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Research paper

Spatial interpolation methods of determination of digital elevation models for forestry planning

Métodos de interpolação espacial para determinação de modelos digitais do terreno no planejamento florestal

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ABSTRACT: Topographic data acquisition methods are generally subject to measurement errors and subsequent digital terrain models (DTM) interpolation models can propagate these errors. For the forestry sector, the use of the DTM facilitates the planning stage in the road construction and mechanization phase in mountainous areas, especially in subsoiling, pesticide application and logging operations. To evaluate the results of interpolation methods, it is very common to use indicators such as the multiple determination coefficient and the residual error. This study aimed to compare and choose the best interpolation method in an elevation dataset to construct a DTM by applying the Taylor diagram to graphically analyze the results. Seventeen different methods of spatial interpolation were tested. The Spline method was selected as the best model tested over geostatistical models, most adopted in spatial variability assays. The statistics of all methods were very similar, with slight variations, with the square mean square root error and the Spline method correlation being closer to the observed data, as easily shown by the Taylor diagram.

Keywords: Digital models, Graphical analysis, Spatial data analysis.

RESUMO: Os métodos de aquisição de dados topográficos geralmente estão sujeitos a erros de medição e os modelos de interpolação de modelos digitais do terreno (MDT) subsequentes podem propagar esses erros. Para o setor de florestas plantadas, o uso do MDT facilita a etapa de planejamento na fase de construção de estradas e na de mecanização em áreas montanhosas, principalmente em operações de subsolagem, aplicação de agrotóxicos e extração de madeira. Para avaliar os resultados dos métodos de interpolação, é muito comum o uso de indicadores, tais como o coeficiente de determinação múltipla e o erro residual. Este estudo teve como objetivo comparar e escolher o melhor método de interpolação em um conjunto de dados de elevação para construir um MDT, aplicando o diagrama de Taylor para analisar graficamente os resultados. Foram testados 17 métodos diferentes de interpolação espacial. O método Spline foi selecionado como o melhor modelo testado, em detrimento dos modelos geoestatísticos, mais comumente adotados em ensaios de variabilidade espacial. As estatísticas de todos os métodos foram muito semelhantes, com pequenas variações, sendo que o erro raiz quadrada média quadrada e a correlação do método Spline estavam mais próximas dos dados observados, conforme evidenciado com facilidade através do diagrama de Taylor.

Palavras-chave: Modelos digitais, Análise gráfica, Análise espacial de dados.

INTRODUCTION

A Digital Terrain Model (DTM) is defined as any digital representation of a continuous relief variable in space. Its generation process consists of three stages: data acquisition, model generation and quality control (BURROUGH; MCDONNELL; LLOYD, 2006). Digital Surface Models (DSM), similar to Digital Terrain Models (DTM), are altimetric topographic models, resulting from three-dimensional geographic information, but the DSM portrays the surface as a whole, including everything that exists on it from buildings to vegetation and the DTM only the land excluding the rest (PINTO, 2019).

Data collection is one of the costliest stages in representing the relief of the earth's surface, both financially and time wise (GIACOMIN et al., 2014). For example, using the data sampling and interpolation technique allows the determination of altitude of a non-sampled point through the altitude of neighboring points. Therefore, representation with the use of interpolators aims to reduce data collection effort, prioritizing the quality of the generated product, as well as obtaining the most out of terrain information. Thus, the accuracy of DEM determination may be elevated if a higher number of input points are interpolated (MACEACHREN; DAVIDSON, 2016).

There are many interpolation methods which can be used to help refine data collected in the field and allowing the generation of DEM, such as nearest neighbor, natural neighbor, inverse distance, TIN, Topo to Raster and Spline (MIRANDA et al., 2018) and Kriging (GIACOMIN et al., 2014). Depending on the algorithm used for interpolation, several results can be appreciated, as can be seen in Childs (2015). Interpolator quality results are usually obtained by evaluating the observed and estimated data (cross validation).

