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[1] Department of Agricultural Engineering, Iwate University, Morioka, Japan
[2] Project Research Team, National Agriculture Research Center, Tsukuba, Japan

Use of Cokriging to Estimate Surface Air Temperature from Elevation

T. Ishida[1] and **S. Kawashima**[2]

With 8 Figures

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Summary

Surface air temperature in central Japan was predicted from the temperature recordings from sensors in the Automated Meteorological Data Acquisition System (AMeDAS), using seven different procedures: the usual simple and universal kriging and cokriging estimators, the traditional regression analysis and the inverse distance weighted method. The cokriging estimator integrated digital elevation data as well as the air temperature readings. The performance of the procedures was evaluated and compared using cross-validation.

The kriging estimator provided a better estimate than the traditional regression analysis that treated the data as spatially independent observations. The kriging estimate was also better than the inverse distance weighted method. Further improvement in the estimation accuracy was achieved by using cokriging procedures because of high correlation of air temperature with elevation. The accuracy of spatial prediction decreased due to nocturnal cooling in winter and daytime heating in summer. This decrease implies that a strong radiation balance at the surface, whether positive or negative, causes a relatively short-range variation in surface air temperature through the effects of local environments.

1. Introduction

Surface air temperatures tend to have more similar values as more neighboring data are compared. The extent of this similarity depends on spatial dependence of surface air temperature. Geostatistical analyses can provide a way to quantify and utilize the spatial dependence for practical purposes of estimating surface air temperature. The geostatistical analysis has two main stages: a spatial analysis of data with results in the form of semivariograms, and interpolation, i.e., local estimation, using the semivariogram with a certain procedure. The previous paper (Kawashima and Ishida, 1992) showed that the first stage is applicable for surface air temperature data obtained from the Automated Meteorological Data Acquisition System (AMeDAS). Thus, this paper examined whether the second stage is applicable for the same data.

Several studies have been performed on the interpolation of the AMeDAS data. Kurihara and Murakami (1982) estimated a monthly mean air temperature at intersections of a 1 km square grid in Hiroshima Prefecture in western Japan, using a multivariate regression method with topographical factors as independent variables. This method attained a satisfactory accuracy for the interpolation. However, Kawashima (1990) could not obtain a similar degree of accuracy for the hourly data using the same method as Kurihara and Murakami (1982). This difference in accuracy can be explained as the result of differences in the effects of the climatic parameter on air temperature between the two periods. Many external and internal factors are intricately related to the spatial distribution of surface air temperature on a local scale. The external factors are, for example, solar radiation, precipitation, atmospheric movement on a larger scale and various sizes of eddies. On the other hand, some internal factors are topography, vegetation and soil wetness. Hourly air temperature distribution is directly influenced by the external factors. However, mean air temperature distributions during longer periods, such as monthly mean air temperature, are mainly affected by the internal factors because spatial variations in the external factors are averaged over longer periods and thus their effects on spatial prediction of the mean air temperature disappear. Thus, for multiple regression methods for interpolation using only topographical factors, interpolation errors are larger for hourly air temperature than for the mean air temperature.

Cokriging, a geostatistical analysis, is considered to be more effective than the traditional regression methods in the sense that the regression methods account only for local correlation between surface air temperature and other parameters, while cokriging takes into consideration other factors as well, including spatial dependence of surface air temperature data and information on distribution of data.

Thus the objectives of the present paper are to evaluate the usefulness of geostatistical approaches, especially of cokriging, on the spatial prediction of surface air temperature, and to seek dominant factors affecting the spatial prediction.

2. Data

2.1 Study Area

Contour lines of the study area and observed sites are shown in Fig. 1. This area involves a major part of the Kanto plain. The size is about 250 km by 300 km. This area includes wide varieties in surface conditions such as a mountainous area, flat inland area, coastland and plateau area. A detailed description of the study area is presented elsewhere (Kawashima and Ishida, 1992).

2.2 AMeDAS Air Temperature Data

A total of 130 AMeDAS stations are found within the study area (Fig. 1). Data were collected during two periods, January and August 1990, because the two months are considered to be representative of winter and summer months, respectively. A detailed description of AMeDAS is presented by the Japan Meteorological Agency (1982).

