Published January, 1988



# Spatial Variability of Remotely Sensed Surface Temperatures at Field Scale

S. R. YATES,* A. W. WARRICK, A. D. MATTHIAS, AND S. MUSIL

## ABSTRACT

**Bare soil surface temperatures (BST) and crop canopy temperatures (CCT) were collected from a 1-ha field in central Arizona using an infrared thermometer to determine whether they were spatially correlated. The measurements were taken from a two-dimensional random sampling pattern for selected dates and times to investigate the spatial and temporal distribution. Three measures of the correlation distance including two integral scales were calculated. Kriging, which produces the best linear unbiased estimator, was used to show the spatial pattern of the BST and CCT in the field on selected dates. The results indicate that the BST and CCT are spatially dependent random functions with integral scales that varied from 2 to 15 m for wet and dry conditions, respectively. The autocorrelation as the lagged distance approaches zero was greater than 0.4 except under wet soil conditions, where the autocorrelation for the CCT was found to be lower. The results are important because, to date, no geostatistical study has shown that the CCT is a spatially dependent random function.**

S.R. Yates, U.S. Salinity Lab., USDA-ARS, Dep. of Soil and Environmental Sciences, Univ. of California, Riverside, CA 92521; and A.W. Warrick, A.D. Matthias, and S. Musil, Dep. of Soil and Water Science, Univ. of Arizona, Tucson, AZ 85721. Contribution from the Univ. of Arizona Agric. Exp. Stn., Tucson. Arizona Agric. Exp. Stn. Paper no. 4316. Received 6 Nov. 1986. *Corresponding author.

Published in Soil Sci. Soc. Am. J. 52:40–45 (1988).

***Additional Index Words:*** **geostatistics, kriging, semivariogram, integral scales.**

RECENTLY, METHODS have been developed that use surface temperatures as an indicator of the state of a particular property. Examples include methods for determining the moisture status of plants (Wiegand and Namken, 1966; Tanner, 1963; Jackson, 1982, 1983; Howell et al., 1984), the crop yield (Diaz et al., 1983; Gardner et al., 1981), and the rate of evapotranspiration (Jackson et al., 1983; Hatfield et al., 1983).

For purposes of water stress detection or yield prediction over the entire field, the spatial distribution of the crop canopy temperature (CCT) is an important consideration. For example, if the sites chosen for sampling are not characteristic of the entire field, errors may be introduced and propagate throughout the season. Thus, even small errors can accumulate and adversely affect the results. Knowledge of the spatial distribution can be useful in determining the appropriate statistics to be used in the analysis as well as aiding the determination of efficient sampling schemes.

Few studies have been concerned with the spatial variability of CCT. Exceptions include Hatfield et al.

(1982), who measured the CCT in a large agricultural field using an airborne scanner; Hatfield (1983) and Hatfield et al. (1984), who measured the CCT for cotton (*Gossypium hirsutum* L.) and grain sorghum [Sorghum bicolor (L.) Moench] along transects up to 100 m in length. In each of these geostatistical studies, the CCT was found to be randomly distributed in space.

Evidence that the CCT may be spatially distributed was found qualitatively by Soer (1980), who estimated the regional evapotranspiration and soil moisture content from remotely sensed CCT. Thermal radiation data over an area of approximately 25 km$^2$ were obtained and the CCT over discrete ranges were printed out by pixel. Millard et al. (1978) investigated crop water stress in wheat (*Triticum aestivum* L.) fields near Phoenix, AZ, and showed (see their Plates 1–4) that the CCT is a spatially dependent random variable.

The bare soil temperature (BST), another remotely sensed surface temperature, has been used to estimate the evaporation and moisture status of the soil (Ben-Asher et al., 1983; Vauclin et al., 1982). Vauclin et al. (1982) determined the autocorrelation for BST for two transects and found that the BST was spatially dependent with a semivariogram range that was approximately 10 to 15 m.

The purpose of this study was to investigate the spatial variability of BST and CCT and determine if the CCT (for cotton) obtained from a furrow-irrigated field is a spatially correlated random function.

## MATERIALS AND METHODS

The field site was an approximately 1-ha field located at the Univ. of Arizona's Maricopa Agric. Ctr., east of Maricopa, AZ. The field was approximately 260 m long and 40 m wide, and the soil is classified as a fine-loamy, mixed, hyperthermic, Typic Natriargid. There were 35 rows (oriented north–south) separated by approximately 1 m that extended down the field to the west. The field was furrow irrigated with irrigation commencing from the east.

