DETERMINING THE SPATIAL REPRESENTATIVENESS OF AIR-TEMPERATURE RECORDS USING VARIOGRAM-NUGGET TIME SERIES

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Abstract: In climatology, spatial representativeness can be measured as the degree to which an instrumental temperature record resolves the climatic variability across an area. Some station records may disproportionately resolve characteristics of their immediate surroundings and, therefore, have less utility in representing climate (or weather) over larger spatial scales. To evaluate spatial representativeness of historical air-temperature records, a modified geostatistical procedure was developed. The procedure measures the spatial representativeness of a station based on variogram parameter estimates—in this case the nugget. This application is novel for two reasons: (1) variogram models are fit to station-specific or "point-centered" semivariance and (2) variogram models are fit to semivariance computed at intervals in a time series. Fitting variograms to point-centered semivariance may be used to create time series of nuggets for each station in a network. Nugget time series may show subsets of a time series that are spatially unrepresentative. These periods could be omitted from climatological analyses without excluding the entire station record. Examples from the central-U.S. subset of the Daily Historical Climatology Network illustrate how anomalous nuggets or step changes in nuggets can be identified relative to station changes. [Key words: climatology, air temperature, spatial analysis, variogram models.]

INTRODUCTION

The spatial representativeness of a specific climate-monitoring station is a function of regional climatic variability, measurement site characteristics, and observational practices. Some stations may be strongly influenced by an unusual or changing microclimate within their immediate surroundings and, therefore, have less utility in representing climate over larger spatial scales. Because of their atypical microscale environment, those stations have limited spatial representativeness and add local-scale signals and noise to the spatial climate field. Stations whose representativeness changes with time may add uncertainty to regional- and global-scale air-temperature trends and, therefore, confound efforts to attribute large-scale

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variations to specific causes such as greenhouse gases, atmospheric aerosols, or solar variability.

Spatial representativeness can be evaluated by examining both the local-scale environs of a station and the degree to which a station's data resolve coherent spatial variability across an area. Because detailed observations of local environmental characteristics of climatic stations—and how they change with time—are not readily available for many locations, this research focuses on the evaluation and quantification of spatial coherence in regional-scale air-temperature networks. The purpose of this paper is to describe a new technique for determining the spatial representativeness of a station and to demonstrate its application across the central United States.

A modified geostatistical procedure was developed to examine historical air temperature records at individual stations relative to regional air-temperature patterns. Diurnal temperature range (DTR, the difference between daily maximum and daily minimum air temperature) was used as the indicator variable for spatial representativeness. DTR has a higher degree of spatial coherence than minimum, maximum, and mean air temperature and, as a difference variable, is sensitive to many kinds of local-scale (and nonclimatic) biases (Dai et al., 1999). This procedure is flexible and can be applied to data from one snapshot or aggregate of time or over many time steps of a climate time series. A time-series application allows unrepresentative periods in a station's record to be differentiated from more-representative periods. Since these stations may lead to inaccuracies in regional assessment of air-temperature change during some periods, their effects should be minimized.

DATA DESCRIPTION, STUDY AREA, AND DATA QUALITY

Data Description

Daily maximum and minimum air-temperature time series from 1948 to 1997 were derived from the U.S. Daily Historical Climatology Network (HCN/D). The HCN/D contains more than 1000 stations with daily maximum and minimum air temperature (Easterling et al., 1999). The methods described later in this article were applied in a regional context to a subset of 301 HCN/D stations from the central United States (Fig. 1). Density is relatively even across the study area with the exception of the southeast and south-central portions. The average distance between nearest neighbors is 42 km. The study area is primarily upwind of the Great Lakes' influence; however, near-shore locations may contain some anomalous air temperatures during periods of onshore flow. Since a majority of stations are located at elevations of 150 m to 350 m, topographic change across the region is not large enough to dominate the spatial pattern of air temperature. Although some of the locations have digital records before 1948, they are often not serially complete and only represent a fraction of the network. The study period from 1948 to 1997 is suitably long, inasmuch as decadal-scale climatic variability can be resolved.

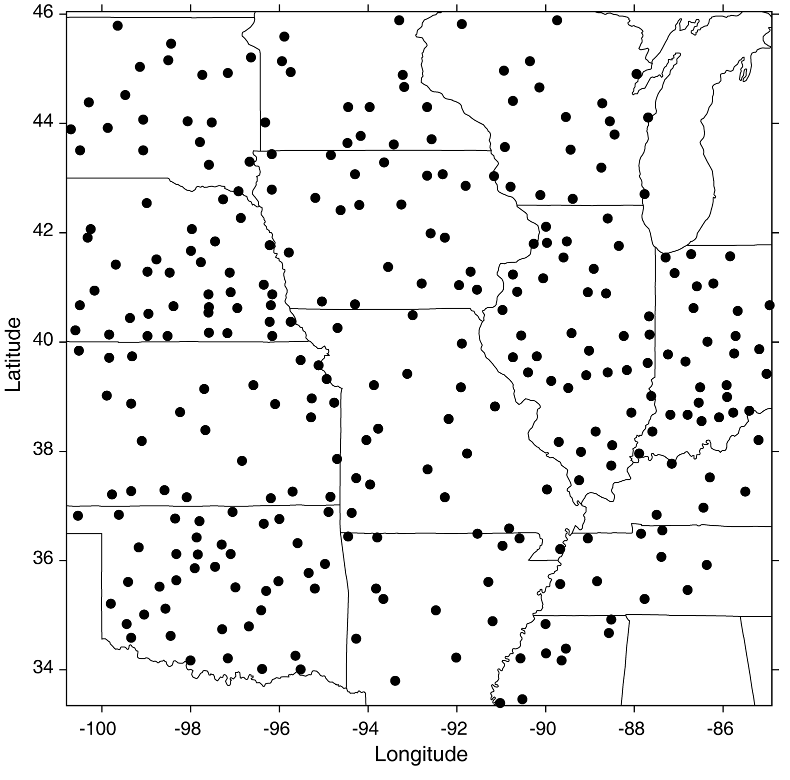

Fig. 1. Spatial distribution of a 301-station subset of the Daily Historical Climatology Network across the central United States.

