring points within a certain area of coverage. This method is based on the premise that things that are closer tend to be more alike than those that are farther away (Canãda Torrecilla, 2007), which is why points closer to an unknown location exert a greater influence on the estimate than more distant points (Panigrahi, 2023). The estimation of a value Z(x0) at an unknown point x0 is given by:

$$Z(x_0) = \frac{\sum_{i=1}^{N} w_i Z(x_i)}{\sum_{i=1}^{N} w_i} \tag{1}$$

where:

- $Z(x0)$ is the estimated value at point $x0$;
- $Z(xi)$ are the known values at neighboring points xi;
- N is the number of neighboring points considered in the interpolation;
- wi are the weights assigned to each point xi, calculated based on the distance di to $x0$.

The Spline interpolation method adjusts a smooth, radial-based polynomial function that intersects each of the sample points, ensuring a smooth transition between them. The goal is to minimize the curvature of the interpolated surface. The most common radial function for mapping applications is the TPS (Akima, 1970), whose equation is defined by:

$$S(x,y) = \sum_{i=1}^{N} w_i \varphi(d_i) \tag{2}$$

where:

- $S(x,y)$ is the interpolated surface;
- wi are weights adjusted for the known points;
- di is the distance between the interpolated point and point i.
- $\varphi(d) = d^2 \backslash ln(d)$ is the radial basis function that controls the smoothness of the surface.

Spline interpolation is frequently used to calculate smoothed surfaces from a large number of sample data. According to Cañada Torrecilla (2007), this method presents good results when the surface varies moderately, but tends to be less appropriate when there is a large variation of values over short horizontal distances, or when it is suspected that the sample is prone to errors or some uncertainty.

Finally, Kriging assumes that the data follow the principle of spatial variability and that there is an autocorrelation between nearby points. The method uses the semivariogram, a function that describes how data variability changes with distance. This stochastic interpolation has many variations that can be found in the literature (Yamamoto & Landim, 2013). In our study we used Ordinary Kriging:

$$Z(x_0) = \sum_{i=1}^{N} \lambda_i Z(x_i) \tag{3}$$

where:

$Z(x0)$ is the estimated value at the unknown point $x0$;

$Z(xi)$ are the known values at neighboring points xi;

λi are the weights assigned to each point xi, calculated based on the spatial dependence determined by the semivariogram;

N is the number of points considered in the interpolation;

The weights λi are determined by solving the Kriging system of equations, which minimizes the mean squared error of the estimate:

$$\sum_{j=1}^{N} \lambda_j \gamma(x_i, x_j) + \mu = \gamma(x_i, x_0) \quad (4)$$

$$\sum_{j=1}^{N} \lambda_j = 1 \quad (5)$$

where:

γ(xi,xj) is the semivariogram, which measures the spatial variability between points *xi* and *xj*;

γ(xi,x0) is the semivariogram between the known points *xi* and the point to be interpolated *x0*;

μ is a Lagrange parameter, necessary to ensure that the sum of the weights is 1.

The semivariogram is essential in Kriging and defines the relationship between data variability and distance. It can also be adjusted by a theoretical model, such as spherical, exponential, and Gaussian (Yamamoto & Landim, 2013).

METHODOLOGICAL ASPECTS

VARIABLES USED

For empirical analysis, two data sets were collected to represent a physical-territorial element and a socioeconomic aspect of a city – in this case, the urban area of the municipality of Chapecó, located in the west of Santa Catarina (southern Brazil), with an estimated population, in 2025, of approximately 282 thousand inhabitants.

As a physical variable, point data of terrain altitudes (Imbituba vertical datum), recorded in the field using a GNSS receiver, derived from the municipal digital cartographic base, were used. It is, therefore, a continuous spatial variable, whose nature often requires its representation in the form of sample (point) field data (Longley et al, 2015).

The socioeconomic variable adopted was the average price per square meter of vacant urban land, calculated from the compilation of data (square footage and price) contained in sale advertisements, available on real estate company websites and online classifieds, in the year 2024. This, in turn, corresponds to a discrete point variable (Longley et al, 2015), given that each piece of land has a unique price, although this is influenced by a set of external factors (infrastructure and available services, average land values in the vicinity, topography, among others).

The option was made to use real data from a Brazilian urban area instead of carrying out a simulation, as this provides situations more consistent with research that employs interpolation methods.

