Use of Kriging Estimation to Enhance the Integrity of Geospatial Climate Data for Infrastructure Management

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Roadway pavements, one of the largest transportation infrastructure asset classes in terms of total value, deteriorate over time because of load (traffic) and nonload (climate) factors. Research studies over the years have shown that the nonload share of pavement damage can be as high as 60%. Historically, deterioration modeling has used coarse climate data extracted from regional or national climate maps because of insufficient local data or lack of efficient processes to refine the data. Many national and state databases contain significantly coarse climate data, and when such data are used in deterioration and cost models, the potential exists for significant misspecification. To address the problem, this paper implements kriging estimation, a geostatistical method that uses the spatial distance and autocorrelation of data collection sites to impute unobserved data values within a random field. Kriging estimation can produce gradient maps of the geospatial variable as well as point predictions of the variable at locations along a linear path such as a roadway centerline. This paper presents a case study of I-65 in Indiana, which used data from 59 statewide weather stations of the National Oceanic and Atmospheric Administration. The use of kriging estimation yielded a continuous prediction curve along the roadway centerline, which was an improvement over the discrete and coarse steplike nature of traditionally reported climate data.

In the United States, transportation agencies at the federal, state, and local levels are responsible for $2.75 trillion of transportation infrastructure assets, all of which need periodic maintenance and rehabilitation to combat deterioration to preserve their structural integrity and level of service (*1, 2*). Studies have shown that the nonload (climate) share of pavement damage can range from 20% to as much as 60% (*3, 4*). Several states, including Indiana, that experience high levels of precipitation and moderately low winter temperatures are expected to be at the upper end of this range (*5*). It is, therefore, useful to include detailed climate variables in models that explain the extent or progression of pavement deterioration. Most climate variables have values that are continuous over space; however, past practice indicates that most agencies typically express climate effects with discrete climate data because of insufficient data or a lack of an efficient process to provide spatially continuous (and, therefore, more reliable) values. The use of discrete climate data may hamper the understanding of the true impact of climate in pavement deterioration. For example, in states that use county-level climate data, a pavement segment that crosses a county border could be assigned two very different levels of a climate variable: one level for the pavement section in the first county and another level for the section in the next county. Additionally, two pavement assets that are tens or even hundreds of miles apart are typically assigned the same characteristic only because they are located in the same county. This issue is exacerbated even further when the climate data are aggregated by large geographical regions or zones, as in the case of nationwide climate zones.

Kriging estimation is a geospatial statistical approach to process spatially variant data to yield estimates that are more refined in terms of their smoothness and continuity. Kriging estimation was developed as a geostatistical approach in the early 1950s by D. G. Krige in an attempt to improve the accuracy of gold-mining practices in South Africa (*6*). Several researchers in the 1960s, including most notably G. Matheron and L. S. Gandin, improved on Krige's approach by including a more defined spatial process called the best linear unbiased predictor. Their improvements provided the framework for the modern kriging estimation method (*6, 7*). Since then, kriging estimation has been applied in numerous fields, including meteorology and statistics, but may be best known for its application in forestry because of the spatial process framework developed by Matérn (*6*).

The three main variants of kriging estimation are simple, ordinary, and universal kriging. Simple kriging assumes the first moment (mean) is known and constant over the entire domain; ordinary kriging assumes the first moment is unknown and constant over a local neighborhood; and universal kriging assumes the first moment is a trend over the local neighborhood (*6–9*). This paper used ordinary kriging to estimate unknown values from known data collection sites; this method is demonstrated in a case study that estimated the freeze index of pavement assets in Indiana along I-65 on the basis of the freeze index observed at 59 statewide weather stations. Agencies can easily adopt the methodology to their own set of climate data stations and infrastructure assets. The paper begins with a review of the current literature in the fields of data imputation techniques, climate variables, and asset deterioration. It continues with a discussion of the methodology, including the observed trends and model framework. Lastly, the methodology is applied to a case study in Indiana with the results and conclusions described in detail.

REVIEW OF CURRENT LITERATURE

Recent decades have seen vast advancements in the field of meteorology and climatology data collection because of improved technologies, such as next-generation weather radar, automation of surface data collection (weather stations), and increased computing power for processing data (*10*). Therefore, transportation agencies

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have access to extensive databases of raw climate data for use in asset-deterioration and cost modeling. However, agencies have been rather slow to exploit fully such available data because of, in large part, a lack of efficient processes for refining the raw data into a usable form. This situation is further exacerbated by differences in the climate and pavement data sets. Raw climate data are generated at specific data collection locations (*11*). A simple approach used by transportation asset managers is to attribute the values from a single location to a larger corresponding region, such as a county or management district. Analysts seeking more continuous estimates have turned to climate contours or climate zone maps developed outside of their agencies (*12–16*); this practice is demonstrated by the continued use of the Köppen-Geiger climate classification system depicted in Figure 1. These types of climate data are valuable for national-level forecasting but are less useful at the local and state levels. Furthermore, asset managers in a specific jurisdiction (region, province, or state) still face the task of ascribing the climate data to specific asset locations throughout their jurisdictions.

