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THE MAPPING OF COMPOSITE POLLEN FROM POINT SAMPLED DATA AND CARTOGRAPHIC GENERALIZATION

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1. INTRODUCTION

Pollen grains are microgametophytes produced by angiosperm and gymnosperm plants. They are responsible for transporting genetic material and carrying out fertilization. The study of pollen has numerous practical applications such as plant biodiversity, paleoclimatology, archaeology, allergy studies, the study of nectar sources in honey (melissopalynology), searching for sources of petroleum, and more recently, using pollen as a trace evidence component in forensics. Once pollen grains become airborne, their dispersal is controlled by a number of physical factors that determine the deposition distance from their source area. The purpose of this work is to study spatial pattern of composite pollen in Big Bend National Park using pollen information contained in the top soil layer, test the accuracy of four interpolation methods and use cartographic generalizations to present the results. The focus is on a composite pollen group that is a member of the Asteraceae plant family and is a prolific producer of airborne pollen (Figure 1).

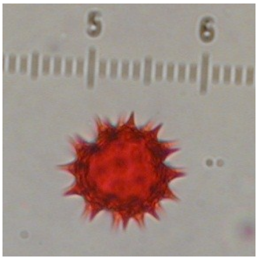

FIGURE 1
POLLEN GRAIN OF HELIANTHUS (ASTERACEAE)

The development of continuous surfaces assumes the existence of non-random distribution of mapping variables. If spatial continuity is completely random then variogram modeling and geostatistical methods such as kriging would reduce computations to calculating the traditional mean and variance. The role of spatial analysis is to capture spatial relationships of a continuous variable and to predict its behavior at non-sampled locations. Such attempts provide revealing patterns of studied phenomena that can generally be accepted as representing given environmental conditions and relating to other ecological forces that might be involved in generating existing patterns.

One of the goals in cartography is to convey visually attractive and spatially accurate geographic information about natural and socio-economic phenomena. A cartographic generalization is a key aspect of the mapping process, and it has a dominant effect on the graphic output in a digital environment (McMaster and Shea, 1992). We define the term "cartographic generalization" as a process of selecting and presenting spatial information that is as geographically accurate as possible while also visually appealing. It is a challenging task that requires maintaining a "balance" between these two aspects. Spatial data often contains errors before tools of spatial analysis are used. These errors continue to propagate during data conversion and spatial model developments. For example, one of the frequently used methods in spatial analysis is the overlay operation. If two raster files are used in an overlay operation and the error in each grid cell of both files is approximately ten percent, then using the additive function in geographic information systems (GIS) produces a final map that will also contain at least a ten percent error. However, when the multiplicative function is used in the spatial operation process, then the resulting error is inflated up to 20 percent for each grid cell of the final map. The magnitude of errors naturally increases with an addition of every new layer entering the overlay process (Veregin, 1995). In an ideal situation, spatial metadata should provide users with information about a variety of errors that are inherent in the data sets.

In order to study spatial patterns and the relationships between objects or geographic layers, continuous surfaces are sometimes constructed. The process of interpolation, however, is not without flaws. One of the goals of this project is to develop a surface model for the spatial distribution of composite pollen, evaluate its spatial patterns, and develop the optimal cartographic representation. The specific objective of this paper includes determining, analyzing, and evaluating the errors from four interpolation methods that are frequently used in geosciences and suggest the optimal solution for developing continuous surfaces via a tradeoff between accuracy and cartographic visualization.

The mapping of pollen distribution patterns using geostatistics is a viable task because pollen quantities conform to the concept of regionalized variables (Siska *et al*., 2001; Siska *et al*., 2006). The following questions arise: Is this the most appropriate method for mapping spatial data or do non-geostatistical methods produce results that are equally accurate? This question can be answered by studying the distribution of errors from surfaces constructed by different interpolation methods and by comparing the visual quality of maps. The magnitude of errors and their propagation in geographic databases have been studied systematically since the beginning of the 1990s (Goodchild *et al*., 1992; Veregin, 1995; Siska and Hung, 2000) and continued with recent work by Hengl *et al*. (2010). The effort to obtain the most accurate information from digital or hard copy maps is a never ending process because it is impossible to transfer information from the real world (3D) into maps (2D) without any distortions. This is due not only to imperfections in projection systems that transfer data from geoid into a digital database but are also due to the limitations that are associated with the sampling design and strategy as well as measurement errors.