Next, Table 1 gathers the descriptive statistics of the variables used, while Figure 1 presents the respective spatialization.

Variable	Number of samples	Minimum value	Maximum value	Mean	Standard deviation
Land price per m²	240	53,90	7.901,26	1.010,12	1.045,399
Quoted point	76	530	826	704,1	63,851

Table 1 – Descriptive statistics of the variables. Source: Prepared by the authors.

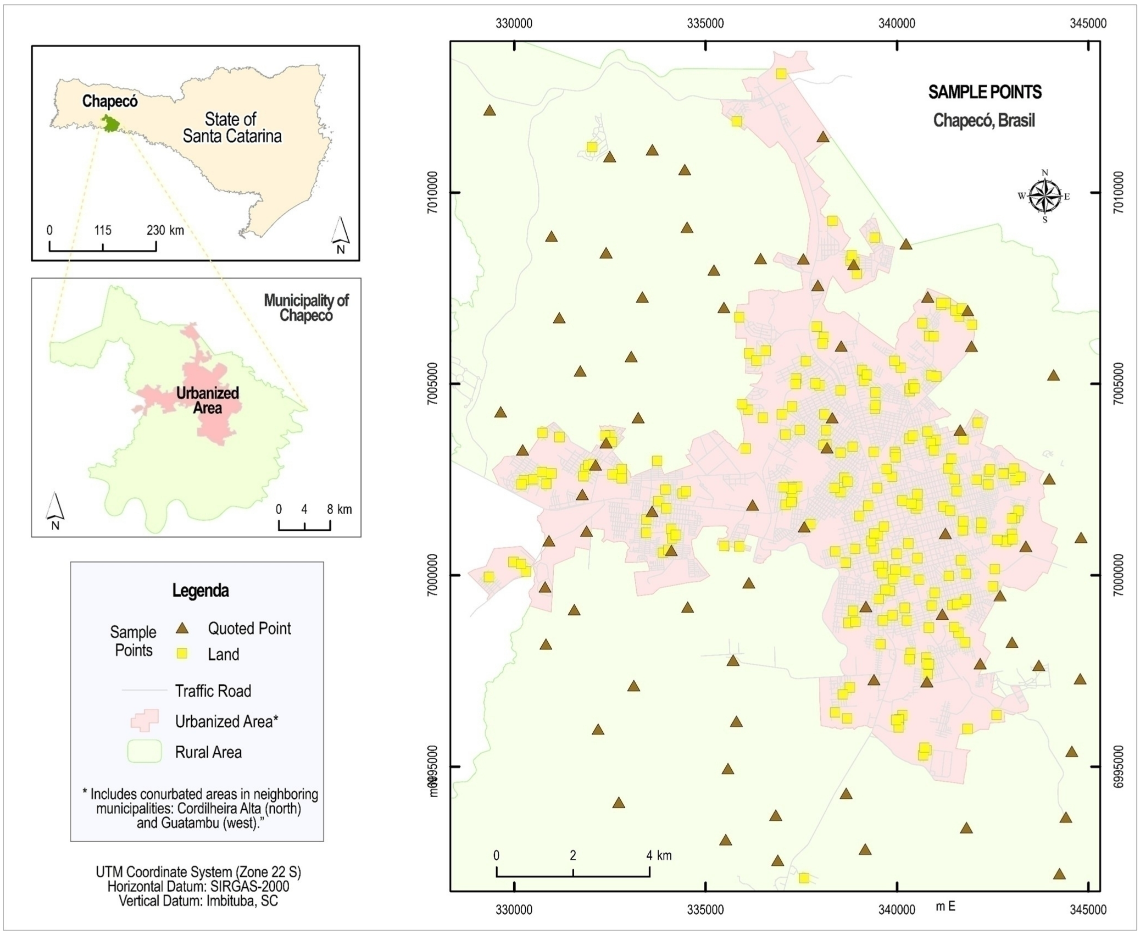

Figure 1- Spatial distribution of sample points used in interpolation tests. Source: prepared by the authors, with cartographic bases from IBGE (2024) and the Municipal Prefecture of Chapecó (2025).

Interpolation surfaces were generated by testing the three interpolators already mentioned – IDW, Spline, and Ordinary Kriging – using the R Studio® software, and with additional use of the ArcGIS ArcMap ® software (Geoestatistical Analyst module) for final cartographic editing. The availability of the R language script resulting from the experiments is highlighted, with which it is possible to reproduce them with other variables and from other spatial contexts.