Data Quality Issues

Inhomogeneities in land-based observations of air temperature may dampen, accentuate, or introduce noise to estimates of long-term air temperature trends. Inhomogeneities caused by operational changes to weather station are considered "nonclimatic" (e.g., change from liquid-in-glass to thermistor-based thermometers; Quayle et al., 1991). Inhomogeneities that affect the fidelity of long-term air temperature but that are not caused by alterations in the measurement practices are considered "apparent" (e.g., introduction or discontinuance of stations that results in variability caused by changing network configurations; Robeson, 1995). Adjustment procedures for many discontinuities have been developed (Karl and Williams, 1987; Easterling and Peterson, 1995) and used to create more temporally homogeneous climatological time series (Eischeid et al., 1995; Vincent et al., 2002). Since many procedures use spatial relationships (such as correlation) to aid adjustments, it is appropriate to evaluate the fidelity of those spatial relationships before homogeneity adjustments.

MEASURES OF SPATIAL VARIABILITY

Background

Semivariance and related *geostatistical* techniques of *kriging* grew from mining research in the late 1950s but did not gain widespread use until the 1978 publication by Journel and Huijbregts (Cressie, 1990). Geostatistical techniques have been used in many scientific applications, such as explaining the distribution and density of plants and animals (e.g., Robertson, 1987; Rossi et al., 1992), determining spatial scales of variation and sampling strategies in remote sensing (e.g., Curran and Atkinson, 1998; Atkinson and Tate, 2000; Burcsu et al., 2001), and approximation in climatology (e.g., Hudson and Wackernagel, 1994; Gunst, 1995; Holdaway, 1996).

When recorded or observed at many locations and treated as a spatially varying surface, climatic variables usually display variability that can be approximated by deterministic and stochastic components. Near-surface air temperature, for instance, can be formulated as the sum of (1) a deterministic function describing the spatial mean or trend, (2) a function describing the spatially correlated variation, and (3) spatially uncorrelated random noise. Variables that can be formulated in this manner are called *regionalized variables* (Burrough and McDonnell, 1998).

In regionalized variable theory, the first assumption is (spatial) stationarity in the local mean (Cressie, 1986), or *a priori* removal of spatial trends called "drift" to obtain stationarity (Gunst, 1995). The second assumption is that differences between locations are a function of their spatial separation. The corollary is that air temperature observations closer in space should be more similar than air temperature observations farther apart. The second assumption is the foundation for nearly all spatial interpolation algorithms (Burrough and McDonnell, 1998). While the concept of spatial similarity may seem obvious and, therefore, is nearly always assumed, not all climatic variables (at all time scales) exhibit this property (e.g., annual wind speed data analyzed by Robeson and Shein, 1997).

Traditional Semivariance

Semivariance is a measure of *dissimilarity* of a spatial variable that has been observed at different locations. Semivariance, given by the average squared difference between station-values separated by distance h, is defined by:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{(i,j)|h_{ij} = h} (x_i - x_j)^2 \tag{1}$$

where $N(h)$ is the number of station pairs that are separated by a distance h. Distance h or spatial "lag" is accompanied by a lag tolerance to create distance intervals over which semivariance is computed. If the lag is 50 km and the increment is 25 km, for example, then the semivariance for the 50-km interval is computed from stations that are 25–75 km apart. Assignment of lag values generally depends on the density of the observation network (Isaaks and Srivastava, 1989). Semivariance, unlike spatial correlation or covariance, is applicable here because

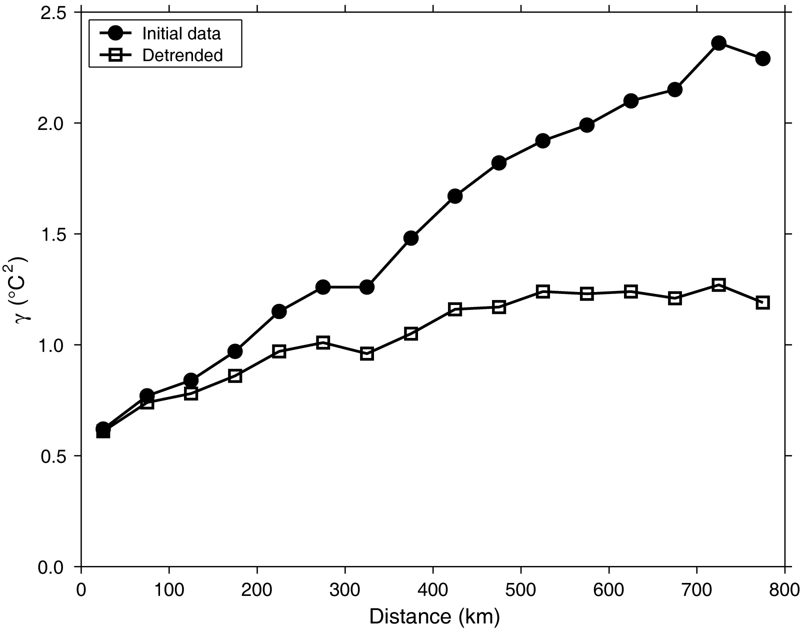

Fig. 2. Experimental variograms for 1948–1997 mean fields of diurnal temperature range (represented by dot) and mean fields detrended (represented by square) with respect to latitude and longitude.

it does not standardize the station values in any way. This is an important characteristic, as a local-scale signal may affect either the mean or variance. Alternately, if the mean is dominating the spatial signal, standardization may be performed prior to calculating semivariance.