2. STUDY AREA

In an ideal world, spatial data would be collected on a dense enough regular grid or at least on a pattern that would provide data of a sufficient density for analysis. This is not always possible due to time and financial constraints. One example is the pollen data study that were collected in and around the Big Bend National Park region located in West Texas along the United States boundary with Mexico (Figure 2). The area is hot, arid, and remote from main population centers. Therefore when collecting any type of data set, one must consider the safety of the field crew, access to private property, and travel over rough terrain. Because of these constraints and other factors related to time and funding, potential sample locations were restricted to areas along the main roads in some cases.

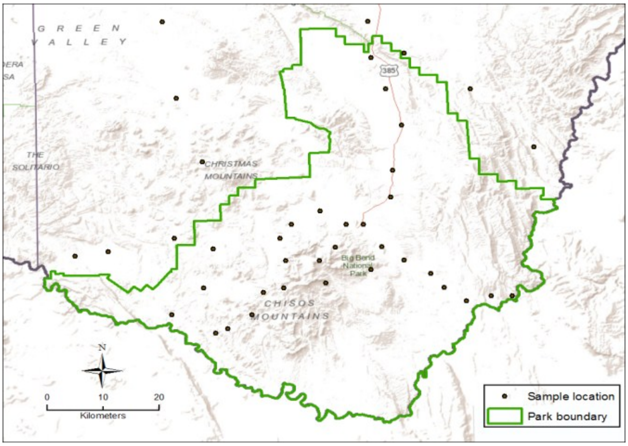

FIGURE 2
GEOGRAPHIC LOCATION OF POLLEN SAMPLES IN BIG BEND NATIONAL PARK

One problem of this type of sampling is that it is difficult to interpolate because of the spatial irregularity of sample locations. Therefore, the spatial analysis prior to interpolation has to deal with two major sources of errors: a) errors associated with the sampling strategy, and b) measurement errors. To investigate the effect of errors upon the eventual analysis, four different interpolation methods were compared to determine which interpolation would be optimal for mapping areas where there were biases created by the sampling methods.

3. METHOD AND OBJECTIVES

3.1 SPATIAL CONTINUITY

In order to use stochastic models for interpolation such as kriging or co-kriging, the existence of spatial autocorrelation was evaluated using a semi-variogram model. As Figure 3 indicates, the composite pollen quantities are represented by exponential models that are one of four semi-variogram models usually used in geostatistical analysis. The steep rise of the curve (semi-variogram range) before its flattening indicates the presence of spatial dependency. Hence, interpolation methods that take spatial autocorrelation into consideration benefit from this phenomenon and are usually more accurate. If there is no indication of spatial continuity, then their sophisticated algorithms will not be different than the simple averaging of sample data. Testing for the Poisson Homogeneous Process is another form to determine the existence of randomness or autocorrelation in the data. The Poisson model is as follows:

$$p(x) = e^{-\lambda} \lambda^{x} / x!$$

where x is the random variable (in this case the count of composite pollen grains), λ is the parameter and p is the probability of x. The null hypothesis of this statistical test is: H_0: $x \sim$ Poisson. The results from the test indicated a value of 4.842. This value is compared to the Chi-square value of 1.9024 from statistical tables that correspond to 39 degrees of freedom and a p-value of 0.001. Hence the Poisson test clearly rejected H_0 and confirms that the spatial distribution of composite pollen grains in the Big Bend is not random. On contrary, there are some natural mechanisms involved that cause the pollen rain to form certain patterns on the desert surface.

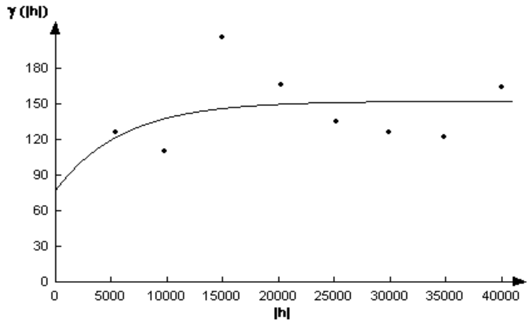

FIGURE 3
SEMI-VARIOGRAM MODEL OF COMPOSITE POLLEN
WITH A LARGE NUGGET EFFECT

The nugget effect, determined by the intercept of the semi-variogram curve with the vertical axis, indicates the distance from the zero value of the graph. Theoretically, the nugget effect should be zero and its displacement is due to the previously mentioned errors (sampling and measurement errors). The nugget effect later inflates the interpolation prediction error (*e.g.*, kriging variance) and hence increases an uncertainty of estimated values, which in return devaluates the quality of the continuous surfaces. Examples for a comprehensive analysis of variogram properties and their effects in mapping can be found in numerous publications (Atkinson, 1997; Hengl, 2010). The nugget effect for composite pollen data (as we can see from the previous graph) is almost 80. The fitted semi-variogram model $\gamma(h)$ is 78.08 + 153.5 Exp. h/18,008. The high nugget effect (78.08) indicates that an experimental error, and the errors due to the short scale variation is more than 50%. Hence the spatial analysis, prior to interpolation, possesses two major sources of errors: a) errors associated with the sampling strategy, and b) measurement error.