Bare soil temperatures were collected in situ on 25 May 1984 and 11 June 1984 prior to the emergence of the cotton plants. Crop canopy temperatures were collected 5 d between 5 June 1984 and 20 Aug. 1984. A hand-held Everest Interscience Model 112 infrared thermometer (IRT) was used that has a 15° field of view, spectral bandpass of 8 to 14 μm, ±0.1 °C resolution, and ±0.5 °C accuracy.

The sampling scheme, shown in Fig. 1, consisted of a total of 93 randomly sampled locations (points) and an additional nine systematically located sites (crosses) evenly spaced down the center of the field, providing a total of 102 sampling locations. At each location a sample was taken by holding the IRT in a westerly direction at approximately 45° from the horizontal. The importance of the view angle on the temperature has been shown by O'Toole and Real (1984). The region sampled was an ellipse with an approximate area, length, and width of 0.2 m$^2$, 0.6 m, and 0.4 m, respectively. Each datum value consisted of an average of five readings taken over approximately 5 s.

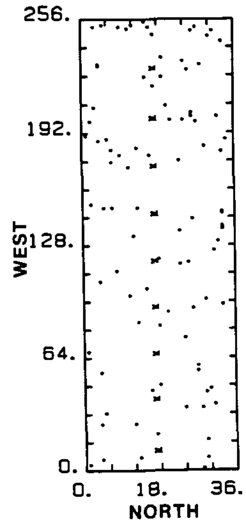


**Fig. 1. Field sampling scheme for the Maricopa Agric. Ctr. Ninety-three random (•) and nine systematic (x) sampling locations. The *x* and *y* axes are in meters.**

Sampling was undertaken at various times daily to determine if the spatial correlation existed throughout the day. For the two data sets used for kriging (i.e., 27 May and 16 July), the duration of the sampling period was approximately 1 h, and the midpoint of the sampling interval was about 1230- and 1245-h MST (mountain standard time), respectively.

For the two data sets (i.e., 5 July and 9 July) that were taken early or late in the day, a correction was applied to account for changes in the heating of the soil or plant canopy due to changes in the sun angle and air temperature. The formula used to calculate the corrected temperature, $T_{corr}$, was

$$T_{corr} = T_{uncorr} + \overline{\Delta T}\,[(\bar{t} - t)/(t_f - t_i)] \qquad [1]$$

where $T_{uncorr}$ is the uncorrected temperature, $\overline{\Delta T}$ is the average change in temperature over the sampling interval and $t$, $\bar{t}$, $t_f$ and $t_i$ are the sample, average, final, and initial times, respectively. Samples were taken at five to 10 locations, both at the beginning and end of the sampling period, to determine the average change in temperature for the sampling interval. It is implicitly assumed in Eq. [1] that the change in temperature over the sampling interval is approximately linear. When this is not true (i.e., for a long sampling duration), use of Eq. [1] would introduce a bias into the data.

Descriptive statistics for the data sets are given in Table 1. As shown, the mean value varied from approximately

**Table 1. Descriptive statistics for Maricopa Agric. Ctr. data sets.**

| | | | Surface temperature (°C) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Date (1984) | Type | Time | Mean | Var | CV | Max | Min | *KS*† | $KS_t$‡ | N |
| May 27 | BST | 1230 | 63.9 | 3.08 | 2.76 | 68.2 | 61.0 | 0.121 | 0.116 | 92 |
| June 11 | BST | 1115 | 46.1 | 1.08 | 2.27 | 48.6 | 43.4 | 0.118 | 0.122 | 90 |
| July 05 | CCT | 1600 | 35.5 | 2.77 | 4.74 | 41.7 | 32.8 | 0.134 | 0.124 | 59 |
| July 09 | CCT | 0830 | 27.7 | 0.53 | 2.64 | 30.3 | 26.0 | 0.059 | 0.064 | 86 |
| July 12 | CCT | 1100 | 30.2 | 1.05 | 3.40 | 32.4 | 27.3 | 0.056 | 0.054 | 81 |
| July 16 | CCT | 1245 | 29.4 | 1.02 | 3.45 | 32.5 | 27.9 | 0.092 | 0.086 | 96 |
| July 23 | CCT | 1045 | 30.2 | 0.42 | 2.18 | 31.7 | 28.9 | 0.110 | 0.106 | 38 |
| Aug. 08 | CCT | 1300 | 32.9 | 2.94 | 5.24 | 36.8 | 25.3 | 0.166 | 0.180 | 92 |
| Aug. 20 | CCT | 0945 | 30.2 | 0.78 | 2.96 | 32.7 | 28.6 | 0.084 | 0.080 | 39 |

† Kolomogorov test statistic (data not transformed). ‡ Kolomogorov test statistic (natural logarithmic transformed data).