EVALUATION OF INTERPOLATIONS

The analysis of the effectiveness of spatial interpolation methods depends on several factors, such as data distribution and spatial variability (Bohling, 2005). To evaluate the interpolators, it was essential to compare different techniques, using visual analysis and cross-validation statistics. In the visual aspect, the quality of the interpolated surface map was evaluated (whether the patterns were consistent with the data distribution) and the residual plot (whether the errors were randomly distributed). However, spatial surface models cannot be evaluated only visually, and statistical metrics are necessary to remove any possible perception bias.

The cross-validation technique has been used more frequently in machine learning models (Ramos et al., 2023). It consists of evaluating models by separating the data into parts and training algorithms on each of them. Thus, 80% of the land price and quoted point data were divided as training; the remaining 20% of the data were used as interpolation validation. The idea was to compare the interpolated training values with the real values using error metrics. For this purpose, two metrics already consolidated by the literature (Oliveira et al., 2015) were employed: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

The Mean Absolute Error (MAE) measures the average difference between the observed values Z(xi) and the estimated values Z (xi):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Z(x_i) - \hat{Z}(x_i)\right| \qquad (6)$$

The Root Mean Squared Error (RMSE) penalizes larger errors and measures the precision of the interpolation:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Z(x_i) - \hat{Z}(x_i)\right)^2} \qquad (7)$$

Both MAE and RMSE presenting smaller values indicate a better result in validation.

RESULTS AND DISCUSSION

Figures 2 and 3 present the interpolated surfaces of the variables "land price per m²," generating a surface of urban land values, and "quoted points," resulting in a hypsometric map.

Visually, the socioeconomic variable example is more concentrated in space than the physical variable. A synthesis of the representations reveals that the IDW method presented a more segmented surface, with abrupt transitions between the interpolated areas, reflecting the strong influence of the nearest sample points. In some points this generated what is colloquially known as a “bullseye effect.” The Spline interpolator, on the other hand, generated a smoother surface, with more gradual transitions, but also presented extrapolated values in areas with few samples. In turn, Kriging maintained a spatial pattern with smooth gradations in the face of spatial variability, but, on the other hand, excessively smoothed some sections.

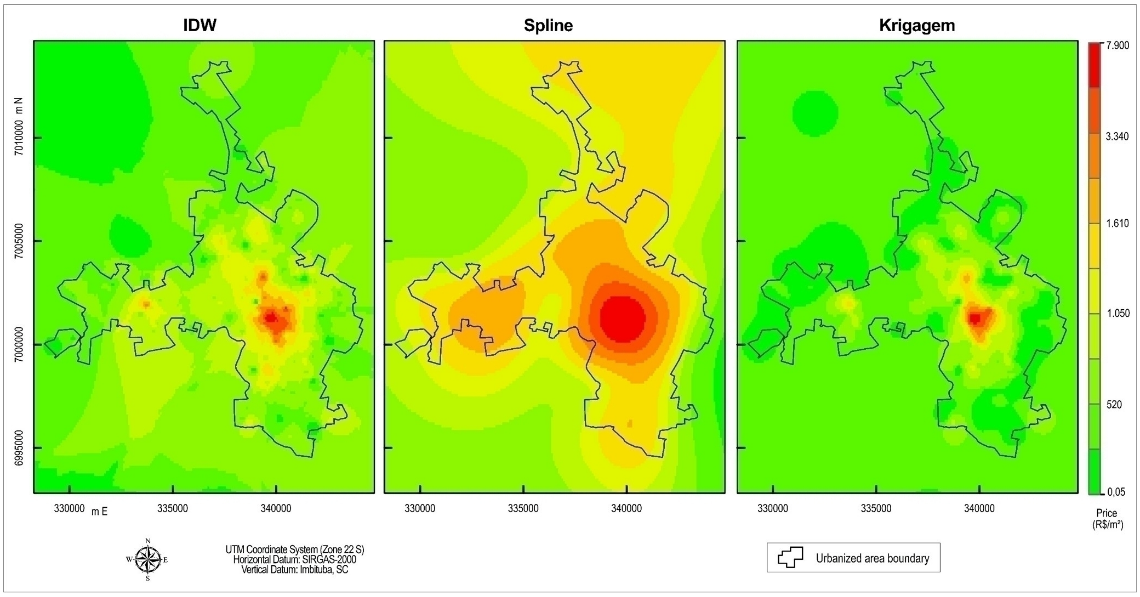

Figure 2 – Different spatial interpolations for the variable land price per square meter. Source: the authors (2025).