3.1.1 Simple and Complex Interpolation

As mentioned above, spatial data are often auto-correlated, *i.e.*, the similarity between locations is inversely correlated with the distance. One of the most commonly used methods for mapping continuous surfaces is the IDW (inverse distant weighting method). It is based on a simple algorithm that is easy to understand. The algorithm is in the form of:

$$\hat{z}(x_o) = \frac{\sum_{i=1}^{N} z(x_i) d_{ij}^{-r}}{\sum_{i=1}^{N} d_{ij}^{-r}}$$

where z are the sample values, d is the distance between the sample values and the location for which we wish to have an estimate, and r is an exponent associated with linear, quadratic, cubic, *etc*., as functions of the distance, besides the distance relationship that is depicted by IDW. Kriging is a stochastic interpolator implementing the underlying functional relationship that controls the distribution of the samples over space and is depicted by a semi-variogram model. The general kriging model is of the form: $z(x_0) = m(x) + \gamma(h) + \varepsilon$ where *m(x)* is a deterministic function, *γ(h)* is a spatially correlated relationship depicted by a variogram, and ε is random error. The most frequently used kriging model is ordinary kriging (OK). It is used when no global trends are assumed in the interpolation processes. The splines are piece-wise functions that are fitted to a small number of data. The completely regularized splines (CRS) used in GIS were derived by Mitasova and Mitas (1993) and can have the lowest error in interpolating pollen data (Siska *et al.,* 2006). The CRS includes a tension parameter that controls the character of the interpolation function. The CRS also have smooth cartographic properties that are visually appealing to audience.

The fourth method used in this work is co-kriging. The co-kriging system is similar to kriging; however, it uses a secondary variable that adds more information to the primary variable and therefore should contribute to a better estimation of values at non-sampled locations. The equation for co-kriging is as follows:

$$\hat{z}(x_0) = \sum_{i=1}^{N} \lambda_i p_i(x_i) + \sum_{j=1}^{M} \omega_j a_j(x_j)$$

where $\hat{z}(x_0)$ is the estimated (predicted) value at location (x_0), p_i are the N neighboring sample values of a primary variable that are weighted with λ_i, $a_j(x_j)$ are sample measurements (M) of a secondary variable at the location x_j weighted with factor ω_j.

The evaluation of these methods is based on a comparative analysis of errors that emanate in the database from the interpolation process. Spline, kriging, and co-kriging are mathematically complex models and require an understanding of higher mathematics. Hence, these three complex methods are a “black box” for most users and practitioners. On the other hand, they are also often ignored for the same reason or used with interpolation parameters set blindly. Therefore the question arises: When should we use these complex functions and when should we not? In addition, we test the performance of simple versus complex algorithms under the stress of interpolating sparse data that contain a significant nugget effect (measurement error), and were collected in linear fashion along the road lines with large areas of empty spaces between them.

Numerous examples with similar goals can be found in scholarly literature; however, each study is unique in terms of data structure, the strength of spatial autocorrelation, type of application, combinations of algorithms, and types of error analysis. Lam (1983) reviewed all interpolation methods and explained the smoothness effect of splines. An excellent discussion comparing the accuracy of kriging and spline is provided by Laslett (1994). The kriging outperforms GCV splines as a predictor in specific circumstances, particularly if the data are highly clustered and there are little regional trends; prediction is required in spatial regions where spatial correlation is weak. Especially, when the data are not sampled on a regular grid, kriging has the potential to outpredict splines because it involves the translation of information on the covariance of data values from intensely sampled regions to sparsely sampled regions; splines and nonparametric regression procedures do not have this ability (Laslett, 1994). Lloyd and Atkinson (2002), tested IDW, OK and KT kriging for the construction of a digital surface model (DSM) from LiDAR data. The results indicated that the linear algorithm performed satisfactorily with the high density of LiDAR data; however, with decreasing density, the performance of complex algorithms became more accurate and KT kriging became the best predictor. Mueller *et al.* (2004) compared the performance of IDW and OK methods using two different grids: 30.5 and 61.0 m of soils data. At the denser grid scale, the multiple stepwise regression models for measuring interpolation errors indicated that the OK performance steadily improved relative to IDW as the range of spatial autocorrelation increased and the fit of the semi-variogram improved. However at the 61.0 m grid scale, the performance of OK relative to IDW diminished even though the semi-variogram fit improved and the range of autocorrelation increased. The focus in this study is unique in exploiting the performance potential of four predictors on the Big Bend data where the string of data is surrounding a big "pocket" of empty space with no information about composite pollen percentages. The semi-variogram indicates a large nugget effect; hence, predictions depend on the extrapolation of the estimated variogram towards the origin. The results are presented in various visual scenarios that contribute to an understanding of cartographic generalizations.