46.1 to 63.9 °C for the BST and 27.7 to 35.5 °C for the CCT. The coefficients of variation were less than about 3.1% for all the data sets, which is consistent with values reported in the literature (i.e., Hatfield et al., 1982; Hatfield et al., 1984). The Kolomogorov-Smirnov test statistics (Sokal and Rohlf, 1981) were calculated and reported in Table 1. In general, the data sets were found to be neither normally nor lognormally distributed.

## The Semivariogram and Covariance Functions

For an intrinsic random function, $Z(x)$, sampled at $n$ locations: $x_1, x_2, \ldots, x_n$, the estimate for the semivariogram $\gamma^*(h)$, with respect to the separation distance, $h$, between all the pairs of locations is given by (Journel and Huijbregts, 1978)

$$\gamma^*(h) = \sum_{i=1}^{N(h)} [Z(x_i + h) - Z(x_i)]^2/2N(h) \qquad [2]$$

where $Z(x_i)$ is the sample value and $N(h)$ is the number of couples used in the estimation process for a lagged distance $h$. Under second-order stationarity, the covariance, $C(h)$, and the correlation, $\rho(h)$, functions can be written in terms of the semivariogram as

$$C(h) = C(0) - \gamma(h) \qquad [3]$$

and

$$\rho(h) = C(h)/C(0) = 1 - \gamma(h)/C(0) \qquad [4]$$

where $C(0)$ is the covariance at zero lag, that is, the variance. Models for the covariance or correlation functions can be found by incorporating the spherical semivariogram model

$$\gamma(h) \qquad [5]$$

$$= \begin{cases} 0; & h = 0 \\ C_0 + C_1\,[1.5\,h/a - 0.5(h/a)^3]; & 0 < h \leq a \\ C_0 + C_1; & h > a \end{cases}$$

into Eq. [3] or [4], where $C_0$, $C_1$ and $a$ are the nugget, sill minus nugget, and range of the semivariogram, respectively.

To investigate the distances for which the BST and CCT are spatially correlated, three spatial correlation measures were calculated. The first two are the integral scales, $\lambda$ and $\lambda^*$, which were used by Bakr et al. (1978)

$$\lambda = \int_0^\infty \rho(h)\,dh \qquad [6]$$

and Russo and Bresler (1981), respectively,

$$\lambda^* = \left[2\int_0^\infty h\rho(h)\,dh\right]^{1/2}. \qquad [7]$$

The third measure is the zone of influence described by Gajem et al. (1981) and provides a conservative test of the hypothesis that the autocorrelation is zero using the $Z_k$ statistic (Davis, 1973). Within the zone of influence, where the values are correlated, the test statistic is greater than the two-tailed deviation, $Z_\alpha$. For a given probability level, $\alpha$, the zone of influence can be found by finding the $h$ that satisfies

$$Z_\alpha = Z_k = \rho(h)\,(n - h/dh)^{1/2} \qquad [8]$$

where $n$ is the number of lags, and $dh$ is the distance between lags.

## Punctual Kriging

For a random function, $Z(x)$, defined on a point support and sampled in two-dimensional space at the points $x_1, x_2, \ldots, x_n$, the ordinary kriging estimator $Z^*(x_0)$ for a location $x_0$ is given as a linear combination of the sample values (Journel and Huijbregts, 1978)

$$Z^*(x_0) = \sum_{i=1}^{n} w_i\,Z(x_i). \qquad [9]$$

To ensure an unbiased estimate (i.e., $E[Z^*(x_0) - Z(x_0)] = 0$) requires the constraint that the sum of the weights, $w_i$, must be equal to unity.

The ordinary kriging equations result from minimization of the variance of errors where a Lagrange multiplier, $\mu$, is introduced into the minimization process due to the constraint on the weights (Journel and Huijbregts, 1978; Vauclin et al., 1983).