Traditional semivariance (γ) computed across the entire network from 1948–1997 averages of DTR has a characteristic form of increasing values as spatial separation increases (Fig. 2, Table 1). As expressed by small semivariance ($\gamma < 1°C^2$), stations close to one another (within 200 km) have similar DTR. As station separation increases (to within 500–600 km), DTR differences become larger and, while accounting for spatial trends, semivariance increases to a plateau ($\gamma = 1.2°C^2$). When estimated without accounting for spatial trends, however, variograms tend to drift or be unbounded (semivariance steadily increases beyond 600 km). The effect of spatial trends also can be illustrated by comparing a map of the mean field with a map of the detrended field (Fig. 3). Period-of-record averages of DTR display a slight northeast to southwest trend across the central United States. As a result, spatial fields are detrended or made stationary with respect to latitude and longitude and an interaction term. After removing a low-order polynomial surface, DTR has a more gradual spatial variation with a more coherent spatial decay function. The impact of detrending is most pronounced at the largest spatial lags. For example, semivariance for DTR at distances across the spatial domain (800 km) is 1.0°C^2 greater for nondetrended data.

Table 1. Sample Sizes, Spatial Lags, and Semivariance for 1948–1997 Mean DTR Fields and Mean Fields Detrended with Respect to Latitude and Longitude

Lag (km)	DTR semivariance (°C^2)	Detrended DTR semivariance (°C^2)	Sample size
25	0.62	0.61	162
75	0.77	0.74	644
125	0.84	0.78	1,033
175	0.97	0.86	1,312
225	1.15	0.97	1,634
275	1.26	1.01	1,778
325	1.26	0.96	1,921
375	1.48	1.05	2,087
425	1.67	1.16	2,236
475	1.82	1.17	2,274
525	1.92	1.24	2,377
575	1.99	1.23	2,424
625	2.10	1.24	2,398
675	2.15	1.21	2,394
725	2.36	1.27	2,375
775	2.29	1.19	2,354

Point-Centered Semivariance

Semivariance is traditionally used to describe the spatial variance across a spatial domain (region). All possible station pairs are examined and one integrated measure of spatial variability results. With straightforward modifications, spatial variability can be analyzed with regard to a specific location, producing a "point-centered" semivariance (Burcsu et al., 2001). In point-centered semivariance, each station is examined separately (e.g., x_j, $j = 1$) and differences are calculated between its value and all other station-values in the domain (e.g., x_i, $i = 1, \ldots, n_s$, $i \neq j$). This procedure can be repeated until each station in a network has an associated point-centered semivariance:

$$\gamma_j(h) = \frac{1}{2N(h)} \sum_{(i,j)|h_{ij} = h} (x_i - x_j)^2 \qquad j = 1, n_s \quad j \neq i \tag{2}$$

where n_s is the number of points in the station network. Point-centered semivariance also may be performed on an *ensemble* of spatial time series. If the change in semivariance with time (k) is of interest, then a point-centered semivariance time series can be produced:

$$\gamma_{j,k}(h) = \frac{1}{2N(h)} \sum_{(i,j)|h_{ij} = h} (x_{ik} - x_{jk})^2 \qquad j = 1, n_s \quad j \neq i \qquad k = 1, n_t \tag{3}$$

where n_t is the length the time series. A time step (k) might be one month, whereby $\gamma_{j,k}(h)$ represents the spatial variation radiating outward from station j for month k.