4. RESULTS

4.1 UNCERTAINTY IN SPATIAL DATA

One of the methods for checking the results from interpolation is cross-validation. The difference between predicted and sample values indicates an error. The error variance ($Var(X) = E\,[X - \mu]^2$) is one of the most important parameters used to analyze interpolation errors; it explains the effectiveness of interpolation. In general, increasing the variance of errors decreases our confidence in predicted values and consequently increases the uncertainty about the content of the raster data file. In addition, this uncertainty will affect the subsequent analysis in GIS, particularly in an overlay operation. The results from this research indicated that the spline interpolation yielded the highest error variance whereas the kriging and IDW error variance was significantly lower.

4.1.1 Magnitude of Error

The magnitude of errors is usually a significant parameter frequently used in the evaluation for predicting the performance of spatial interpolation. By definition, the sum of errors is equal to zero if no systematic bias is involved, so the absolute value of errors can be used to evaluate the accuracy of the interpolation. The results showed that co-kriging interpolation indicated the least absolute error of 8.94, lower than ordinary kriging's 9.11. The absolute errors from the inverse distance weighting method are in linear form; however, with a variance of 9.42 in third place. In contrast, the spline interpolation indicated the highest absolute error equaling 12.19.

Another parameter is the root mean square error (RMSE); it is frequently used in evaluating errors in remote sensing, GIS, and GPS mapping. RMSE is defined as the square root of an average squared difference between the observed and predicted values:

$$RMSE = \sqrt{\frac{SSE_i^{\,2}}{n}}$$

where *SSE* is the sum of errors (observed – estimated values) .

Similar to the absolute magnitude of errors, the RMSE was the smallest in the co-kriging interpolation (11.57) while the ordinary kriging method yielded an RMSE value of 12.37. The inverse distant weighting method performed very closely to kriging with an RMSE of 12.38. The spline interpolation inflated the errors the most (RMSE = equals to 16.53). The reason why IDW indicated similar results as OK lies in a high nugget effect of semi-variograms; during cross-validation semi-variograms are constructed from data located in close proximity to the predicted value. The northwestern locations of the study area indicated a smaller nugget effect and consequently kriging benefited from a stronger autocorrelation (spatial dependency). The local variograms from the rest of the study area exhibited a weaker spatial autocorrelation.

The best results by the aforementioned criteria were achieved by co-kriging that benefited from secondary information (elevation data). The RMSE value was 11.57 indicating that the secondary information in the form of elevation data positively contributed to the model. This contribution occurred in spite of a weak negative correlation between composite pollen quantities and elevations, as indicated by the correlation coefficient -0.22. The composite pollen distribution data are correlated more significantly with the pollen distribution data from Poaceae (grass pollen) in the same samples where the r value = - 0.48. However, interpolations with the grass pollen distribution did not indicate better results due to the same location (Goovaerts, 1998).

The analysis of the variance ANOVA showed that at the alpha levels of 0.05 and also 0.1, the differences between the mean absolute errors were not significant since the test failed to reject the zero hypothesis that $\mu_1 + \mu_2 + \mu_3 + \mu_4 = 0$. The Tukey grouping confirmed that there was no significant difference between the mean absolute errors that emanated from all of the four interpolation methods used. Hence statistically, all methods performed similarly with no significant difference. However, in a more rigorous sense, when the alpha level was greater than 0.1, the co-kriging, kriging and IDW methods performed significantly better than the spline interpolation did.