This results in the following kriging equation:

$$\sum_{i=1}^{n} w_i\,C(x_i - x_j) - \mu = C(x_0 - x_j); \qquad [10]$$

$$j = 1,2,3,\ldots,n$$

and kriging variance (or estimation variance)

$$\sigma_k^2 = C(0) + \mu - \sum_{i=1}^{n} w_i\,C(x_0 - x_i). \qquad [11]$$

# RESULTS AND DISCUSSION

Shown in Fig. 2A and 2B are the sample covariance functions calculated from the BST data sets for 27 May and 11 June, respectively. A spherical semivariogram model (lines) was applied to the sample covariance function using Eq. [3], and the constants were validated using the jackknifing procedure (Vauclin et al., 1983; Russo, 1984a, b). The results are given in Table 2 and include the reduced mean, $R_\mu$, and reduced variance, $R_{\sigma^2}$, which should be approximately 0 and 1, respectively (see Vauclin et al., 1983 and Russo, 1984a, b), for a "valid" semivariogram. Directional semivariograms were calculated, but the shape of the field (260 by 40 m) caused erratic results in the short direction due to insufficient numbers of pairs for each lagged distance. Therefore, the semivariograms were assumed to be isotropic.

The sample covariance function for each of the BST data sets indicates that the BST is a spatially correlated random function with a range of about 25 to 35 m. Also, calculating the sample semivariogram (not shown) shows a well-defined "sill" (which is an indication that the random variable is stationary; see Journal and Huijbregts, 1978) as well as the existence of a small nugget. This observation was also "verified" using the jackknifing procedure.

The sample and model covariance functions for the CCT are shown in Fig. 3 and demonstrate that the CCT exhibits spatial dependence (although for the 9 July data set the spatial correlation is not very strong). In an attempt to characterize how strongly the CCT is spatially correlated, the autocorrelation as the lagged distance approaches zero (i.e., as $h \rightarrow 0^+$), $\rho(0^+)$, was calculated. Since the autocorrelation is unity for perfect correlation between the samples, or zero if they are randomly distributed, the autocorrelation as the lagged distance approaches zero gives a qualitative measure of the maximum expected correlation for a given separation distance and the observed nugget ef-

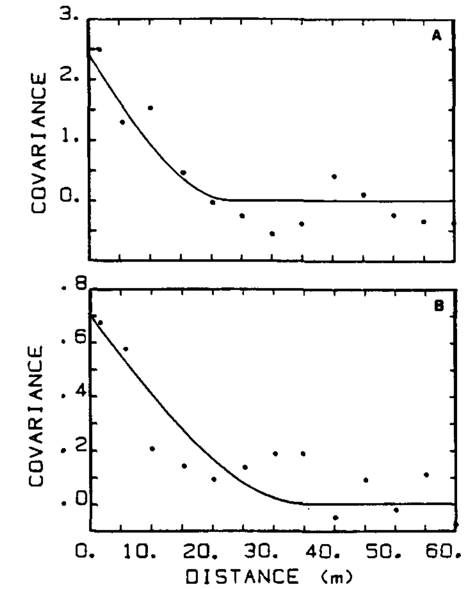


Fig. 2. Covariance functions for the bare soil temperature. (A) and (B) correspond to the 27 May and 16 July data sets, respectively.

fect. The method used for this calculation was to divide the value of the model covariance function as $h \rightarrow 0^+$ by either the sill of the semivariogram (column 5, Table 3) or the sample variance (column 6, Table 3). Therefore, $\rho(0^+)$ is less than $\rho(0)$ whenever a nugget is present.

Because the points for the sample covariance are discrete and there is some subjectivity in determining the constants using the jackknifing procedure, the results of Table 3 are only approximate. What is important to note is that, in general, as the lagged distance approaches zero, the CCT is autocorrelated at a level typically >0.4.

Also shown in Table 3 are the integral scales ($\lambda$ and $\lambda^*$) and the zone of influence (ZI) calculated using Eq. [6] to [8]. These values show that the distance for which the BST is correlated is between 6 and 16 m, depending on which method and date are used.

**Table 2. Summary of covariance models for Maricopa Agric. Ctr. data sets.**

| Date (1984) | Type | Model† | Nugget | Sill | Range | $R_\mu$‡ | $R_\sigma$‡ |
|---|---|---|---|---|---|---|---|
| May 27 | BST | sph. | 0.70 | 3.10 | 23.0 | 0.029 | 1.083 |
| June 11 | BST | sph. | 0.35 | 1.05 | 35.0 | 0.052 | 1.013 |
| July 05 | CCT | sph. | 0.85 | 3.05 | 40.0 | 0.003 | 1.048 |
| July 09 | CCT | sph. | 0.47 | 0.55 | 40.0 | −0.005 | 0.998 |
| July 12 | CCT | sph. | 0.65 | 1.10 | 18.0 | 0.025 | 1.019 |
| July 16 | CCT | sph. | 0.17 | 1.09 | 28.0 | 0.021 | 1.068 |
| Aug. 08 | CCT | sph. | 1.50 | 2.50 | 25.0 | −0.081 | 1.030 |

† Sph. indicates a spherical model (see Journel and Huijbregts, 1978).
‡ $R_\mu$ and $R_\sigma^2$ are the reduced mean and variance, respectively, from the jackknifing technique (Vauclin et al., 1983; Russo, 1984a, b).