2.3 Digital Elevation Data

The Geographical Survey Institute has collected geographical or map information in digital form, and produced the nationwide digital topographic data base from 1:25,000 scale maps (Miyazaki and

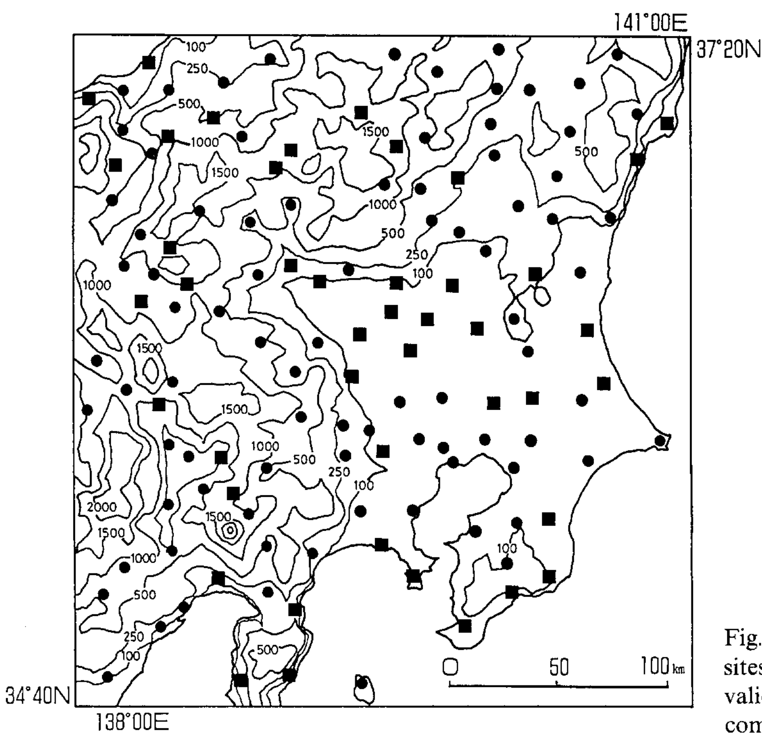


Fig. 1. Map of central Japan showing AMeDAS sensors sites. Square and circle marks show the sites for both validation and computation of semivariogram, and for computation of semivariogram only, respectively

Tsukahara, 1987). Thus, the digital elevation data could be collected for every 250 m grid over the study area. The elevation ranged from 0 m to 3760 m with an average of 499 m.

3. Geostatistical Analyses

The geostatistical techniques called kriging and cokriging (Journel and Huijbregts, 1978) are now briefly reviewed.

3.1 Kriging

The interpolated value of a property (in this case hourly surface air temperature) at any point is estimated as a linear combination of the observed values in that neighborhood. Weights can be assigned to the observed values by determining the spatial dependence of the property in terms of semivariograms.

If expressions of drift are incorporated into the system of simultaneous equations used to determine the kriging weights, the kriging system is called universal kriging; otherwise, it is called simple kriging. The kriging variances can be used as measures of the accuracy of predictions at unobserved locations.

3.2 Cokriging

Cokriging is a strong means of spatial prediction when values of surface air temperature depend on those at neighboring observed points, and further, can be related spatially to values of elevation data. We applied cokriging estimations for undersampled problems. That is, the cokriging technique is applied to predict hourly surface air temperature from a few irregularly spaced AMeDAS data values (Fig. 1) and from densely and regularly spaced sample points of elevation data.

Similar to a case of a single variable, spatial dependence between two variables can be described by a cross-semivariogram. Cross-semivariances can only be calculated at locations where both variates are measured. The inclusion of drift terms into the cokriging system allows a distinction to be made between simple and universal cokrigings in the same way as for kriging. The cokriging variances can also be used as measures of the accuracy of predictions at unobserved locations.

4. Set of Estimation Methods

To compare the quality of seven estimation methods for hourly air temperature, we used the usual method of validation known as cross-validation. The cross-validation was performed over only 42 station sites (square marks in Fig. 1) in order to exclude peculiar estimates resulting from complicated factors such as urbanization. The selected sites were not considered to be much influenced by the factors.

For each method of estimation, we computed an index from observed and estimated values of the 42 sites with regard to the validation. The index is given by Eq. (1) and hereafter is called the mean squared prediction error (MSPE):

$$\mathrm{MSPE} = \frac{1}{N_h N_s} \sum_h \sum_s (Z_{\mathrm{obs}} - Z^*)^2 \tag{1}$$

where N_h and N_s are equal to 744(31 × 24) and 42, respectively. The estimated values, Z^*, were computed using each estimation method as described below.