4.2 CARTOGRAPHIC GENERALIZATIONS

The accuracy in mapping various types of phenomena is only one side of spatial data analysis and presentation. Another side of this, which is equally important, is the aesthetical value of presented spatial data. From the beginning of cartography, the appearance of spatial information has been given serious consideration; even now maps are designed in ways that encourage their use for decorative purposes. Hence, cartography is both an art and a science. Sometimes, map images are required to attract the attention of viewers and thus some accuracy may be sacrificed for the sake of appearance. Pollen grains are microscopic particles not visible to the naked eye. Therefore, their distribution patterns on the ground can be revealed only through the interpolation of point sample data. These distribution patterns can then be correlated with other environmental factors such as the wind direction and slope orientation as well as vegetation patterns that represent sources for pollen distribution on the ground.

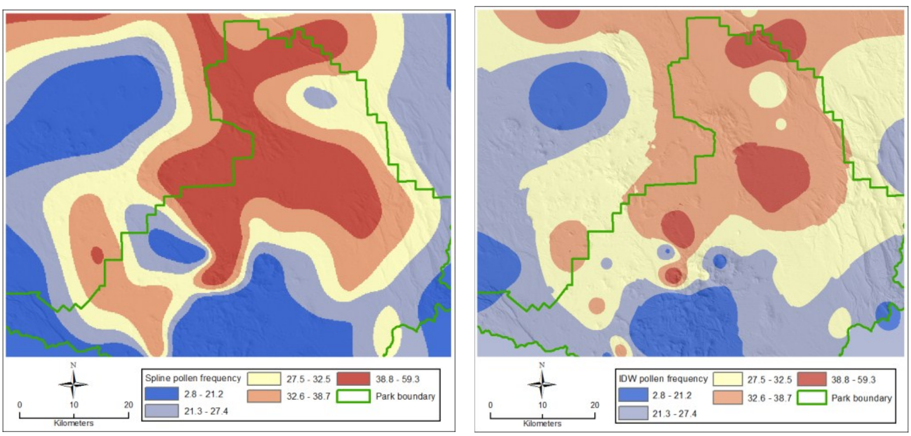

FIGURE 4
COMPARISON OF SPLINE (LEFT) AND IDW IMAGES

The results from this research indicate that what is most appealing, in terms of visualization, is not necessarily the most accurate from a spatial science perspective. From a cartographic point of view, the most appealing maps are often those generated by using the spline interpolation method. However, the results in this research indicate that spline algorithms yielded the least accurate surface representation of composite pollen data, yet the surface is fairly smooth and appealing (Figure 4). In addition, it is able to reveal the cause of spatial pattern, which in this case is prevailing wind directions. On the other hand, the inverse distance weighting method exhibited higher precision, but it presented a less appealing visual appearance.

Many practitioners assume that highly sophisticated interpolation methods would also yield better continuous surfaces. A simple algorithm was able to produce the accuracy that was almost as good as a complex and complicated kriging method. The co-kriging algorithm performed the best in terms of accuracy and also cartography. However, according to Goovaerts (1998) it requires using two data sets that must be correlated and collected in different locations rather than the primary data. In addition, co-kriging is a very complex interpolation algorithm, and its learning curve is extremely long. Hence the decision between appearance and accuracy can be a difficult one. For example, aggregation addresses the difficulty of displaying more than six or seven visually distinct gray tones or even color schemes in consistent sequence (Monmonier, 1996). Hence, the broadening of map categories or the changing of variogram parameters in GIS can also change the spatial patterns of pollen distribution due to accuracy. Similarly, unwanted patterns (*e.g.*, sharp edges, "bulls-eyes") can also be avoided by aggregation. Creative cartographic generalizations introduce the risk of a mapped pattern that distorts spatial trends in the data; they can improve the aesthetic value of mapping phenomenon although distortions may occur. Three- dimensional modeling can serve as another example to improve spatial presentation.

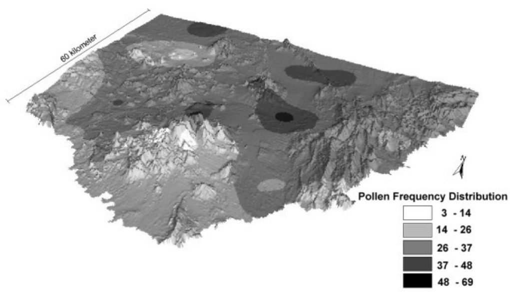

FIGURE 5
COMPOSITE POLLEN GENERATED WITH IDW

4.2.1 Three-Dimensional Visualization

Figure 5 shows the continuous surface of a composite pollen distribution that was generated by using IDW draped over the digital elevation model of the Big Bend National Park area; the focus of the viewer's attention is pulled towards the elevations, and the visualization of cartographic insufficiencies in the IDW are reduced. One of the most criticized phenomena is the "bulls-eye" pattern that causes users to mistrust surfaces that were generated by the IDW. The three-dimensional visualization, together with aggregation and image rotation, brings another view of the continuous surface overshadowing the weaknesses of interpolation methods. Figure 6 shows the differences in the spatial patterns of composite pollen distribution between the surfaces generated by co-kriging versus that of the spline interpolated surfaces.