**Table 3. Autocorrelation as the lagged distance approaches zero, $0^+$, for Maricoopa Agric. Ctr. data sets.**

| | | Surface temperature (°C) | | | | | | ZI |
|---|---|---|---|---|---|---|---|---|
| Date | Type | Sill | Var | $\varrho(0^+)$† | $\varrho(0^+)$‡ | $\lambda$ | $\lambda^*$ | ($\alpha$ = 0.05) |
| May 27 | BST | 3.10 | 3.08 | 0.774 | 0.779 | 6.7 | 9.1 | 11.7 |
| June 11 | BST | 1.05 | 1.08 | 0.667 | 0.648 | 8.8 | 12.8 | 16.3 |
| July 05 | CCT | 3.05 | 2.77 | 0.721 | 0.777 | 10.8 | 15.2 | 15.1 |
| July 09 | CCT | 0.55 | 0.53 | 0.145 | 0.130 | 2.2 | 6.8 | 0.0 |
| July 12 | CCT | 1.10 | 1.05 | 0.409 | 0.430 | 2.8 | 5.1 | 2.5 |
| July 16 | CCT | 1.09 | 1.02 | 0.844 | 0.902 | 8.9 | 11.5 | 12.1 |
| Aug. 08 | CCT | 2.50 | 2.94 | 0.400 | 0.340 | 3.8 | 7.1 | 3.2 |

† Values calculated by dividing model covariance function by the sill of the semivariogram.
‡ Values calculated by dividing model covariance function by the sample variance.

The results for the CCT are more varied. For three data sets, the correlation distances are less than about 5.0 m. For the other two CCT data sets, the correlation distances range from 9 to 15 m, which is similar to the behavior of the BST. At the $\alpha$ = 0.05 level, the zone of influence from Eq. [8] was found to be zero for the 9 July data set. Unlike the integral scales, the zone of influence does not involve an integration, therefore an autocorrelation function with a large nugget value may produce a zero value for the correlation distance. This is an example of the conservative nature of the test (Davis, 1973).

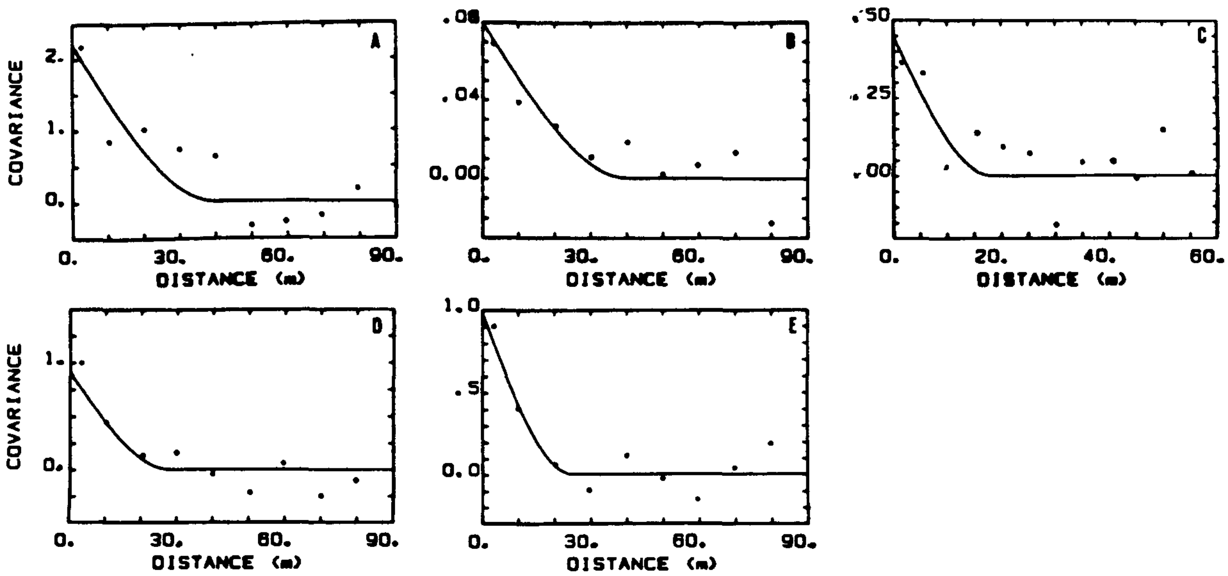


Fig. 3. Covariance functions for crop canopy temperature. (A), (B), (C), (D), and E correspond to the 5 July, 9 July, 12 July, 16 July, and 8 August data sets, respectively.