This paper uses I-65 in Indiana as a case study to investigate the feasibility of generating continuous climate data at points along a linear transportation asset, such as a roadway. Several different specifications are used to apply ordinary kriging estimation to climate data to produce a statewide gradient map as well as a set of point predictions at ¼-mi increments along I-65, with the latter being much more useful to asset managers.

Data Imputation Techniques

The techniques for climate data imputation currently in use by many transportation asset managers can be broadly classified into two categories. The first technique is to attribute the climate data (precipitation, temperature, freeze index, etc.) of a nearby weather station to a given asset (*17*). This practice can be considered as a geographical point-to-point estimation, and many open-source geographic information system software packages can assist in determining the closest weather station. This technique can be expanded by a calculation of the mean value of a number of nearby stations (typically, no more than five); this mean value is then attributed to a given asset (*18*). This technique is used in the *Mechanistic–Empirical Pavement Design Guide,* which uses hourly climate data from the nearest weather station to the project site to determine weather-related parameters for the project design life (*19*). In general, this technique uses climate data from a range of 2 to 20 years of observation (*19, 20*).

The second technique is to use single or multiple climate values as a proxy for the general climate condition of a region, and the resulting region is typically labeled as a climate zone (*20, 21*). This technique

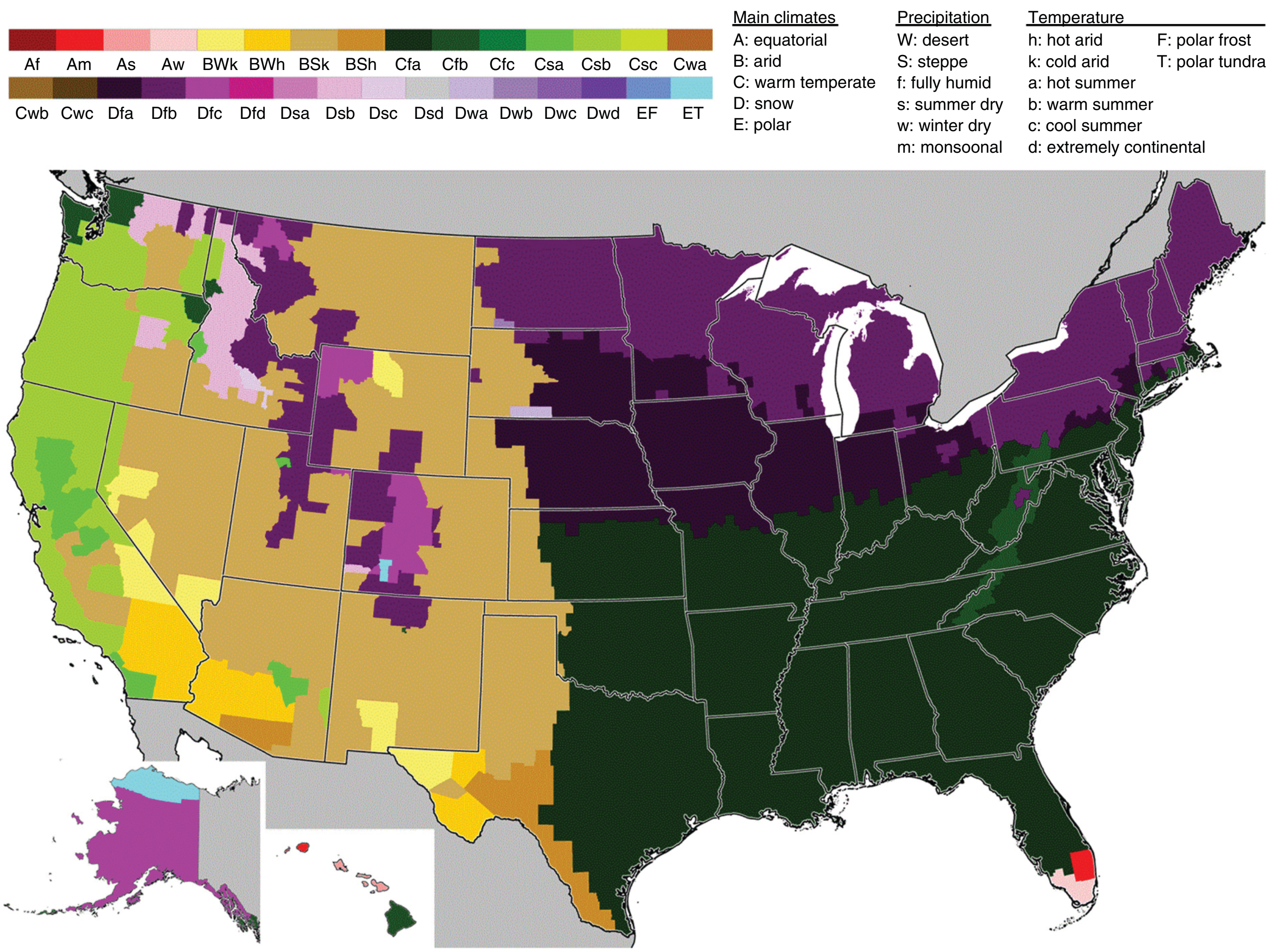

FIGURE 1 The Köppen-Geiger climate classification by U.S. county (*15*).