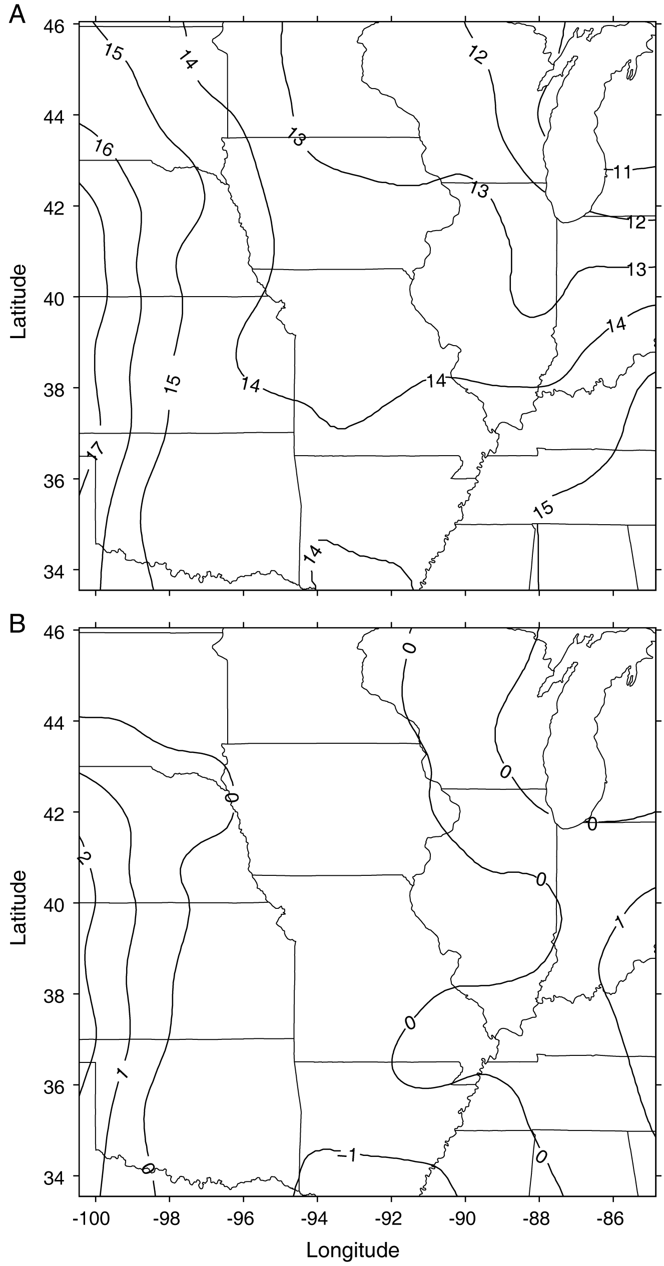

Fig. 3. Spatial fields of (A) 1948–1997 mean diurnal temperature range (DTR) and (B) 1948–1997 detrended-mean DTR.

Although many forms of semivariance analysis include directional effects (Isaaks and Srivastava, 1989), point-centered approaches are more limited in that regard. Compared to traditional semivariance, point-centered semivariance produces fewer

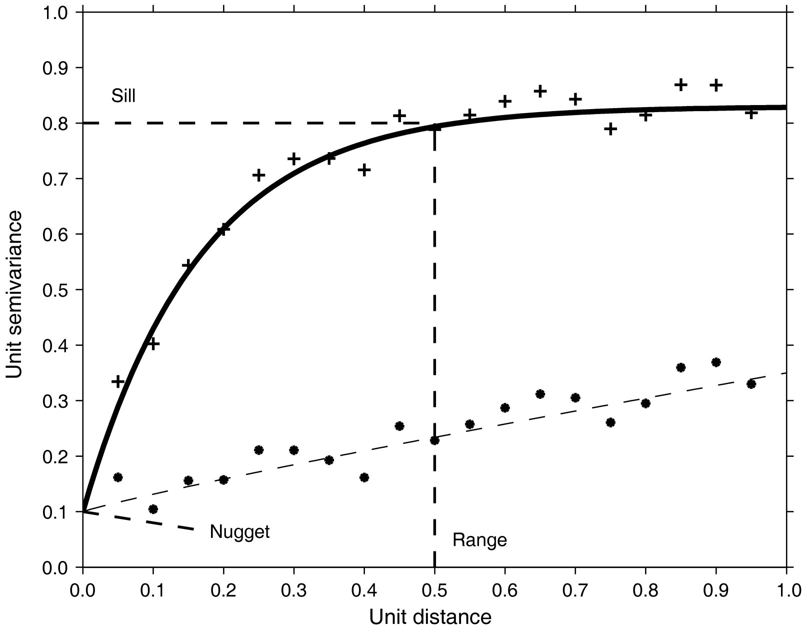

Fig. 4. Schematic diagram of semivariance (+) fitted with an exponential model (solid line) with parameters: nugget (0.10), sill (0.80), and range (0.50). Schematic diagram of semivariance (•) fitted with a power model (broken line) with the parameters: nugget (0.10), scale (0.25), and shape (0.90).

interstation pairs to be used in the calculation of semivariance at each lag. As a result, it frequently is not possible to reliably estimate directional effects within point-centered semivariance analysis. Although very dense networks of station could allow for the estimation of directional effects, the network of climate stations that we use in this analysis is too sparse to produce directional point-centered semivariograms.

Variogram Models

Semivariance plotted as a function of average lag separation is typically called the *semivariogram*. Three parameters can be derived when most functions are fit to semivariograms: the *sill*, *range*, and *nugget* (Fig. 4). Although there can be considerable variation among semivariograms and variogram models, these parameters can be described generally (Isaaks and Srivastava, 1989). The sill is a plateau in semivariance that occurs at a distance defined by the range. At distances greater than the range, the regionalized variable is independent (of itself). Within the range, regionalized variable theory applies. The nugget is the estimated *nonzero* semivariance as distance approaches zero. The nugget accounts for fine-scale variations that are unresolved by the sampling network. The nugget of a point-centered variogram model, therefore, can be used to estimate the degree to which the regional values approximate the target station value. A large nugget indicates that, over short distances, semivariance behaves differently than the larger-scale spatial pattern would have otherwise predicted. Because nugget estimates are variance extrapolated to zero distance, a paucity of nearby neighbors could introduce greater uncertainty into nugget estimates. The efficacy of these extrapolations is one of the potential limitations of our method.

To estimate variogram parameters, models can be fit to the semivariograms using least-squares regression (Pardo-Igúzquiza, 1999). Our initial exploration of estimating reliable nugget parameters focused on the exponential variogram, a stable function that performs well with semivariograms that contains nugget effects. However, because some of the semivariograms that we are examining do not have well-defined sills, we use the power model (Fig. 4):

$$\hat{\gamma}(h) = c_0 + c_1 h^a \tag{4}$$

where c_0 is the nugget (°C^2), c_1 is the scale parameter (°C^2/km), and a is a dimensionless parameter known as the *shape*. The power model does not have a sill and, therefore, no finite range. The shape parameter typically has values between 0 and 2 (with $a = 1$ producing a straight line). Here, we allow the scale parameter to be unbounded to account for the possibility of an inverse semivariance relationship with lag distance (i.e., a negative scale parameter). Within the context of point-centered semivariance analysis, a negative scale parameter would indicate a location that has a degenerative form of spatial dependence and, therefore, is not spatially representative. Both the scale and nugget, therefore, are useful for diagnosing the spatial representativeness of air-temperature records. We use the power model to produce point-centered nuggets for each station over the entire period of record and for successive time periods to produce a time series of nuggets.