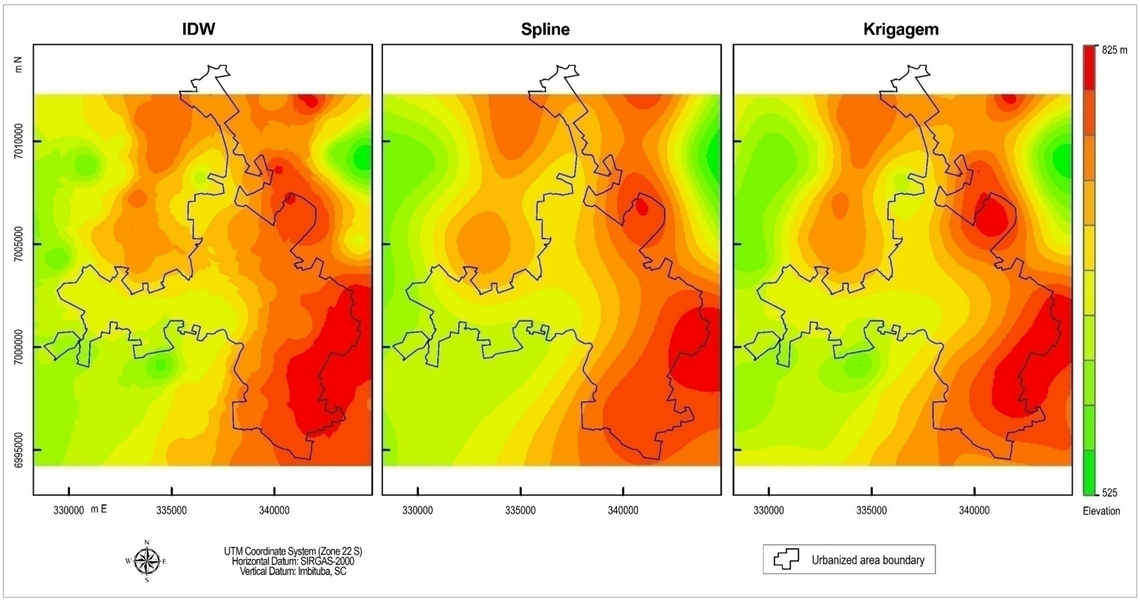

Figure 3 – Different spatial interpolations for the variable quoted point. Source: the authors (2025).

Table 2 presents the results of the error metrics. According to the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE), the best interpolator for land price per m² is Kriging, followed by IDW and Spline. As for hypsometry, RMSE and MAE indicate IDW as the best model, followed by Kriging and Spline interpolations. The results make it explicit that the choice of the appropriate interpolator is fundamental for the reduction of residuals in the representation of the generated surface. For example, according to the RMSE of the socioeconomic variable, Kriging reduced the error by 18.53% compared to IDW.

Interpolated Variable	Error Measure	*Spline*	IDW	Krigagem
Land price per m²	RMSE MAE	965,0718 478,8806	943,0169 486,9618	768,3174 404,7592
Quoted points	RMSE MAE	60,9189 38,7243	41,7260 34,1379	48,2884 36,2115

Table 2 – Error Measures of the different types of spatial interpolation for the analyzed variables.
Source: the authors (2025).

Corroborating the results, Figure 4 allows viewing the comparison of residuals. Kriging presents less dispersion along the ideal line (where observed values would be equal to estimated values) compared to IDW and Spline, indicating a better ability to capture the spatial structure of the land price variable.