is widely used for macro-level modeling of regional climate characteristics for a multitude of purposes. Climate zone classification uses either primary climate measures (temperature, precipitation), secondary climate measures (freeze index) derived from primary measures, or a combination of both. Examples of this technique can be seen in the National Oceanic and Atmospheric Administration (NOAA) temperature zones and AASHTO's moisture and temperature zones (*13, 14*). This technique incorporates long-term climate data that range from 30 to 90 years (*12, 13*).

Climate Variable and Asset Deterioration

The climate data collected at 59 locations in Indiana were obtained from the NOAA database (*11*). There are numerous climatic factors that can affect the rate and extent of pavement deterioration. Temperature extremes have been shown to cause accelerated failure of asphalt pavements, while temperature fluctuations have been shown to cause accelerated failure of portland cement concrete pavements (*22*). Variations in temperature and precipitation can cause the underlying ground to swell or shrink, specifically during the spring season; these changes can cause a multitude of pavement failures (*23*). Given this reality, there are numerous climate variables that are of interest to asset managers. This paper uses one measure of climate severity, the freeze index; however, the methodology can easily be applied to any of the several climate variables. The freeze index, a gauge of relative climate intensity, is the difference between the mean daily temperatures and freezing for all days whose mean temperature is below freezing. It is defined as

$$\text{freeze index} = \begin{cases} \sum_{i=1}^{365} (32 - \text{MDT}_i) & \text{for } \text{MDT}_i < 32 \\ 0 & \text{for } \text{MDT}_i \geq 32 \end{cases} \quad (1)$$

where MDT_i is the mean daily temperature for day i in °F (*17*). This process of determining the freeze index is illustrated in Figure 2. This paper used the average freeze index from 1970 to 2000 calculated at each NOAA data collection site. Regions with a greater freeze index may have greater rates of pavement deterioration because of increased joint faulting and spalling in portland cement concrete pavements and an increased depth of frost penetration for all pavements (*24–26*).

METHODOLOGY

Kriging estimation allows for the interpolation of an unobserved point value from known values and is just one of many distance-based interpolation algorithms (*8, 9*). Kriging estimation has the benefit of accounting for the covariance in spatially clustered data sites, attributing less weight to locations within the cluster. In this paper, several ordinary kriging estimation frameworks are applied to determine the optimal approach for the current data set.

Treatment of Trends

The ordinary kriging used in this paper is omnidirectional, assuming the directions (north, south, east, and west) between the unobserved and observed points are treated equally and only the Euclidean distance is considered. Therefore, trends occurring across all the sampled data points (global trends) resulting from theoretically proven spatial conditions, such as correlation of temperature and latitude, should be removed prior to kriging estimation to discern unobserved spatial autocorrelation (*8*). The coordinate system is converted from latitude–longitude to Cartesian coordinates; as a result, the true distances can be better represented because the measurements in degree–minute–second are not equal in latitude and longitude. The loss in information caused by projecting the three-dimensional surface coordinates (latitude and longitude) to the two-dimensional Cartesian coordinates is negligible at the state level.

Model Framework

The kriging estimation for an unknown value is obtained with weighted linear combinations of the known values defined as follows (*8, 9*):

$$\hat{z} = \sum_{1}^{n} (w_j k) \quad (2)$$

where

$\hat{z}$ = predicted value,
k = known value, and
w_j = weight.

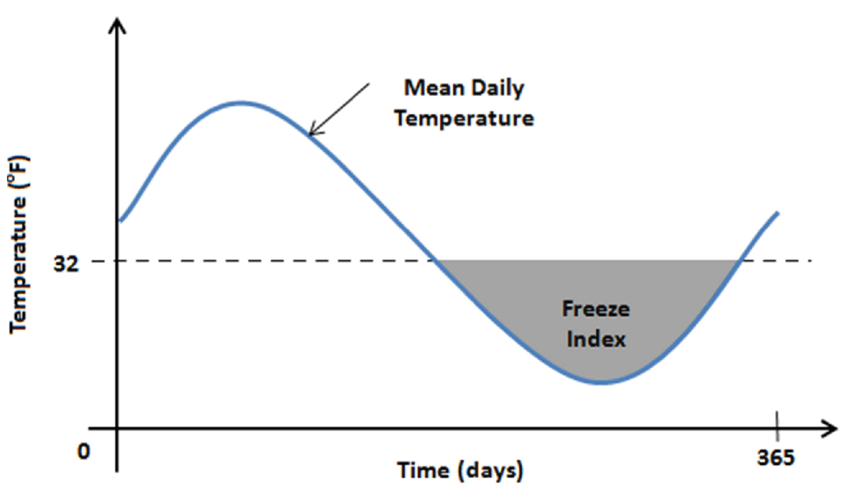

FIGURE 2 Illustration of the freeze index.