Several statistics may be calculated by cross validation, such as square root of the mean square of normalized differences (NRMSE), Pearson's linear correlation coefficient (R), standard deviation (σ), Normalized Bias (NBIAS) (HILLEBRAND, 2021). Antal, Guerreiro and Cheval (2021) used the following statistics: mean error (ME), mean absolute error (MAE), mean square error (RMSE), Pearson's correlation coefficient (R) and the Taylor diagram. Three factors contribute to the uncertain quality of DEM: (1) source data errors from the acquisition of spatial data; (2) interpolation models used; (3) the level of complexity in terrain variation (SHI; LI; BEDARD, 2014). Thus, it is possible to synthesize cross validation of multiple interpolators through Taylor diagram, in which several statistical parameters can be synthesized in a single bi-dimensional diagram point (TAYLOR, 2001).

For a well-defined DTM applied in forestry, among other advantages, we highlight the greater precision of the information (related to the terrain, the spatialization of trees, the definition of permanent preservation areas), resulting in a harmonious planning of economic, environmental and operational factors (BROZA et al., 2012). According to GIONGO et al. (2010), the use of modeling through spatial data also makes it possible to estimate several forest variables, such as: basal area, diameter, volume, biomass, carbon and amount of combustible material. It also has great potential in forest exploration planning and road construction activities. FERREIRA et al. (2017) highlights that the topography needs to be known for the proper allocation of forest machines, which have high costs, especially forest harvesting. In forest harvesting planning, DTMs are used as a subsidy for the creation of slope maps, which indicate the places that each type of forest machine will operate, according to the equipment specifications, with reflections on safety, productivity and costs of production.

Thus, the inclusion of spatial data analysis tools in the planted forest sector is important in forestry planning to program operations such as mechanization of soil preparation, application of herbicides, cutting, extraction and harvesting and forest transport.

In view of the above, the objective of this work was to compare methods of interpolation of a set of quoted points for the construction of the best DTM in order to plan the movement of machines for soil preparation until forest harvesting in eucalyptus plantations in the southern region state of Espírito Santo, Brazil.

METHODOLOGICAL PROCEDURES

The studied area is located in the western half of the southern state of Espírito Santo (ES), Brazil, São José do Calçado municipality. This area has mild temperatures, usually with 60 to 90 dry days per year and more than 1,000 mm of annual rainfall. The existing forests, adjacent to the project, fall within the Atlantic Forest domain. The studied area was mainly pasture, with predominance of grasses, and where there were successions with forest plantations of eucalyptus.

The studied area is in the southern Espírito Santo (ES) state, Brazil, (UTM coordinates: 226.445, 7.683.333 SIRGAS 2000 Datum, 24S zone). It is approximately 10,30 hectares and an average declivity of 36.5%. The altitude of the property varies between 577.35 and 708.96 m (**Figure 1**).