RESULTS

Period-of-Record Point-Centered Variograms

Point-centered semivariance was computed for 301 HCN/D stations in the central United States. Semivariance initially was calculated from October monthly DTR and the 1948–1997 period was averaged to create a time-averaged experimental semivariograms for each station. Because cloud amount and humidity are both relatively low across the region during this time (Gaffen and Ross, 1999; Hahn and Warren, 2003), local-scale spatial variability of DTR would be greatest. Local scale variations—frequently resulting from poor instrumentation exposures—may be more easily detected during strong nocturnal cooling that occurs under clear skies.

Power variogram models were fit to each point-centered experimental variogram. The frequency distribution of modeled nuggets contains a natural break at 4°C^2 with eight stations having nuggets greater than 4°C^2 (Fig. 5A). Of the 301 HCN/D stations in the central United States, 79% had nuggets less than 2.0°C^2. What constitutes a large nugget can be viewed as both network-dependent (i.e., network configuration and density) and climate-dependent (i.e., the inherent regional variability of the variable of interest). However, in nearly any context, a

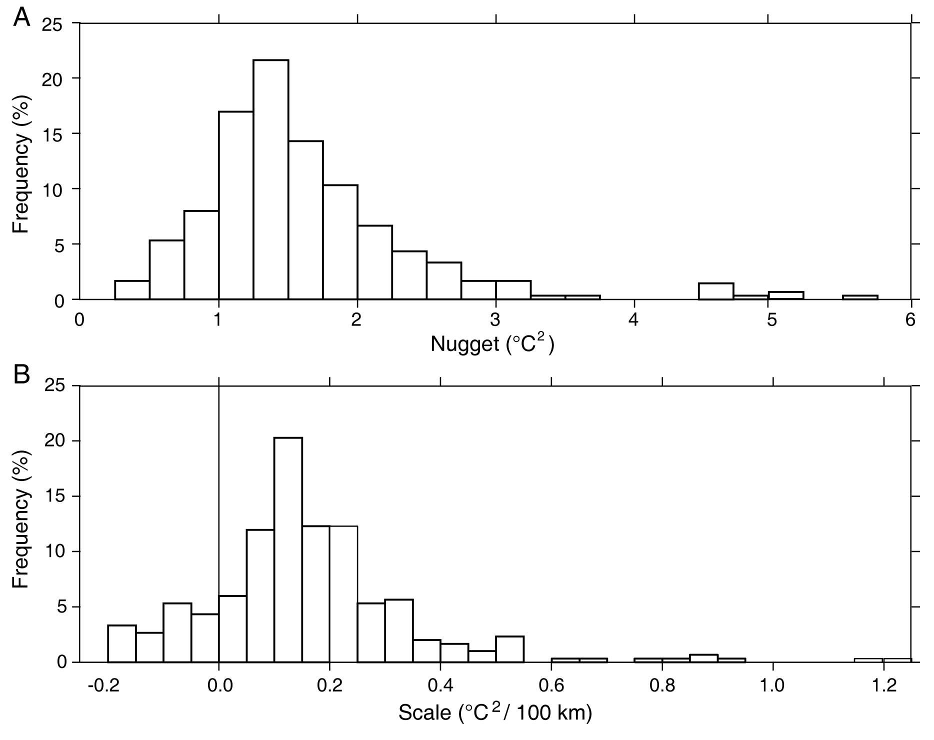

Fig. 5. Frequency distribution of period-of-record point-centered (A) nugget and (B) scale variogram parameters for 301 HCN/D stations in the central United States.

network (or location) that cannot resolve temperature variance on the order of 4°C^2 would be considered inadequate. Some of the skewness in nuggets also may be associated with stations on the edges of the study area; three stations in western Nebraska and Kansas, for example, displayed elevated nuggets. Although not a universal finding, some the large nuggets may be due to edge effects and should be examined under another geographic window.

Regarding the other parameters in the power model, the large majority of HCN/D stations have shape parameters in the range of 0.7 to 1.1, indicating quasilinear spatial dependence. However, 16% of the stations had negative scale parameters (Fig. 5B), including several stations with large nuggets. The combination of a station having a large nugget and a negative scale parameter suggests that a station is not representative of regional air-temperature patterns.