The reason the 9 July data set does not show a strong autocorrelation is probably due to a reduced variability because of a recent irrigation (irrigation was on 6 July and the soil surface was reported to be wet on 9 July). This effect of reduced variability for wet conditions was reported by Aston and van Bavel (1972) and Hatfield et al. (1984). Another possibility may be the time the data were collected (i.e., 0738–0942 h), since the effect of the correction for the heating due to changes in sun angle could have introduced errors into the covariance function.

## Estimates of the Bare Soil Surface Temperature and Crop Canopy Temperature

To show the spatial pattern of the BST and CCT in the field, 231 estimates were generated on a 6- by 8-m grid system using the ordinary punctual kriging method outlined above. The five nearest data values to an estimation point were used in kriging an estimate. The maximum allowed radius for a point to be included in the estimation process was 23 and 28 m for the BST and CCT, respectively. The covariance functions used in the estimation process are given in Table 2.

Shown in Fig. 4A is the spatial distribution of the BST in the field. Generally, the north side of the field ($x$ = 36 m) is cooler in temperature than the south side with a difference of about 3 to 4 °C. The north and south sides have temperatures of about 62 and 65 to 66 °C, respectively. Along the east side of the field ($y$ = 0 m) the temperature is approximately constant at 63.5 °C. The northwest and southwest ends of the field are approximately 65.5 and 63 to 64 °C, respectively. In the center of the field the temperatures tend to follow the furrows and seem to show an anisotropic behavior, although this could not be quantified from the covariance functions.

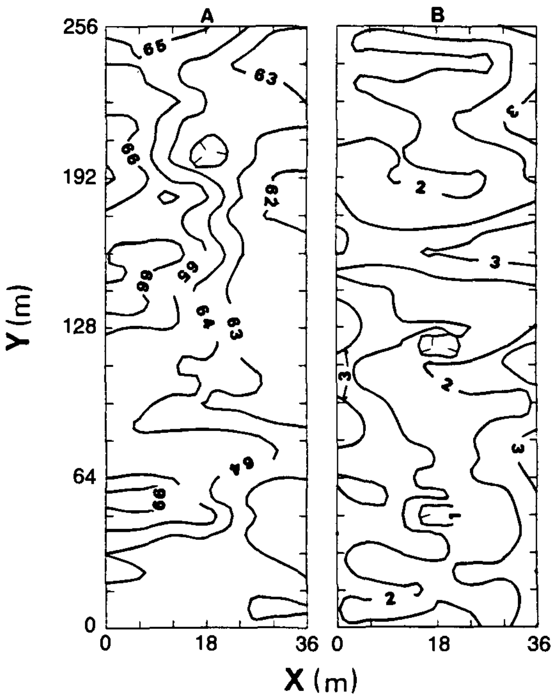


**Fig. 4. Estimated soil temperature (A) and the associated kriging variance (B) for the 27 May data set.**

The spatial pattern of the CCT in the field, which tends to be more uniform than the BST is shown in Fig. 5A. Most of the field temperature was between 28 and 29.5 °C except for the west end of the field, which was about 32 °C.

The temperature distribution for the BST and CCT in the field may be explained by two factors. First is the irrigation methodology. Irrigation commenced from the east end of the field, which would produce a soil-water depth profile that would be wetter at a greater depth at the east end of the field compared to the west end. Therefore, it would be expected that at some point during the drying cycle after irrigation, the west end of the field would become warmer than the east end. In addition, the prevailing winds in this area move from the southwest toward the northeast, and as the warm, dry air moves across the field, evaporative losses from the soil near the southwest edge of the field are greater than the northeast. As the soil dries, the surface temperature increases due to diminishing evaporative cooling compared to other parts of the field.

The contour maps of the estimation variance for the BST and CCT are shown in Fig. 4B and 5B. The change in the estimation variance with position is a reflection of the sample density in a particular region. The deep depressions at locations (18, 48) and (18, 120) are due to the exact interpolative properties inherent with kriging.