Figure 1. Location of the studied area with elevation points

Universal Transversa Mercator Projection
SIRGAS 2000 Zone 24S
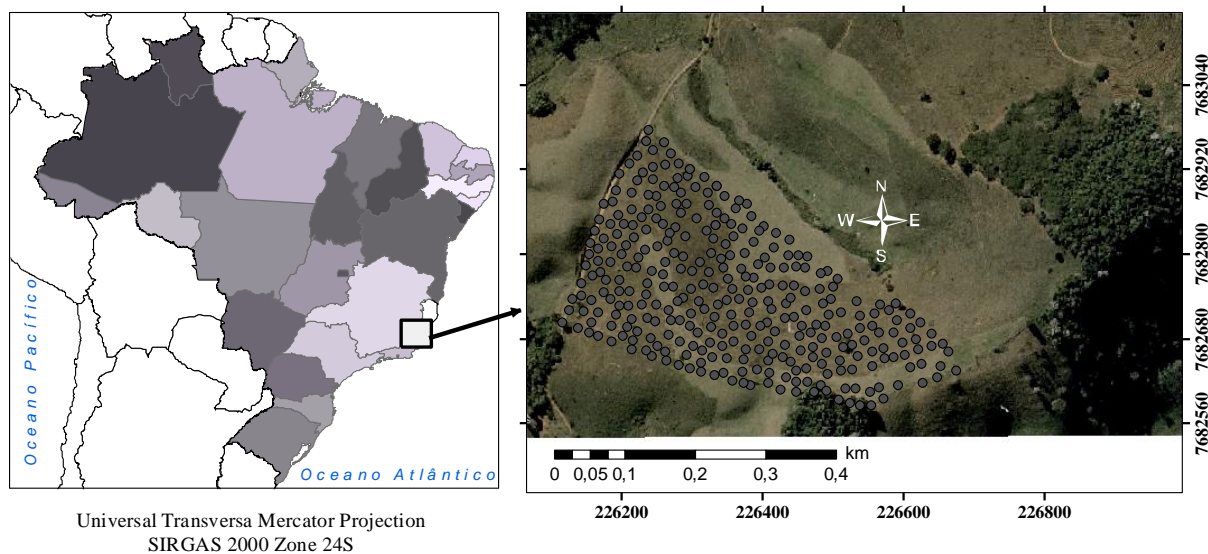
Geographical coordinates and altitude were measured using Total Station and Topographical GPS for data collection. Initial densities of 700 points were randomly obtained walking around all area, to obtain points more faithful to the original site topography. Then followed an exploratory data analysis, carried out on Matlab (MATLAB, 2010) for visualization of dispersion measurements and frequency histograms for an outliers' data analysis. Outliers are values plotted 1.5-fold the interquartile range above the first quartile, and 1.5-fold the interquartile range below the first quartile.

MDT's generated was evaluated and classified according to their positional accuracy, in accordance with Brazilian Decree-Law nº 89.817, of 1984 and by NBR 13.133, which

provide for the assessment of positional quality in cartographic products. The values of altitude sampled points were interpolated on Matlab Software and GIS Environment, using 17 different methods to obtain the digital terrain model (DTM), with 2 x 2 m resolution. The results were validated to assess interpolators' performance, using statistical indexes of cross validation, i.e., comparing real versus estimated data to analyze the accuracy of estimates data generated by the interpolation.

Cross-validation is one of the most widely used data resampling methods to estimate the true prediction error of models and adjust model parameters (BERRAR, 2018). Cross validation procedure involves eliminating each of the sampled points and estimating the value for the sampled location based on the other points for each interpolation method. So, the best interpolation method was chosen considering a few statistical indexes. This choice was also graphically made through Taylor diagram (TAYLOR, 2001).

Since the x and y coordinates are independent variables in UTM Datum SIRGAS 2000, Zone 24S, the interpolators used were: a) inverse distance, using powers 1 through 6 (BURROUGH; MCDONNELL; LLOYD, 2006); b) geostatistical analysis by ordinary kriging for semi variance modeling for linear, spherical, exponential and Gaussian models (VIEIRA, 2000); c) Spline (SANDWELL, 1987; AMORIM et al., 2008); d) nearest neighbor (MCROBERTS, 2012); e) Simple regression using linear, quadratic and cubic polynomial models (BURROUGH; MCDONNELL; LLOYD, 2006); and f) Topo to Raster (CHILDS, 2015), based in ANUDEM interpolator (HUTCHINSON, 1989).

Even though it was not necessary to create a drainage network, we chose to insert the Topo to Raster interpolator, which is an interpolation method specifically designed to create hydrologically correct DTM. This interpolator is based on the principles of ANUDEM's method, thus creating a DTM which considers this drainage network feature (CHILDS, 2015).

O Diagrama de Taylor e os índices estatísticos

To develop Taylor diagram, we considered each method's cross validation data, i.e., the observed data (r) against estimated data (f). Taylor (2001) proposed the creation of a diagram including four statistics: correlation (R); standard deviation of r and f (σ_r, σ_f) and the centered root-mean-square error (E'). The E was calculated to detect how close an interpolated point fits for data points. In other words, to discover how accurate an interpolation method is in filling out empty spaces based on collected data points. For this purpose, all verification points in the same horizontal position were selected and the calculations were done according to Equation (1).

$$E = \left[\frac{1}{N}\Sigma(f_n - r_n)^2\right]^{1/2}$$

(1)

In which: *f, r* means estimated data and observed data, respectively.