Two stations with nuggets greater than 4°C^2—Doniphan, Missouri and Racine, Wisconsin—are analyzed in more depth (Fig. 6). These stations have large nuggets (both over 5°C^2), relatively flat variograms, and negative scale parameters. For these stations, semivariance over short distances is larger than semivariance over long distances, a departure from regionalized variable theory. Although these stations also have relatively few neighbors in their first spatial lag (Table 2), and the small number of stations in the area suggests that each station is "important," these two

Table 2. Number of Neighboring Stations within Spatial Lag, Average Distance to Neighboring Stations within Spatial Lag, and the Experimental Semivariance for Point-Centered Variograms from Doniphan, MO, and Racine, WI

Doniphan, MO			Racine, WI		
Number of neighbors	Average distance (km)	Semivariance (°C^2)	Number of neighbors	Average distance (km)	Semivariance (°C^2)
6	78.2	4.60	3	98.6	5.13
12	187.4	6.74	22	184.8	5.07
32	292.9	5.30	21	293.5	4.45
36	391.0	5.97	34	394.0	4.53
45	504.5	5.31	32	505.0	4.47
43	610.7	4.66	18	607.7	4.03
44	723.7	5.16	39	726.4	4.25

stations are no more isolated than other stations in this network. While the coefficient of determination (r^2) for Racine is 0.80, r^2 for Doniphan is only 0.06. Figure 6A illustrates that scatter in semivariance over short lags is the primary reason for poor model fit at Doniphan. For period-of-record point-centered variograms, we found $r^2 \geq 0.5$ for roughly 50% of the network. Although the remainder of the network may have poor goodness of fit, nearly one-third of the stations have flat semivariance ($-1 \leq c_1 \leq 1$; Fig. 5B). In these cases, the model may be adequately describing the semivariance although the model fit is poor.

Aside from quantifying average spatial representativeness, time-averaged point-centered variograms provide only partial information on how spatial inhomogeneities may affect climate trends. Since most stations undergo changes that affect only a portion of their records, we explore an algorithm modification that captures the effect of these changes. As previously described, point-centered semivariance can be applied to multiple time steps to construct a temporal view of spatial representativeness.

Nugget Time Series

To create nugget time series for each station, we calculated point-centered semivariance for each station in the central United States subset of 301 HCN/D stations using each year's October DTR. Then, for each station, we fitted power variogram models to this "annual" point-centered semivariance. By this process, we created nugget time series for each October at every station for the period 1948–1997. As large nuggets indicate that variance near a station is unresolved by the larger-scale spatial pattern, these nugget time series (along with air-temperature time series and station histories) can be used to identify the onset and duration of spatial inhomogeneities. We also found the scale parameter provides insight to station behavior and may be combined with nugget estimates to establish thresholds for representativeness (the range may provide similar insight as different variogram models are applied). Nugget time series and ancillary information from two stations—Doniphan, Missouri and Racine, Wisconsin—are used to illustrate the application of these techniques.

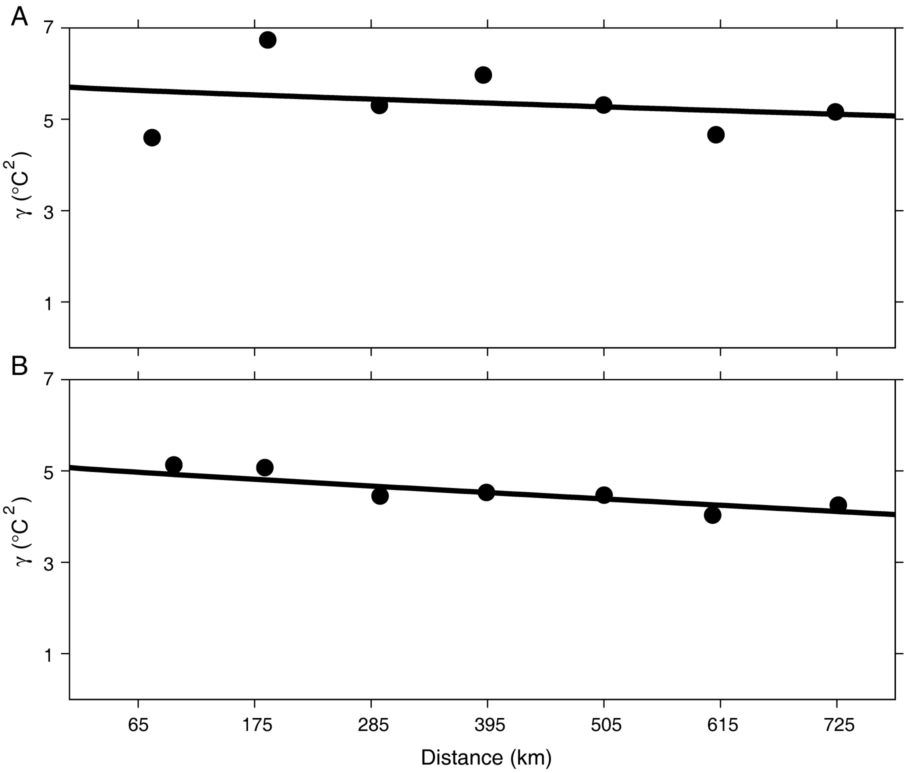

Fig. 6. Point-based semivariance (represented by dot) fitted with power variogram model (represented by thick line) for (A) Doniphan, MO and (B) Racine, WI. Spatial lags are 110 km beginning at 10 km since no station in this network has neighbors within this distance and the maximum distance between neighbors is 117.8 km. Semivariogram is plotted relative to the average distance to neighbors within each spatial lag.

Station location, observer, observation time, elevation, and instrumentation, if accurately documented, may be useful as subjective ancillary information sources. Location changes are described in station histories by distance, compass direction, and sometimes indirectly by station and observer name changes (Table 3). Since even short station moves can result in changing local siting characteristics that are as important as those associated with longer moves, the existence of a move may be as important as the actual distance. Some instrumentation changes also may lead to local siting changes. Since the MMTS (maximum-minimum temperature system; NRC, 1998) instrumentation is hard-wired to the observers dwelling, for example, it is often nearer to built structures than (older) cotton-region shelters.