4.1 Simple Kriging (SK)

Since data at the 42 sites were used for comparing the precision of estimation methods, it is reasonable to compute semivariograms using only data from those sites. However, semivariograms were calculated using data from all 130 sites because the 42 sites were too few to construct a reliable semivariogram. To model a semivariogram for each hourly surface air temperature, one of spherical, exponential and Gaussian models was selected. The model selection was based on results of the cross-validation. The model parameters, nugget variance, range and sill, were determined using the nonlinear least-squares method (Kawashima and Ishida, 1992). The kriging estimate was based on the neighboring eight station sites. These sites were selected by an octant search around the location being estimated.

4.2 Universal Kriging 1 (UK1)

The semivariogram and its model were determined in the same way as the SK estimator. The only difference between this method and the SK is whether or not the effect of drift is taken into account. For the expression of drift, the two-dimensional polynomial equations (Davis, 1973) extend over quadratic trends or six terms. For each hourly data set, various combinations of the model selection and the number of drift terms were compared in order to identify the minimum prediction error over the 42 sites.

4.3 *Universal Kriging 2 (UK2)*

The only difference between this method and the UK1 estimator depends on how the drift term is defined. The drift term for the UK1 was represented as two-dimensional distances from the southwest corner of the study area. On the other hand, this method used one-dimensional distances from the sea. The number of drift terms extended to the fifth power in a similar manner as in UK1.

4.4 *Simple Cokriging (SC)*

In modeling cross-semivariograms between hourly surface air temperature and elevation data, positive definite conditions are essential (Myers, 1982), given by

$$|\gamma_{te}(\boldsymbol{h})| \leqslant [\gamma_{tt}(\boldsymbol{h})\gamma_{ee}(\boldsymbol{h})]^{1/2} \tag{2}$$

where $\boldsymbol{h}$ is a vector representing the lag in distance and angular direction, separating two places. $\gamma_{tt}(\boldsymbol{h})$, $\gamma_{ee}(\boldsymbol{h})$ and $\gamma_{te}(\boldsymbol{h})$ are auto-semivariograms of hourly surface temperature and log-elevation, and cross-semivariogram between the two variates, respectively.

An initial log arithmetic transformation was applied to elevation data, so that the positive definite condition could be more easily satisfied. One of the three models described in Section 4.1 was used to model $\gamma_{tt}(\boldsymbol{h})$ and $\gamma_{te}(\boldsymbol{h})$. The model selection was based on a minimum prediction error criterion. A parabolic model was used for $\gamma_{ee}(\boldsymbol{h})$, as shown in Fig. 2. A global trend in elevation was not removed prior to calculating γ_{ee} because cross-semivariograms obtained using elevation residuals did not show a reasonable pattern. $\gamma_{ee}(\boldsymbol{h})$ could be better modeled using a combination of different models, as pointed out by Mulla (1988). However, the combination was not applied here in order to easily achieve the positive definite condition. This poor estimate of the $\gamma_{ee}(\boldsymbol{h})$ model did not affect the rank of cokriging, as described below in Section 5. This result may be, in part, because kriging estimators are robust with respect to misspecification of semivariogram models (Voltz and Webster, 1990).

A tetra search around the estimated location selected four neighboring station sites. Elevation data were found on nine neighboring nodes of the grid. These nodes were finally smoothed and gridded with 500 m intervals, equal to 2 times the areal coverage provided by the elevation data base.

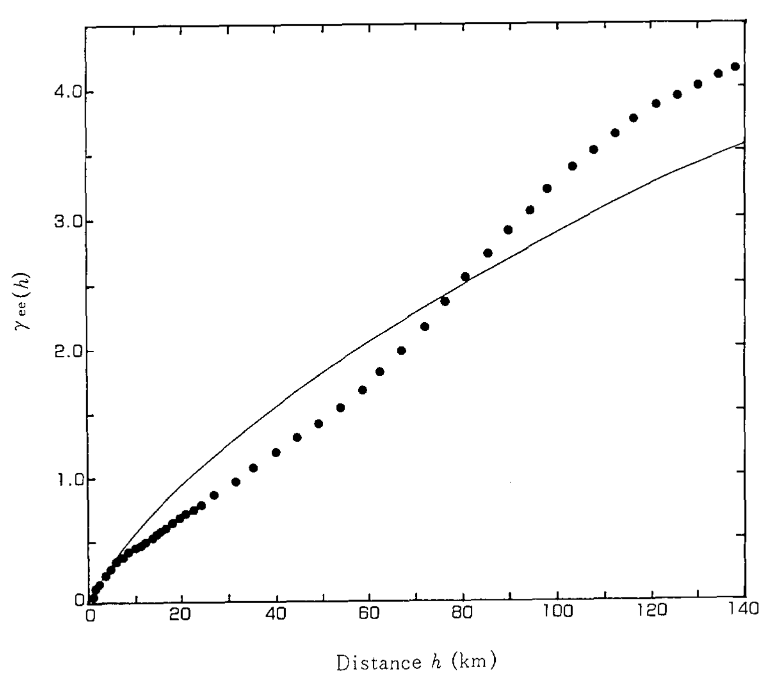


Fig. 2. Experimental semivariogram of log-elevation with a parabolic model fitted

4.5 *Universal Cokriging (UC)*

In addition to the system of the SC estimator, this cokriging estimate incorporated drift terms as described for UK1.