However, because the true value of k is unknown, a stationary random function $Z(x_i)$ is used:

$$\hat{Z}(x_0) = \sum_{i=1}^{n}(w_i(x_0)Z(x_i)) \tag{3}$$

where

$Z(x_i)$ = actual value,
x_0 = location of the unobserved value,
x_i = location of the observed value, and
w_i = weights that are a function of the distance modified by the covariates to account for potential clustering of observed locations.

The error is defined as

$$\varepsilon(x_0) = \hat{Z}(x_0) - Z(x_0) \tag{4}$$

To ensure that the model is unbiased, the sum of the weights is set equal to one:

$$\sum_{i=1}^{n}(w_i(x_0)) = 1 \tag{5}$$

The following equation is used to minimize the error variance:

$$\text{minimize } \mathrm{E}\left[\varepsilon(x_0)^2\right] \tag{6}$$

The covariance is defined as

$$\operatorname{cov}\{x_j, x_i\} = \mathrm{E}\left(\varepsilon(x_i)\varepsilon(x_j)\right) \tag{7}$$

where x_j is the location of the observed value.

Kriging assumes intrinsic stationarity. Therefore, the expected value between two spatially lagged points of distance h is assumed to be equal to zero:

$$E[Z(x+h) - Z(x)] = 0 \tag{8}$$

The variance between two spatially lagged locations of distance h is

$$\operatorname{var}[Z(x+h) - Z(x)] = E\left[(Z(x+h) - Z(x))^2\right] = 2\gamma(h) \tag{9}$$

where $2\gamma(h)$ is the variogram.

Estimated Variogram

The variogram is the variance of the difference between points separated by the same Euclidean distance h. The exponential semivariogram used in this paper takes the following form (*8, 9*):

$$\gamma(h) = C_0 + C_1\left(1 - \exp\left(\frac{-3|h|}{a}\right)\right) \tag{10}$$

where

C_0 = nugget effect (difference in sample values separated by extremely small distances),
C_1 = partial sill [difference between C_0 and the maximum variogram value (sill)], and
a = range (distance between two points at which the variogram no longer increases).

The Matérn semivariogram used in this paper takes the following form (*26*):

$$\gamma(h) = C_0 + C_1\left(1 - \frac{1}{2^{v-1}\Gamma(v)}\left(\frac{h}{a}\right)^v K_v\left(\frac{h}{a}\right)\right) \tag{11}$$

where

K_v = modified Bessel function of the second kind of the order v,
Γ = gamma function, and
v = smoothness parameter.

The Matérn variogram is the same as the exponential variogram when v is 0.5 (*27*).

CASE STUDY

Data Collection

The freeze index values were calculated for each of the 59 NOAA data collection sites in Indiana. Other data included the geographical locations of I-65 at approximately 0.25-mi increments. The data collection sites and the 0.25-mi increment locations along I-65 are presented in Figure 3.

Trends

Because ordinary kriging uses the Euclidean distance between data points, assuming the mean value is unknown and constant, it is

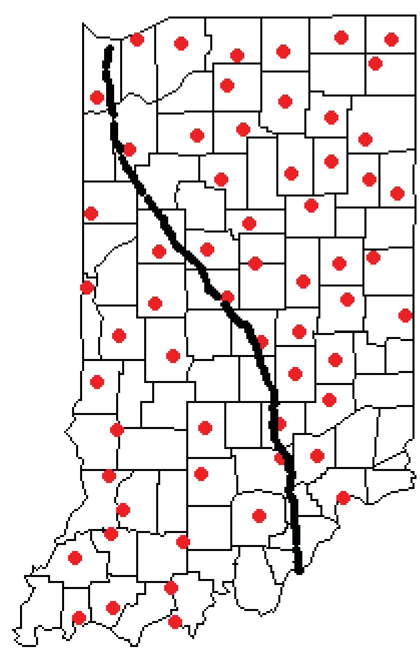

FIGURE 3 NOAA data collection sites (large red dots) and I-65 (small black dots) in Indiana.