The co-kriging model breaks down the continuous green surface into several geographic areas and shows a more detailed spatial pattern; this is due to its higher precision while the spline surface shows smooth transitions from one category to another. There are no rectangular shapes in the spline surface visible to observers either; however, they are apparent in the co-kriging three-dimensional model. The co-kriging generated surface is the most accurate while the spline generated surface is the least accurate in terms of the magnitude of root mean square errors (RMSE). The co-kriging surface shows more details of composite pollen distribution, especially in distribution patterns indicated by the green patches. There are clearly differences in portraying the actual values of composite pollen distribution densities that are not visible to map users. Surfaces generated by the spline method appear smoother and are more believable than the surfaces created by co-kriging, yet they show some geometric patterns that do not occur naturally in the terrain.

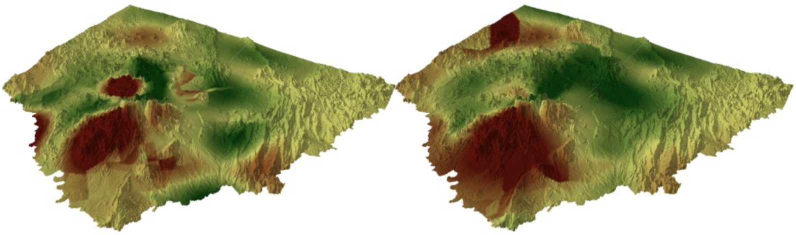

FIGURE 6
COMPARISION OF COKRIGING (LEFT) AND SPLINE (RIGHT)

5. CONCLUSION

The geographic information represented in discrete points has only limited informational purposes; it does not allow the study of spatial patterns or the observation of the major trends in data sets. Due to external circumstances such as time, resources and size of the area, the density of samples is low; on average, there was only one sample per 100 km^2. Hence the data points provide only limited information about spatial patterns of composite pollen. Spatial interpolation methods are the key to converting point data into continuous surfaces. In this project, four different spatial interpolation methods were used and tested for accuracy using arduous pollen data with a high measurement error. The testing involving the Big Bend composite pollen data indicated that the inverse distance weighting method yielded results that were very similar to the results obtained from the mathematically complicated ordinary kriging method. However, IDW is notorious for creating some cartographic deficiencies that are usually not preferred by users. One example is the "bulls-eye" pattern (Figures 4 and 5) that causes audiences to mistrust these results.

The best results in both categories (precision and aesthetic value) are indicated by the co-kriging method. This is the most sophisticated method but has a long learning curve and the highest potential for misuse. In addition, two sample datasets from different geographic locations, other than only a primary data set, must be used to maximize its performance. Using an inappropriately selected co-kriging variable will actually harm the accuracy of the resulting surfaces. We suggest using cartographic generalizations of the simplest algorithm (principle of parsimony) by providing three-dimensional views of the continuous surface created by the IDW algorithm. In addition, with the presence of a high nugget effect (78) as in the case of composite pollen, the accuracy of interpolation decreases to the IDW level. The complex geostatistical algorithms such as kriging and co-kriging have advantages in terms of accuracy, and they offer a minimum error variance; however, there is a high potential for misuse of this algorithm because they require more knowledge of complex mathematical functions.

The visual presentation of spatial data plays a significant role in attracting audiences and "getting the point across." Therefore, cartographic generalization is an important process that makes spatial information more explicit even though accuracy may be somewhat sacrificed. "A good map tells a multitude of little lies; it suppresses truth to help the user see what needs to be seen" (Monmonier, 1996). The patterns of composite pollen distributions were also functions of a cartographic generalization that are dependent on the interpolation method used. The splines method produced smooth surfaces with the highest root mean square error while the inverse distance weighting interpolator with a linear or quadratic exponent resulted in the least visually pleasing surface. Geostatistical algorithms performed best in terms of data accuracy and also cartographic quality because their algorithm took advantage of the spatial dependency among composite pollen data.

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