The centered root-mean-square error (E') corresponds the second part of Equation 1, being Equation 2:

$$E'^2 = s_f^2 + s_r^2 - 2s_f^2 s_r^2 R$$

(2)

In which: s_f, s_r, represent estimated and observed data standard deviations, respectively; R is the correlation coefficient.

Taylor diagram explores the geometric equivalence of the relation of these E', σ_f, σ_r e R statistics and the law of cosines, relating an inner angle of a triangle to its sides ($a^2 = b^2 + c^2 - 2bc\cos\theta$). **Figure 2** represents the geometric result of the application of the law of cosines in Equation 2 (TAYLOR, 2001).

Figure 2. Geometric representation of the relationship of statistics
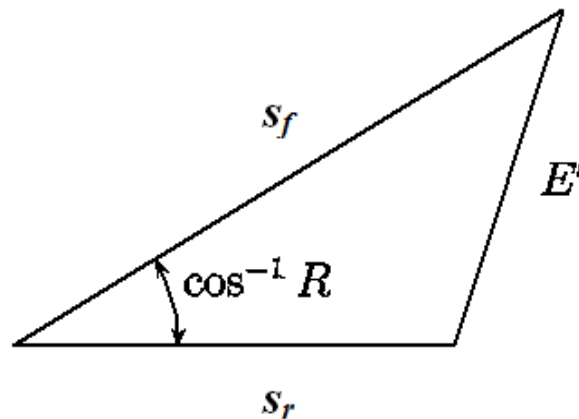
Source: Taylor, 2001

These statistics may be used to study the relationship pattern between e and f, aiming to define if the model is a good estimator. The graph usually illustrates ¼ of a circle, and each method is represented by a symbol, where the radial distance from the point of origin depends on the standard deviation of the interpolated data. The observed and estimated data's R value (correlation) is the point azimuth. The correlation of the reference point with itself is equal to 1 and, therefore, it is in the x axis. Graphically, the closer the point of a method is to the reference, the better the interpolation method.

Taylor diagram provides a convenient way of comparing observed and estimated data, and as illustrated by this research, values of interpolated elevations. Despite its ease of application, it has been little used in agricultural sciences. In this study, the Taylor diagram was created using the Texmaker program (https://www.xm1math.net/texmaker/).

RESULTADOS E DISCUSSÕES

Table 1 shows the descriptive statistics of the original elevation values and interpolated values, obtained through cross validation. The mean altitude value obtained was similar between interpolators, which did not vary much in relation to the reference data. Even though cubic, quadratic and linear polynomial methods presented altitude mean values closer to the reference value, these were more dissonant in relation to standard deviation, E' and correlation (**Table 1**). On the other hand, the standard deviation of polynomial methods was more dissonant in relation to the standard deviation of reference data. The centered root-mean-square error (E') presented high values for linear, quadratic and cubic polynomial methods, which were considered unsatisfactory as the closer to zero, the better. These also presented a lower correlation between interpolators. These results indicate that polynomial interpolators were the least suited methods to reach the proposed objectives.

Table 1. Descriptive statistics of the original and interpolated values of the elevation data

| Parameters Method	Mean	Standard Deviation	E'	R
Reference Data	620.09	27.72	0	1.0
INV1	620.24	26.66	2.49	0.9966
INV2	620.22	26.68	2.43	0.9967
INV3	620.20	26.65	2.54	0.9964
INV4	620.20	26.83	2.74	0.9955
INV5	620.21	26.93	3.01	0.9944
INV6	620.22	27.02	3.28	0.9932
Linear Model	620.11	27.58	0.76	0.9996
Spherical Model	620.11	27.59	0.75	0.9996
Exponential Model	619.99	27.73	2.49	0.9960
Gaussian Model	620.11	27.59	0.75	0.9996
Spline	620.10	27.73	0.59	0.9998
Topo to Raster	620.19	27.71	1.10	0.9992
Nearest Neighbor	620.37	27.85	4.20	0.9886
Polynomial Linear	620.08	24.42	13.25	0.8783
Quadratic polynomial	620.09	24.43	13.27	0.8780
Cubic polynomial	620.09	24.43	13.27	0.8780

Note: E' – centered root-mean-square error; R – correlation.