Figure 7A illustrates a nugget time series as modeled from point-centered semivariance of October DTR at Doniphan. We found large nuggets occurred in 1952, 1963, 1987–1988, and 1990 and coincided with large positive anomalies in DTR time series (Fig. 7B; anomalies were calculated with respect to 1948–1997 averages

Table 3. Subset of Weather-Station History Information for Doniphan, MO, and Racine, WI[a]

Station name and state	Observer identifier	Change date	Move (km) and direction	Observation time	Elevation change (m)	Instrumentation type
Doniphan, MO	A	9/18/36	0.0	1800	0	CRS
Doniphan, MO	A	5/15/72	0.0	0700	0	CRS
Doniphan 2W, MO	B	5/30/73	2.9 WSW	0700	-12.2	CRS
Doniphan 4SE, MO	C	1/21/76	8.37 SE	0700	-3.0	CRS
Doniphan, MO	D	4/1/80	6.44 NW	0700	6.1	CRS
Doniphan, MO	D	8/20/91	0.0	0700	0	MMTS
Racine, WI	A	4/8/42	0.0	1700	0	CRS
Racine, WI	B	8/19/52	2 BS	1800	-2.1	CRS
Racine, WI	B	10/3/64	2.56 W	1800	18.3	CRS
Racine, WI	C	5/13/71	0.64 NW	1800	3.0	CRS
Racine 5W, WI	C	12/1/72	2.72 W	1800	-10.7	CRS
Racine 5W, WI	D	3/8/74	0	1800	0	CRS
Racine, WI	E	5/1/75	6.4S	1600	-19.8	CRS
Racine, WI	E	8/22/77	0.16 E	0800	3.0	CRS
Racine, WI	F	6/5/80	2.24 SE	0800	-13.7	CRS
Racine, WI	F	4/-/86	0	0800	0	MMTS

[a]CRS = cotton-region shelter with liquid-in-glass thermometer, MMTS = maximum-minimum temperature system, and B = number of blocks moved.

of October air temperatures). With the exception of 1963, large positive DTR anomalies were related to large negative minimum temperature anomalies (Fig. 7B). To examine potential causes for these large nuggets, we reviewed station histories. We learned that the station was at the same location with consistent observation practices from 1963 until 1972 (Table 3) and that site sketches depicted trees and built structures within 10 m the station. Between the sketches of 1957 and 1972 a 17-m difference between the instrumentation and the observers' residence was identified. This otherwise undocumented change suggests exposure changes at the site may have been responsible for large nuggets. In 1980, the station relocated to a backyard in a moderate density residential neighborhood. Five years after this relocation a gap in temperature records, elevated nuggets (>5°C^2), and a spike in nuggets were observed (Fig. 7). Installation of MMTS instrumentation in 1991 (Table 3) may have improved exposure or operational characteristics that were causing large nuggets (Quayle et al., 1991 estimated MMTS installation introduced average changes of -0.7°C into DTR). Throughout Doniphan's period-of-record, negative scale parameters were associated with large nuggets, suggesting a combination of large nuggets *and* negative scale for determining spatial representativeness. Although we have not shown scale time series here, we found they are generally consistent with

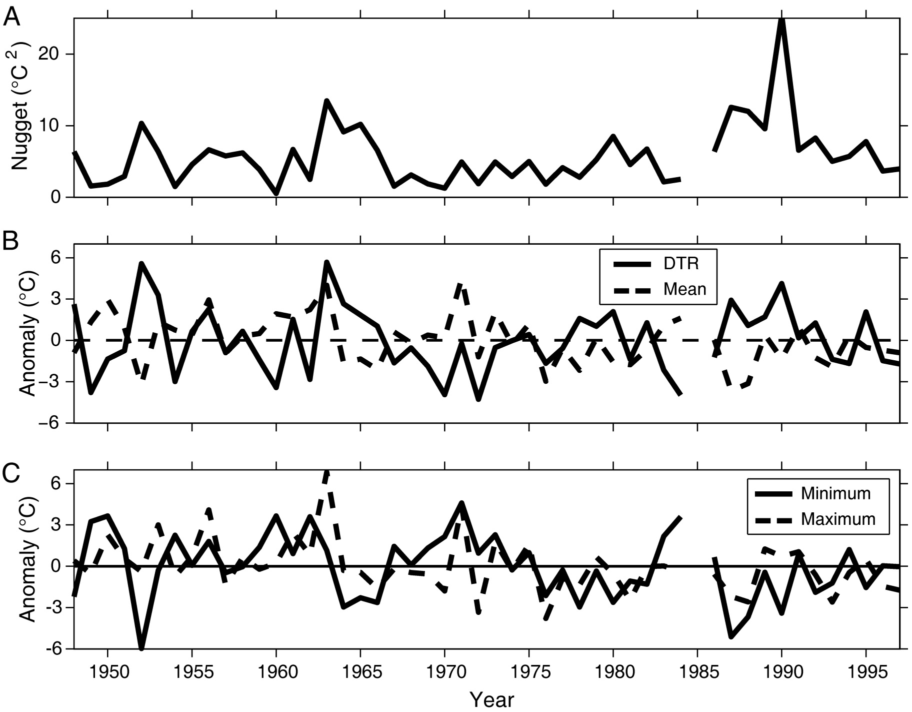

Fig. 7. Time series plots of (A) diurnal temperature range (DTR) nuggets, (B) DTR and mean temperature anomalies, and (C) minimum and maximum temperature anomalies for Doniphan, MO. Anomalies were calculated with respect to 1948–1997 averages of October air temperatures).

nugget time series and would recommend their inclusion in analyses of spatial representativeness.