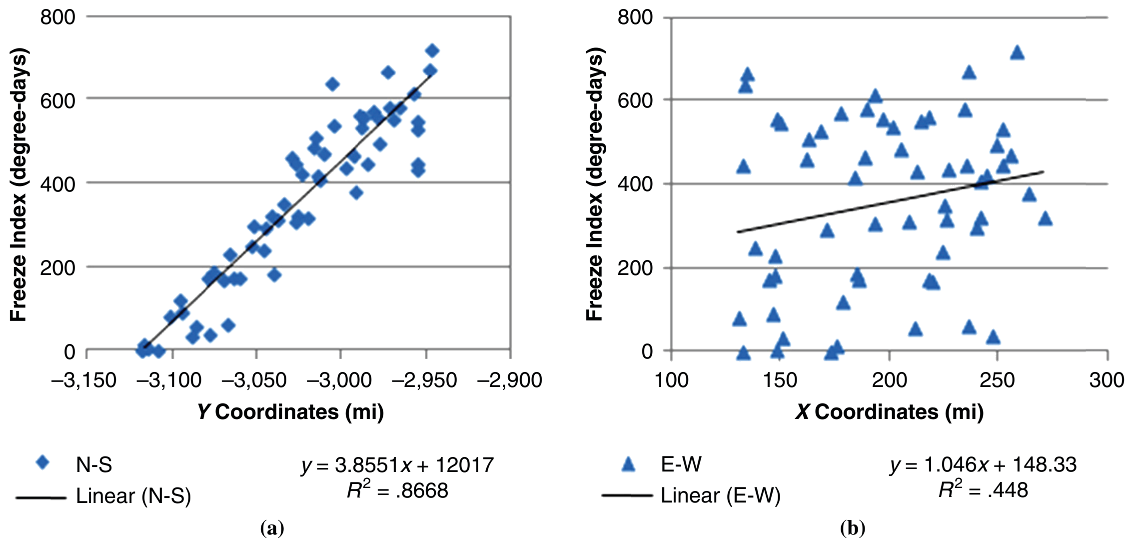

FIGURE 4 Global trends in freeze index data for (*a*) north–south (N-S) and (*b*) east–west (E-W).

important to identify and remove global trends in the freeze index data. Before this step was taken, the coordinate system was changed from latitude–longitude to Cartesian coordinates so that the true distances could be better represented. The freeze index trends in both the east-west and north-south directions were established and investigated (Figure 4).

A linear trend line was determined to be the best fit after various trend line functional forms were fit to the data. A definite global trend was apparent in the north–south direction indicated by the linear trend line with a good statistical fit (R^2 value = .87). There was little discernible trend in the east–west direction. Subtracting the best-fit lines from the data removed the trends; this change produced less correlated data, which is illustrated in Figure 5. Removing the trends allowed the subsequent analysis to focus on the variations in the data from the trend.

The freeze index values with the trends removed and the corresponding Cartesian coordinates of the data collection sites were read into the open-source programming statistical software R, as were the Cartesian coordinates of I-65. All analyses were conducted in the R software (*28*). To implement this framework, an infrastructure agency's managers, engineers, and researchers, in coordination with the highway agency's information and systems technology division, could adopt the code developed as part of this research. The analysis could then be carried out with data from the agency's climate stations and infrastructure asset locations.

Estimated Variogram

The variogram is the variance of the difference between points separated by the same Euclidean distance. Two separate estimators, weighted least squares (WLS) and maximum likelihood, and two separate covariance models, Matérn and exponential, were used to estimate the variogram to determine which approach would produce the

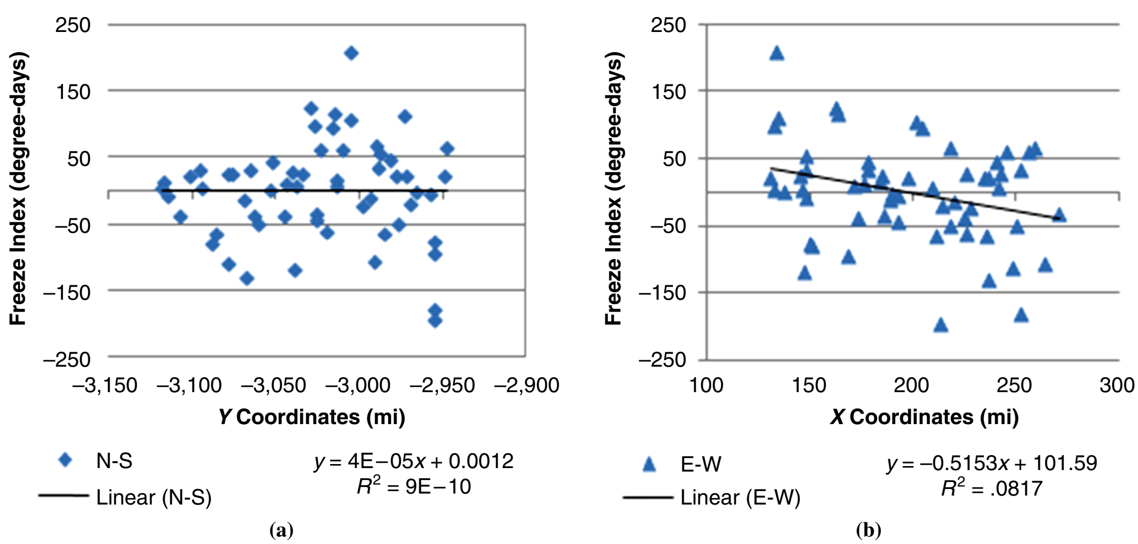

FIGURE 5 Freeze index data with global trends removed for (*a*) north–south and (*b*) east–west.