## Determining Sample Numbers

Hatfield et al. (1984) indicated that for a random and normally distributed variable, the number of samples necessary to estimate the mean value with a given level of certainty is given by

$$N = t^2 s^2 / d^2 \quad [12]$$

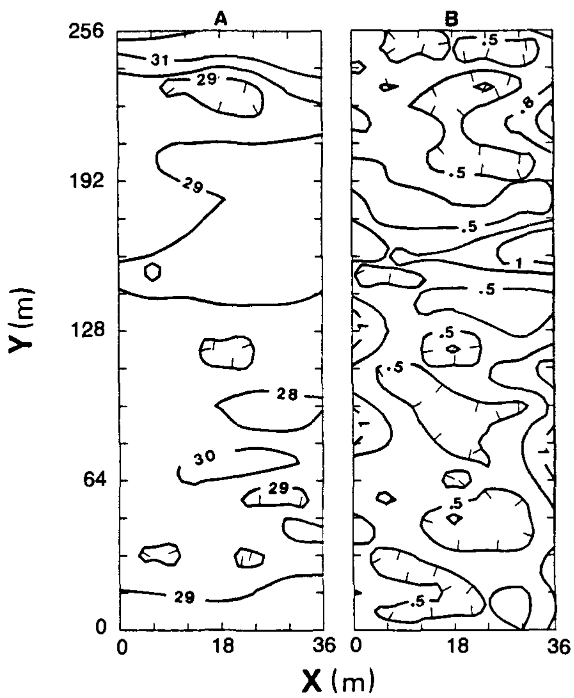


**Fig. 5. Estimated crop canopy temperature (A) and the associated kriging variance (B) for the 16 July data set.**

where $t$ is the students $t$ test variate, $s^2$ is the sample variance, and $d$ is the confidence interval.

Equation [12] may also be used for a spatially dependent and normally distributed random variable if the samples are taken from locations that are separated from each other by sufficient distance so that the samples are independent. This can be accomplished by using either the correlation scales or the range of the semivariogram. In general, it was found that the correlation scales suggest that independence between samples occurs at distances that are less than the range of the semivariogram. Therefore, knowledge of the semivariogram or the correlation scales is important to assure that the samples used to determine $N$ are spatially independent. If the semivariogram is unknown, it may be incorrectly assumed that the random variable is spatially uncorrelated.

## CONCLUSIONS

Spherical semivariogram models were calculated for five of the CCT data sets with nuggets that varied from 0.17 to 1.5 °C$^2$, sills from 0.55 to 3.1 °C$^2$, and ranges from 18 to 40 m. In general, the CCT had an autocorrelation as the lagged distance approached zero of $>0.4$, with only one data set having a lower value of 0.15. This low value for the autocorrelation was attributed to wet-soil conditions and the time of sampling. The correlation zones for the BST and CCT ranged from 6 to 16 and 2 to 15 m, respectively.

It was concluded from this study that the CCT may exhibit spatial correlation. This result differs from those of Hatfield et al. (1982), Hatfield (1983), and Hatfield et al. (1984). Therefore, the spatial correlation should be considered in the design of experiments and the analysis of CCT data.

Although more information is available from a geostatistical analysis, if only an estimate of the population mean is required it is suggested that the distance separating the samples be as large as possible. This will increase the likelihood that the samples will be spatially independent. If the semivariogram is not determined, it will remain unknown whether the samples used in the calculation were truly independent.

The results of this study indicate that estimation methods such as kriging can be used if estimated values of the CCT are required at unsampled locations. Also, in terms of sampling efficiency, if the CCT is spatially correlated, then other more advanced estimation techniques such as cokriging (Vauclin et al., 1983; Yates and Warrick, 1987), disjunctive kriging (Yates et al., 1985a, b), or disjunctive cokriging (Yates, 1986) may be useful in reducing the number of samples required for a given estimation quality or for increasing the amount of information available.

## ACKNOWLEDGMENT

We wish to thank Jeff Meyer and Jack Watson for their assistance in the collection of the data.

## REFERENCES


Aston, A., and C.H.M. van Bavel. 1972. Soil surface water depletion and leaf temperature. Agron. J. 646:368–373.

Bakr, A.A., L.W. Gelhar, A.L. Gutjahr, and J.R. McMillan. 1978. Stochastic analysis of variability in subsurface flows: I. Comparison of one- and three-dimensional flows. Water Resour. Res. 14:263–271.

Ben-Asher, J., A.D. Matthias, and A.W. Warrick. 1983. Assessment of evaporation for bare soil by infrared thermometry. Soil Sci. Soc. Am. J. 47:185–191.

Davis, J.C. 1973. Statistics and data analysis in geology. John Wiley & Sons, Inc., New York.

Diaz, R.A., A.D. Matthias, and R.J. Hanks. 1983. Evapotranspiration and yield estimation of spring wheat from canopy temperature. Agron. J. 75:805–810.