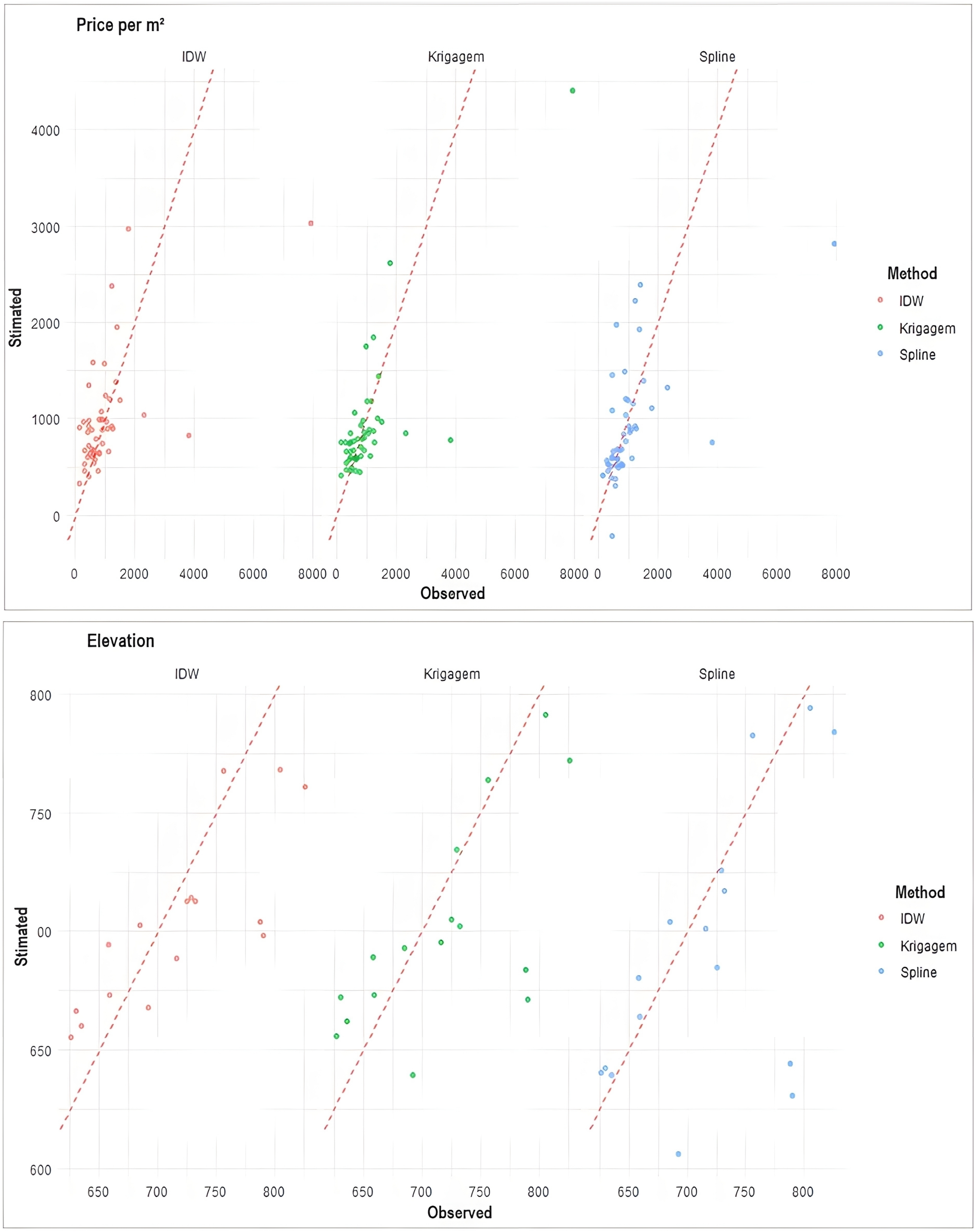

Figure 4 – Relationship between observed and estimated values from the cross-validation of the interpolators. Source: the authors.

In general, the study indicates that deterministic methods (IDW and Spline) are simpler and faster to process, without the need for a robust sample and a strong degree of spatial dependence. The stochastic method (Kriging), on the other hand, is more accurate for variables with greater spatial autocorrelation, as is generally the case for socioeconomic variables, especially in urban areas. However, there is a need for more computational resources and prior statistical analysis, which includes, for example, the construction of the semivariogram.

The study also needs to be understood in the context of its specificities and limitations. Firstly, it is important to consider that the results were obtained from a specific data set, so extrapolation to other areas may require adjustments to the interpolator parameters. Future studies can explore different socioeconomic variables and evaluate the impact of different sample densities on the results.