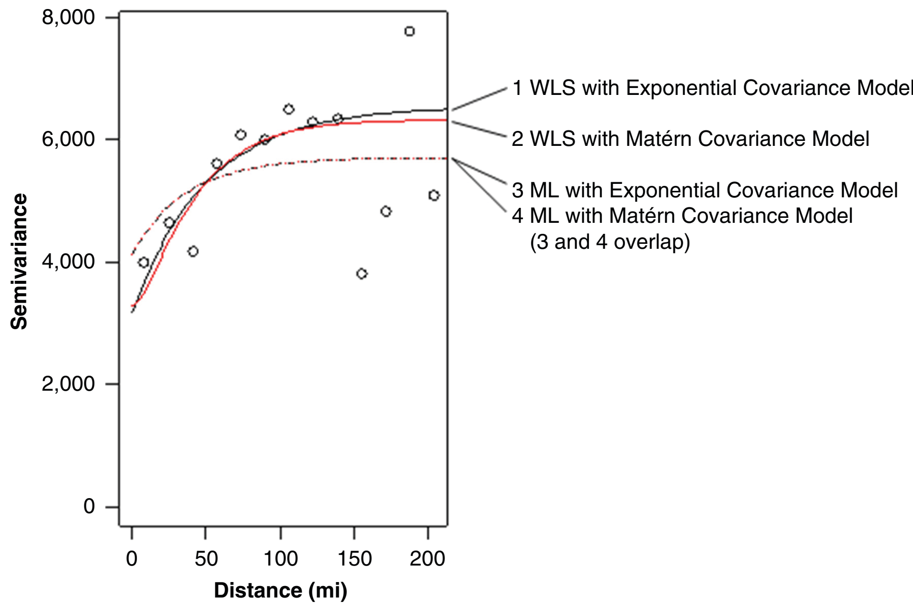

FIGURE 6 Estimated semivariogram functions (ML = maximum likelihood).

best fit. The estimated variogram and four fitted variogram functions are presented in Figure 6. Only three fitted curves appear in Figure 6 because two of the curves overlap.

Results

The mean squared prediction error for each semivariogram was determined by the sequential removal of one data point at a time; prediction of that point, given the remaining data (global neighborhood); and replacement of the removed data point. The four variogram functions are described in detail in Table 1.

The Matérn covariance model outperformed the exponential model for both the WLS and maximum likelihood estimations. Furthermore, the data experienced a large nugget effect, which is the difference in sample values separated by extremely small distances. This result could be attributable to very noisy data or to the large distances between data collection sites. Overall, the WLS estimation and a Matérn model with kappa = 1 (smoothness parameter) best fit the data. However, for comparison, all four models were used in this paper to impute the freeze index for I-65 in Indiana.

Figure 7 presents the kriging estimates and variances across Indiana. The global trends have been removed from the data plotted in this figure. Adding the global trends affects only the magnitude of the kriging estimates for the freeze index and does not affect the kriging variances.

The kriging estimates map shows the pockets of relatively high and low estimates scattered across the state. As expected, lower variances were present in the regions surrounding the data collection sites; variances increased in regions farther away from these sites. The freeze index with the global trends removed was estimated at points approximately every 0.25 mi along I-65 in Indiana. The final freeze index values were produced by the addition of the global trends back into the kriging estimates. Figure 8 shows the final freeze index values obtained from the kriging estimation when each of the four semivariogram functions is used. For comparison, two traditional discrete estimation methods are overlaid in Figure 8. The first discrete method attributes the freeze index calculated at a single NOAA site to all locations in the same county. The second discrete method attributes the freeze index calculated from the closest NOAA site, regardless of whether the NOAA site and the location of interest are in the same county.

Discussion of Results

Because the four semivariogram functions for the ordinary kriging yielded similar predicted values, it is difficult to distinguish between

TABLE 1 Comparison of Ordinary Kriging Results

Reference Number[a]	Estimation Methodology	Covariance Model	Kappa	Nugget	Range (mi)	Partial Sill	Mean Squared Prediction Error [mean of $(\hat{Y}-Y)^2$]
1	WLS	Exponential	0.5	3,184	151.6	3,360	6,290
2	WLS	Matérn	1	3,284	114.27	2,223	5,700
3	Maximum likelihood	Exponential	0.5	4,133	110.49	1,576	6,342
4	Maximum likelihood	Matérn	1	4,133	110.48	1,576	6,139

[a]Refers to numbers in the key to Figure 6.