Gajem, Y.M., A.W. Warrick, and D.E. Myers. 1981. Spatial structure of physical properties of a Typic Torrifluvent soil. Soil Sci. Soc. Am. J. 45:709–715.

Gardner, B.R., B.L. Blad, D.P. Garrity, and D.G. Watts. 1981. Relationships between crop temperature, grain yield, evapotranspiration and phenological development in two hybrids of moisture stressed sorghum. Irrig. Sci. 2:213–224.

Hatfield, J.L. 1983. Spatial and temporal variabilities in air and surface temperature. ASAE Winter Meeting, Chicago. 13–16 December. Am. Soc. Agric. Eng., St. Louis, MO.

Hatfield, J.L., J.P. Millard, and R.G. Goettelman. 1982. Variability of surface temperature in agricultural fields of central California. Photogramm. Eng. Remote Sens. 48:1319–1325.

Hatfield, J.L., A. Perrier, and R.D. Jackson. 1983. Estimation of evapotranspiration at one time-of-day using remotely sensed surface temperatures. Agric. Water Manage. 7:341–350.

Hatfield, J.L., M. Vauclin, S.R. Vieira, and R. Bernard. 1984. Surface temperature variability patterns within irrigated fields. Agric. Water Manage. 8:429–437.

Howell, T.A., J.L. Hatfield, H. Yamada, and K.R. Davis. 1984. Evaluation of cotton canopy temperature to detect crop water stress. Trans. ASAE 27:84–88.

Jackson, R. 1982. Canopy temperature and crop water stress. p. 43–85. *In* Advances in Irrigation. Vol. 1. Academic Press, London.

Jackson, R. 1983. Assessing moisture stress in wheat with hand-held radiometers. Soc. Photo-Opt. Instrum. Eng. 356:138–142.

Jackson, R., J.L. Hatfield, R.J. Reginato, S.B. Idso, and P.J. Pinter. 1983. Estimation of daily evapotranspiration from one time-of-day measurements. Agric. Water Manage. 7:351–362.

Journel, A.G., and Ch.J. Huijbregts. 1978. Mining geostatistics. Academic Press, New York.

Millard, J.P., R.D. Jackson, R.C. Goettelman, R.J. Reginato, and S.B. Idso. 1978. Crop water-stress assessment using an airborne thermal scanner. Photogramm. Eng. Remote Sens. 44:77–85.

O'Toole, J.C., and J. Real. 1984. Canopy target dimensions for infrared thermometry. Agron. J. 76:863–865.

Russo, D. 1984a. Statistical analysis of crop yield-soil water relationships in heterogeneous soil under trickle irrigation. Soil Sci. Soc. Am. J. 48:1402–1410.

Russo, D. 1984b. A geostatistical approach to solute transport in heterogeneous fields and its applications to salinity management. Water Resour. Res. 20:1260–1270.

Russo, D., and E. Bresler. 1981. Soil hydraulic properties as stochastic processes: I. An analysis of field spatial variability. Soil Sci. Soc. Am. J. 45:682–687.

Soer, G.J.R. 1980. Estimation of regional evapotranspiration and soil moisture conditions using remotely sensed crop surface temperatures. Remote Sens. Environ. 9:27–45.

Sokal, R.R., and F.J. Rohlf. 1981. Biometry. 2nd ed. W.H. Freeman & Co., New York.

Tanner, C.B. 1963. Plant temperatures. Agron. J. 55:210–211.

Vauclin, M., S.R. Vieira, R. Bernard, and J.L. Hatfield. 1982. Spatial variability of surface temperature along two transects of a bare soil. Water Resour. Res. 18:1677–1686.

Vauclin, M., S.R. Vieira, G. Vachaud, and D.R. Nielsen. 1983. The use of cokriging with limited field soil observations. Soil Sci. Soc. Am. J. 47:175–184.

Wiegand, C.L., and L.N. Namken. 1966. Influence of plant moisture stress, solar radiation, and air temperature on cotton leaf temperatures. Agron. J. 58:582–586.

Yates, S.R. 1986. Disjunctive kriging III. Cokriging. Water Resour. Res. 22:1371–1376.

Yates, S.R., and A.W. Warrick. 1987. Estimating soil water content using cokriging. Soil Sci. Soc. Am. J. 51:23–30.

Yates, S.R., A.W. Warrick, and D.E. Myers. 1985a. Disjunctive kriging. I. Estimation and conditional probability. Water Resour. Res. 22:615–621.

Yates, S.R., A.W. Warrick, and D.E. Myers. 1985b. Disjunctive kriging. II. Examples. Water Resour. Res. 22:623–630.