According to **Table 1** and considering the centered root-mean-square error (E'), we are able to verify that Topo to Raster, Spline and linear, spherical and Gaussian methods presented better performance, with results closest to zero. For these models, the correlation value (R) were similar, presenting a variation in the fourth decimal place only. R values were high (> 0.87), wherein Spline was the highest and the cubic polynomial was the lowest method.

Observing the standard deviation, the results that came closest to the reference data (27.72) were the exponential, Spline and Topo to Raster models. The Spline model was considered when choosing the highest accuracy interpolator, as it also presented E' and R values closest to the reference data, as shown in **Table 1**, as well as in graphical result of Taylor diagram. The interpolations' graphical result is shown in **Figure 3**.

The large yellow spot on the x-axis shown on **Figure 3** indicates the reference position (observed), and other points with different colors and symbols shown on the diagram represent different interpolator methods used (estimated). The result graphically highlights the data exhaustively presented in table form (**Table 1**). The models showed very close results, which caused an overlap of markers on the diagram (relating to each interpolation method). Even so, the Spline method stood out from the others by its much more prominent and closer position to the reference position.

Figure 3. Application of Taylor diagram graphing statistics and cross-validation, referring to the interpolators used
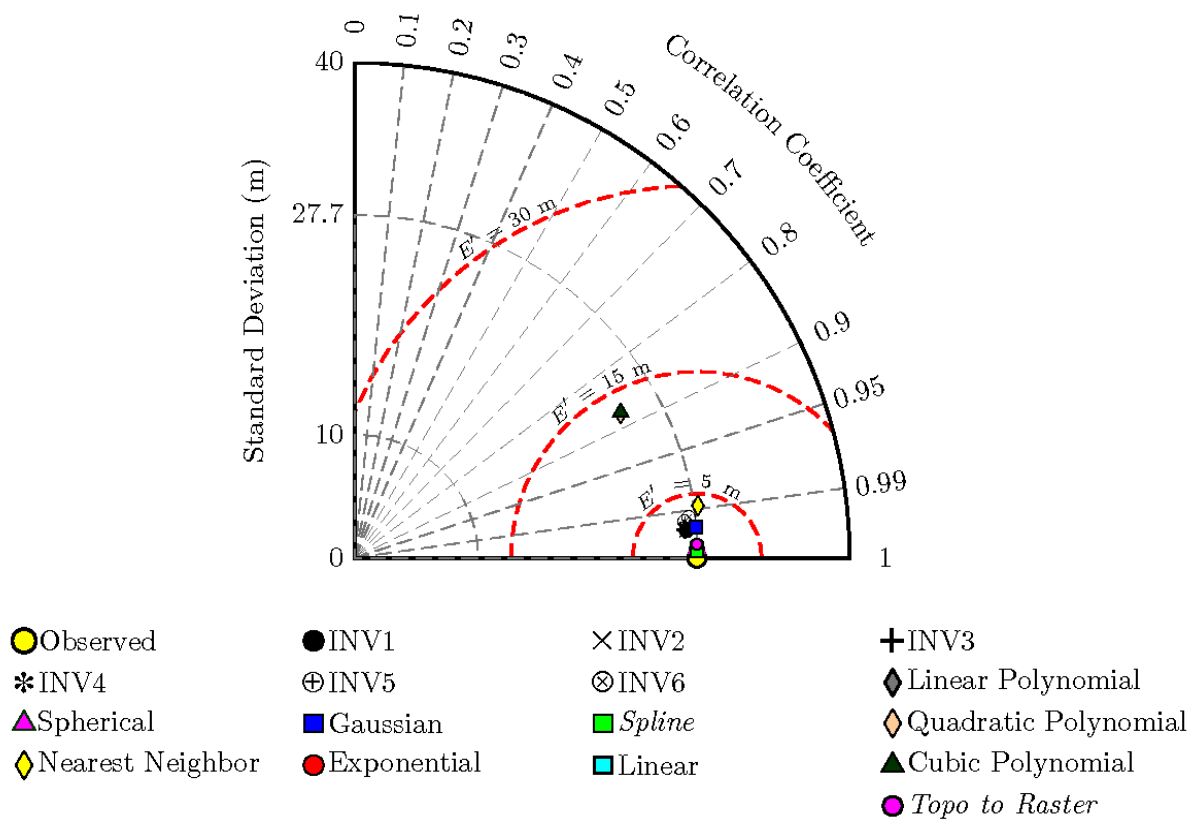
When confronting the graphical result with **Table 1**, the Spline method (green square) obtained better statistics of correlation, standard deviation and E'. These numeric results were closer to the original data. The Topo to Raster interpolator (magenta circle) was the second, just above the Spline. And so on for the others. Consequently, the graphical model showed these best results in a single figure, making its reading and interpretation easier, without comparisons between the 17 methods of interpolation through the table. And this is further justified as more methods are tested (**Figure 3**).