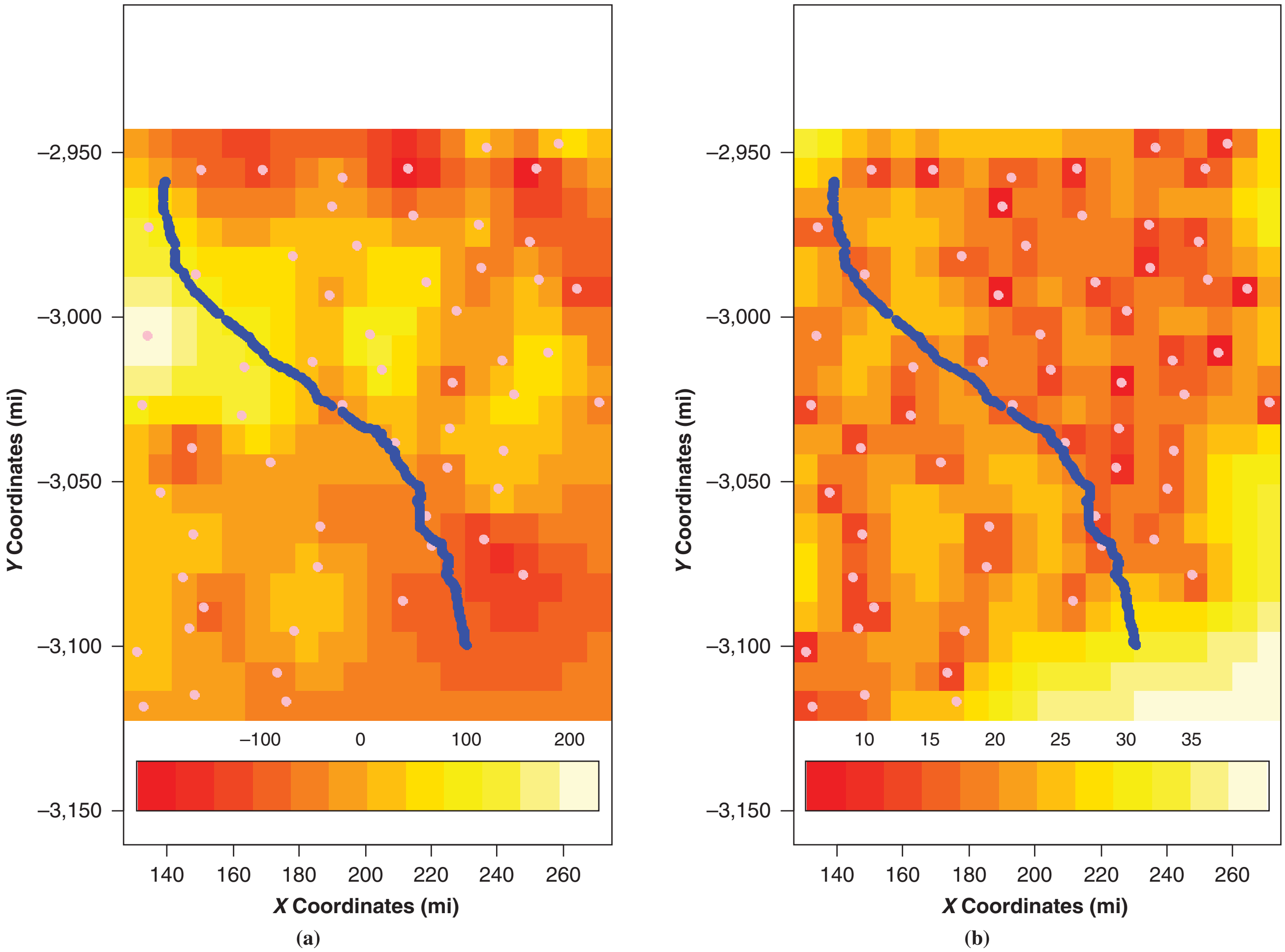

FIGURE 7 (*a*) Kriging estimates and (*b*) standard errors (data sites = light dots; I-65 = dark dotted line; coordinates in miles).

the four estimates in Figure 8. Mile Marker 0 in southeastern Indiana has a freeze index of zero, meaning the average daily temperature for each day never falls below 32°F. The freeze index increases as I-65 progresses northwest, culminating in a freeze index value of approximately 615 degree-days in the northwest corner of the state. Overlaid in Figure 8 are the freeze index values that would be attributable along I-65 when two traditional methods are used. The first traditional method is to attribute the freeze index calculated at the closest NOAA site, and the second is to attribute the freeze index calculated at a NOAA site that lies in the same county. There is a stark difference between the discrete step functions of the traditional approaches and the smooth, logical progression developed with kriging estimation. For instance, the weather stations in close proximity to Mile Marker 63 and Mile Marker 110 led to consistent estimates at these locations. However, the traditional discrete interpolation for the points between these mile markers experienced as much as 30% overestimation and 40% underestimation compared with the kriging estimates. Overall, the traditional discrete step functions overestimated or underestimated the freeze index by as much as 110 degree-days. For regions with a lower density of weather stations, this deviation is expected to be even greater. Additionally, the discrete step functions increased dramatically near Mile Markers 35, 100, 150, and 230; this increase means two assets 1 mi apart had freeze index values that would vary by more than 100 degree-days.

SUMMARY AND CONCLUSIONS

Climate plays a significant role in transportation asset deterioration and, therefore, constitutes a major component of asset cost modeling. Transportation officials have typically applied collection site data in a discrete form by applying a single data collection site or the simple mean of a limited number of data collection sites to a much larger area. When this approach is used the true impact of climate on the deterioration of transportation assets may not be realized. This paper investigated the feasibility of using ordinary kriging to provide more accurate, continuous estimations of climate variables. Kriging estimation is a geostatistical method that uses the spatial distance and autocorrelation of data collection sites to impute unobserved data values within a random field.