Nuggets for Racine, WI became generally larger after 1975 (Fig. 8A). This increase is commensurate with station relocation (6.4 km), observer change, and a 19.8 m decrease in elevation (Table 3). The large increase in nuggets after 1975 is also commensurate with a step change in Racine's anomaly series (Figs. 8B and 8C). Between 1971 and 1980 this station underwent an operational change, on average, every 18 months. The number of changes could inhibit the detection of temporal inhomogeneities. The nature of these changes, however, directly impacted the representativeness of this station with regard to monitoring large-scale climatic change. Specifically, in 1975 the instrumentation was relocated to a rooftop about 3.5 m above the ground. In 1977 the instrumentation was moved to an adjacent building about 6.5 m above the ground. At both locations the roof exposure was a gray aggregate surface. Compounding the station modifications, in 1977 the time of daily observation changed from 1600 LST to 0800 LST (Table 3). Since this change in observation time typically causes a cooling bias (Janis, 2002), it may be partially responsible for the step change in minimum temperature anomalies (Fig. 8C). The largest impact on spatial representation of the station, however, was likely the 1980

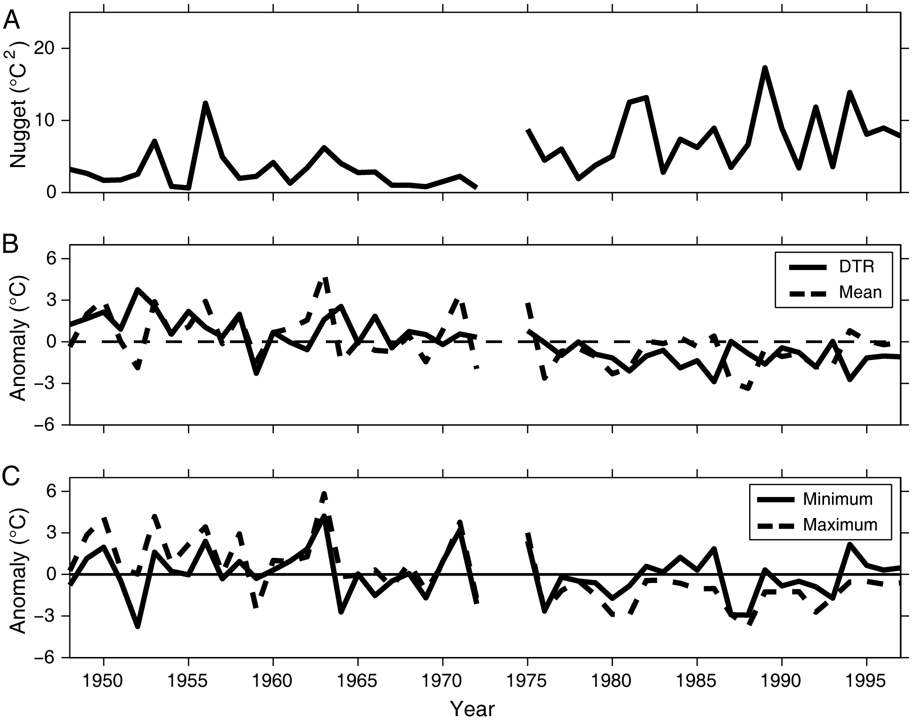

Fig. 8. Time series plots of (A) diurnal temperature range (DTR) nuggets, (B) DTR and mean temperature anomalies, and (C) minimum and maximum temperature anomalies for Racine, WI. Anomalies were calculated with respect to 1948–1997 averages of October air temperatures.

relocation of the station to within 90 m of Lake Michigan. The microscale cooling effect of the lake likely caused the substantial change in maximum temperature anomalies. After the changes of 1975, 1977, and 1980 the station was measuring thermal regimes that were inconsistent with those measured before the moves. Not only did the nugget series identify station inhomogeneities; it also identified which portion of the anomaly series was more reliable. In this case, the station became unrepresentative after 1975.

SUMMARY AND CONCLUSION

Determining spatial representativeness and network coherence is important for numerous reasons, including the attribution of air-temperature change to scale-dependent climatic forcing and the mapping of short-term climatic indices. The procedure demonstrated here places a station in the context of regional air-temperature patterns. Point-centered ensemble semivariance was calculated annually from time series of daily temperature ranges. Nugget series, derived from point-centered ensemble semivariance, were used to identify the existence and timing of spatial representativeness.

Changes to a station's operational characteristics may affect the spatial representativeness of that station as well as introduce temporal inhomogeneities into the records. Unrepresentative periods within a station's time series are not always consistent with recorded metadata or obvious changes in a station's time series. When compiling stations for analysis of climatic change, unrepresentative stations should be culled from the network, decreased in weight, or used only during those periods when their records are deemed spatially representative and temporally homogeneous. Since the effect of unrepresentative stations at sub-regional scales (i.e., states or climate divisions) or near grid nodes may be particularly detrimental, special care should be given to quality assurance when these conditions arise.

A long-term goal of this work is the creation of regionally coherent networks of station time series that minimize local-scale biases. Regionally coherent networks can be used as building blocks for analyses of climatic change monitoring because they seek to minimize smaller scales of spatial climatic variability and represent regional responses to climatic change. Assessing regional climatic variability and its causes is important for agricultural yield scenarios as well as understanding human and environmental impacts and responses to climatic change. Results obtained for the central United States are likely representative of and transferable to adjacent areas. Techniques and methods described can be applied to most of the humid eastern and southern United States. However, in areas with large spatial gradients in air temperature and DTR (e.g., the western United States), the procedures may need modification (e.g., using anomalies) to produce meaningful nugget time series.

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