Antal, Guerreiro and Cheval (2021) used the diagram to compare the performance of seven interpolation methods used to retrieve the average annual rainfall over mainland Portugal. They used Taylor Diagrams to graphically analyze the Pearson correlation and mean standard deviation of rainfall in mainland Portugal. Recent research, adopting the Taylor diagram as an analysis tool, has addressed topics related to soil data (salinity and moisture) and geophysics, producing interesting visual effects, easy to use in intercomparative studies (AGUTU et al., 2021; MOHARANA et al., 2021; ZEYNOLABEDIN et al., 2021).

Agutu et al. (2021) showed the agreement between the individual means of the soil moisture product and the reference mean analyzed in terms of spatial pattern correlations and the magnitude of spatial variability using Taylor diagrams. Investigating salinity distribution using digital soil mapping algorithms in the 5 km buffer zone on both sides of the irrigation canal system in Rajasthan was the subject of the study by Moharana et al. (2021). With the Taylor diagram, they were able to summarize various aspects of the performance

of three evaluated models, such as the agreement and variation between observed and predicted values in a graphic way.

Zeynolabedin et al. (2021) aimed to investigate the extent to which seawater has invaded a coastal area and what is its extent variation in the coastal aquifer of Chaouia, Morocco. Through the Taylor diagram, they were able to compare three different methods for this evaluation. The Taylor diagram was used because of its ability to "graphically" show how different settings affect the output, providing a good visual sense. Wu et al. (2013) applied the diagram to assess the precipitation-surface temperature relationship in 16 climate models, providing the basis for the IPCC (Intergovernmental Panel on Climate Change) Assessment Report. These authors also found that most points from climate model simulations tended to be close to each other. And this indicated a consensus in the simulations between the models tested, as well as the result obtained in this study and evidenced in **Figure 3**. **Figure 4** illustrates some digital elevation models using different interpolation methods.

Taylor diagram was also applied by Pereira et al. (2014) when evaluating 15 spatial interpolators of soil attributes, finding satisfactory results in the choice between the methods. These authors considered it a useful tool, as it enabled to graphically define the best methods of interpolation, as well as allowing them to choose methods within a smaller and more defined set of information.