Four variants of the ordinary kriging were applied to the freeze index values calculated at 59 data collection sites in Indiana. Ordinary kriging with WLS estimation and a Matérn covariance model had the best statistical fit; however, all four models produced similar results. A gradient map of the freeze index values across the state and the associated variances was produced. Additionally, point predictions were estimated every 0.25 mi along I-65. The kriging estimates represent a more natural and intuitive estimation of the climate severity levels along I-65 and between the points of actual observations, compared with estimates implicitly derived from the traditional discrete approach. This paper shows that the deviation of the

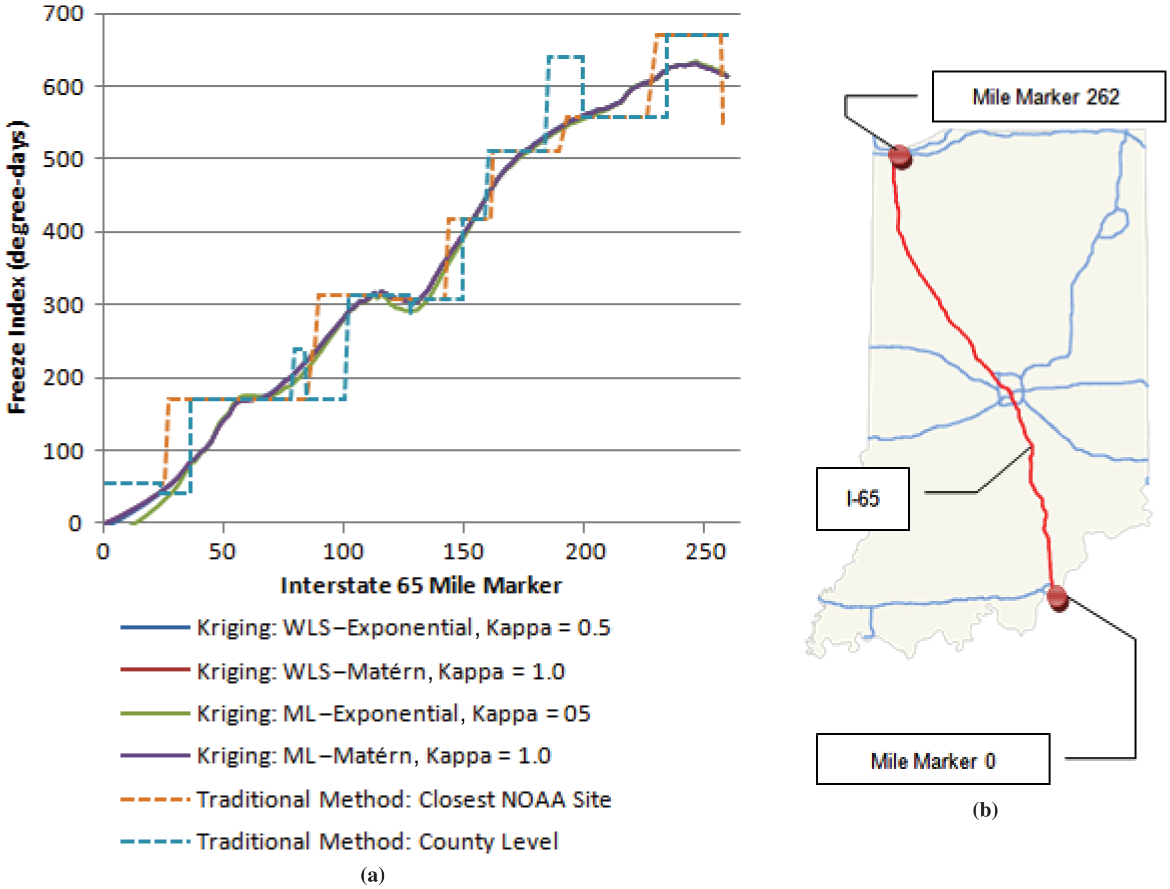

FIGURE 8 Estimated freeze index values along I-65: (*a*) comparison of predicted freeze index values calculated with six different methods and (*b*) corresponding map of I-65.

county-level freeze index from the more intuitive kriging estimate is an overestimation by as much as 30% and an underestimation by as much as 40%. Furthermore, jumps in the traditional discrete step functions could be as much as 120 degree-days.

Kriging estimation can provide location-specific estimates for climate variables along small distance intervals; as a result, transportation analysts can update their existing infrastructure databases with better-quality climate data and develop infrastructure deterioration models that account for the effects of climate in a more reliable manner. The case study in this paper is only illustrative, and the methodology presented can be used with any other measure of climate severity. Additionally, the methodology can be applied to other spatially variable attributes, such as geotechnical conditions, for purposes of more reliable characterization of the relevant spatial attributes of any type of transportation asset distributed in any region of interest. Future research could investigate the feasibility of applying a kriging function that is not only spatial but also temporal to account for any significant changes in the observed data values over time.

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