Furthermore, the study considered only three interpolation methods, leaving out more advanced techniques that might consider modeling with more variables – such as Co-Kriging (Angelico, 2006), Random Forest (Sekulić et al., 2020), and Neural Networks (Wanderley et al., 2014) – and, thus, possibly improving accuracy under certain conditions. Future research on the performance evaluation of spatial interpolators for socioeconomic variables should take other variables into consideration.

CONCLUSION

The objective of this work was to evaluate the most traditional spatial interpolation methods (Inverse Distance Weighting – IDW, Thin Plate Spline, and Kriging) for socioeconomic variables and compare the results with those of a physical variable. As an empirical example, predictions for the spatial variable "land price per square meter" in an urban area, of a socioeconomic nature, were compared with those carried out for hypsometric data in the same area. The results indicate that the socioeconomic variable was interpolated more efficiently by the Kriging method, while the physical variable showed better performance with the deterministic interpolators (IDW and Spline).

The study does not intend to state that one interpolator is better than the other – although one of them performed better for our data set – but, rather, to emphasize that more than one interpolator should be employed in order to produce the best spatial representation. Furthermore, the results are relevant for studies mapping urban phenomena and public policies that require reliable estimates for territorial planning and the evaluation of socioeconomic inequalities and differentiations.

ACKNOWLEDGMENTS

The authors thank the Federal University of Fronteira Sul (UFFS), for the scientific support for the development of this research (PES-2025-0472 process).

DATA AVAILABILITY

https://www.dropbox.com/scl/fi/aq2qx9ul25sk30nrc8e0g/Script.R?rlkey=r1nk9ge8737lg7ch2obfrfjli&st=qnlzaulr&dl=0

REFERENCES

AKIMA, H. A new method of interpolation and smooth curve fitting based on local procedures. Journal of the ACM (JACM), v. 17, n. 4, p. 589-602, 1970. https://doi.org/10.1145/321607.321609.

ANGELICO, J. C. Desempenho da co-krigagem na determinação da variabilidade de atributos do solo. Revista Brasileira de Ciência do Solo, v. 30, p. 931-936, 2006. https://doi.org/10.1590/S0100-06832006000600002.

BARBOSA, R. L.; MENEGUETTE JÚNIOR.; M.; SILVA, J. F. C.; GALLIS, R. B. A.; ITAME, O. I. Análise estatística da qualidade de um modelo digital do terreno gerado com Thin Plate Spline. Revista Brasileira de Cartografia, v. 60, n. 2, 127-132, 2008. https://doi.org/10.14393/rbcv60n2-44875.

BOHLING, G. Introduction to geostatistics and variogram analysis. Kansas Geological Survey, v. 1, n. 10, p. 1-20, 2005.

CAÑADA TORRECILLA, M. R. Técnicas de interpolación espacial deterministas y exactas: media ponderada por el inverso de la distancia y funciones de base radial. In: MORENO JIMÉNEZ, Antonio (ed.). Sistemas y análisis de la información geográfica. 2. ed. Madrid: Ra-Ma, 2007. p. 791-820.

CORÁ, J. E.; ARAUJO, A. V.; PEREIRA, G. T.; BERALDO, J. M. G. Variabilidade espacial de atributos do solo para adoção do sistema de agricultura de precisão na cultura de cana-de-açúcar. Revista Brasileira de Ciência do Solo, v. 28, n. 6, p. 1013-1021, 2024. https://doi.org/10.1590/S0100-06832004000600010.

FARIAS, O. G.; FRANCISCO, C. N.; ALVES, M. C. Avaliação de métodos de interpolação espacial aplicados à pluviosidade em região montanhosa no litoral sul do estado do Rio de Janeiro. Revista Brasileira de Climatologia, v. 13, p. 21, p. 172-185, 2017. https://doi.org/10.5380/abclima.v21i0.52065.

FERREIRA, I. O.; SANTOS, G.; RODRIGUES, D. D. Estudo sobre a utilização adequada da krigagem na representação computacional de superfícies batimétricas. Revista Brasileira de Cartografia, v. 65, n. 5, p. 831-842, 2013. https://doi.org/10.14393/rbcv65n5-43864.

FOLHARINI, S. O.; MELO, S. N.; RAMOS, R. G.; BROWN, J. C. Land use and green crime: Assessing the edge effect. Land Use Policy, v. 129, e106636, 2023. https://doi.org/10.1016/j.landusepol.2023.106636.