Figure 4. Some digital elevation model of the studied area created using different interpolations methods
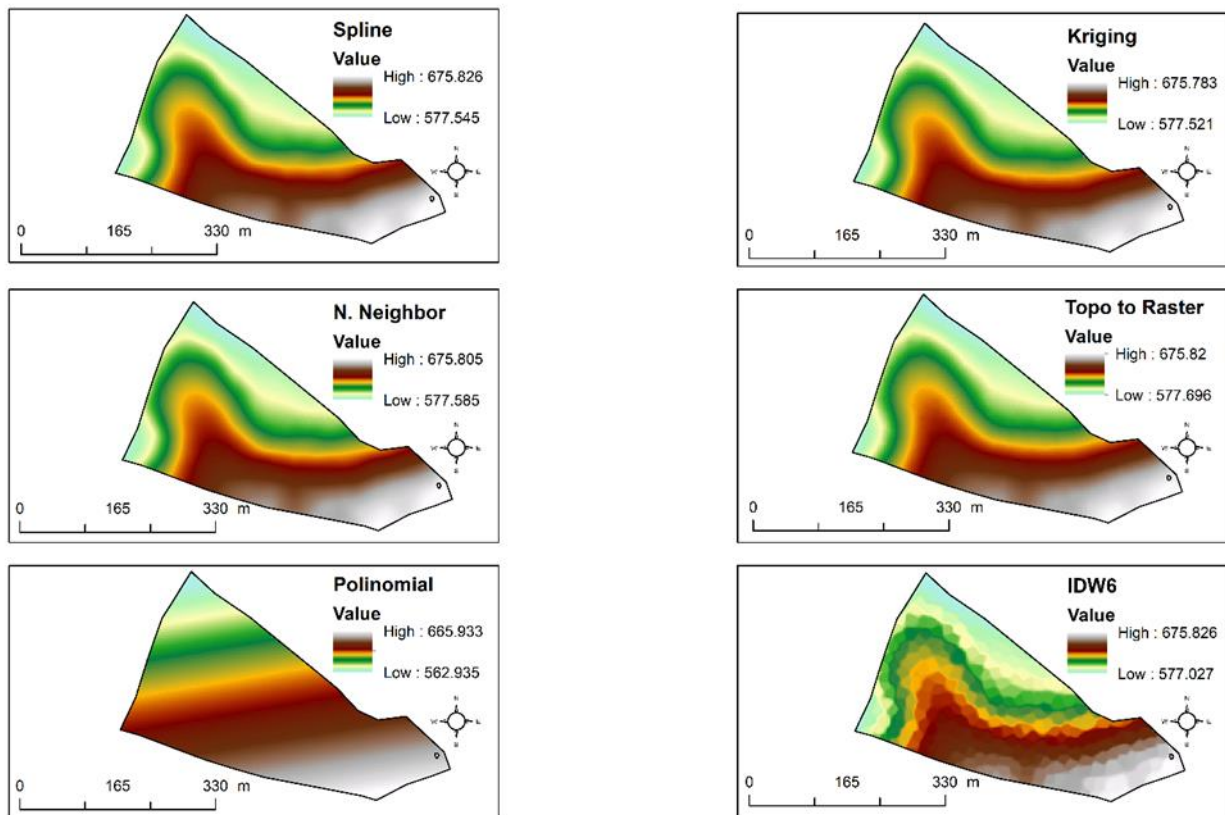
Universal Transverse Mercator Projection
Datum WGS 84 - UTM Zone: 24S

Nota: Altitude em metros.

The cubic spline interpolation function is one of the commonly used curve characterization methods because of its advantages such as simple construction, convenient use, and accurate fit. The proposed approach produces the same effect as polynomial interpolation, but its advantage is that it also overcomes the oscillation phenomenon that can occur in higher-order polynomial interpolation (WEN; LIAO; EMROUZNEJAD, 2021). Because of this interaction, the calculation of DTM's for forest plantations must consider these interpolators, especially on steep areas.

CONCLUSION

The most suitable interpolation method for digital elevation models was Spline, as its generated DTM was the closest to the real terrain surface. We observed that the evaluated statistics: standard deviation, the centered root-mean-square error (E') and correlation (R) were the closest to the reference values.

The results also demonstrated that the minimum sampling grid can be used satisfactorily to generate digital elevation models. The other tested methods were suitable for data interpolation, except for polynomials, whose E' and R values were very distant from the reference data.

Thus, with the ease of choosing the best interpolation method for the DTM, Taylor diagram becomes a decisive tool in forest planning. And this can be of great value, especially in downhill areas where mechanization is more restricted and where it is necessary to create computationally viable digital elevation models.

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