LIU, Z.; ZHANG, Z.; ZHOU, C.; MING, W.; DU, Z. An adaptive inverse-distance weighting interpolation method considering spatial differentiation in 3D geological modeling. Geosciences, v. 11, p. 2, p. 51, 2021. https://doi.org/10.3390/geosciences11020051.

LONGLEY, P.; GOODCHILD, M. F.; MAGUIRRE, D. J.; RHIND, D. W. Geographic Information Science & Systems. 5. ed. New York: Wiley, 2015.

NASCIMENTO, E.; TOMBINI, L. H. T.; RIPPLINGER, F. Espacialização da Covid-19 no Sul do Brasil: a interiorização da doença e o caso da mesorregião Grande Fronteira do Mercosul. Finisterra, n. 27, p. 115, p. 27-35, 2020. https://doi.org/10.18055/finis20367.

OLIVEIRA, J. P. B.; CECÍLIO, R. A.; PRUSKI, F. F.; ZANETTI, S. S. Espacialização da erosividade das chuvas no Brasil a partir de séries sintéticas de precipitação. Revista Brasileira de Ciências Agrárias, v. 10, n. 40, p. 558-563, 2015. https://doi.org/10.5039/agraria.v10i4a4998.

PANIGRAHI, N. Inverse Distance Weight. In: SAGAR, B. S. D.; CHENG, Q.; MCKINLEY, J.; AGTERBERG, F. (eds.). Encyclopedia of Mathematical Geosciences. New York: Springer International Publishing, 2023, p. 1-7.

RAMOS, M. D.; MERINO, E. R.; MONTES, C. R.; MELFI, A. J. Avaliação do uso integrado de imagens de nanossatélites e classificadores baseados em aprendizado de máquina para estudos da dinâmica hidrológica na região da Nhecolândia (Pantanal). Revista Brasileira de Cartografia, v. 75, n. 1, 2023. https://doi.org/10.14393/rbcv75n0a-67656.

RAMOS, R. G.; MELO, S. N. Income inequality and the geography of residential burglaries: A spatial model applied to Campinas, Brazil. Applied Geography, 147, e102787, 2022. https://doi.org/10.1016/j.apgeog.2022.102787.

SEKULIĆ, A.; KILIBARDA, M.; HEUVELINK, G. B. M.; NIKOLIĆ, M.; BAJAT, B. Random forest spatial interpolation. Remote Sensing, n. 12, p. 1687, 2020. https://doi.org/10.3390/rs12101687.

SILVA, A. F.; LIMA, J. S. S.; OLIVEIRA, R. B. Métodos de interpolação para estimar o pH em solo sob dois manejos de café arábica. Idesia (Arica), v. 28, n. 2, p. 61-66, 2010. http://dx.doi.org/10.4067/S0718-34292010000200007.

SILVA, C., MELO, S., SANTOS, A., ALMEIDA JÚNIOR, P., SATO, S., SANTIAGO, K., SÁ, L. Spatial modeling for homicide rates estimation in Pernambuco State - Brazil. International Journal of Geo-Information, v. 9, n. 12, p. 740, 2020. https://doi.org/10.3390/ijgi9120740.

STEIN, M. L. Interpolation of spatial data: some theory for kriging. New York: Springer Science & Business Media, 2012.

WANDERLEY, H. S.; AMORIM, R. F. C.; CARVALHO, F. O. Interpolação espacial de dados médios mensais pluviométricos com redes neurais artificiais. Revista Brasileira de Meteorologia, v. 29, n. 3, p. 389-396, 2014. https://doi.org/10.1590/0102-778620130639.

YAMAMOTO, J. K.; LANDIM, P. M. B. Geoestatística: conceitos e aplicações. São Paulo: Oficina de Textos, 2013.

Author's Affiliation

Melo, S.N. - Professor at State University of Maranhão, São Luís (MA), Brazil.
Nascimento, E. - Professor at Federal University of Fronteira Sul, Chapecó (SC), Brazil.

Authors' Contribution

Melo, S.N. - The author contributed to the elaboration, realization, and manipulation of the data and writing.
Nascimento, E. - The author contributed to the elaboration, realization, and manipulation of the data and writing.

Editors in Charge

Alexandra Maria Oliveira
Alexandre Queiroz Pereira
Eduardo Von Dentz