4.6 *Polynomial Regression (PR)*

Polynomial relationships were formulated by the least-squares method using the cross-plot of elevation or log-elevation versus hourly surface air temperature. Whether or not the log transformation was performed depended on the values of prediction errors for each hourly data set. The number of polynomial terms was determined using the AIC (Akaike, 1974).

4.7 *Inverse Distance Weighted Method (ID)*

Weights were defined as the reciprocal of distance from the observed sites to the location to be estimated. The observed sites were selected in the same way as for the SK estimator.

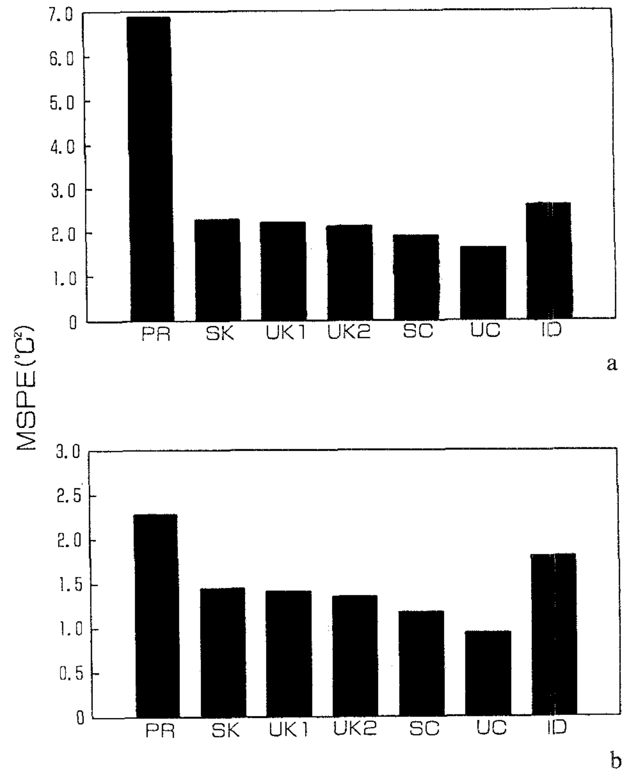


Fig. 3. Dependence of mean squared predicted error (MSPE) on estimation methods over (a) January and (b) August 1990. PR: Polynomial regression, SK: Simple kriging, UK1: Universal kriging with two-dimensional drifts, UK2: Universal kriging with one-dimensional drifts, SC: Simple cokriging, UC: Universal cokriging with two-dimensional drifts, ID: Inverse distance weighted method

5. Results and Discussion

5.1 *Comparing Performance of Estimation Methods*

Figures 3(a) and (b) give MSPE obtained using each technique over January and August, respectively. Depending on the technique, values for MSPE ranged from 1.6 °C^2 to 6.9 °C^2 in January and from 1.0 °C^2 to 2.3 °C^2 in August. Although MSPE has monthly variations, both months show the same trend in the rank of estimation methods. Values for MSPE decreased in the order of PR, ID, SK, UK1, UK2, SC and UC estimators. Values for MSPE are more than 50% smaller with the UC than with the PR. Predictions such as the PR estimator take advantage of a negative local correlation between values of temperature and elevation at the same location. However, those predictions take no account of spatial correlation in variations of temperature; that is, they implicitly assume that the knowledge of temperature at one location provides no information of the value at a neighboring site. In contrast, kriging and cokriging can model areal patterns in temperature variations using semivariograms. Therefore, a difference in MSPE values between the PR and other techniques is ascribed to the inclusion of information on temperature data at adjacent points. The ID estimator is an intermediate rank between the PR and SK estimators. This rank reveals that kriging weights assigned to data at adjacent points are more appropriate than weights driven from simple inverse distance relationships between the points.

Table 1 indicates average values of nugget variance. This average value was obtained from all the semivariogram models selected for each hourly surface air temperature. Frequencies in the selected models are also shown in this table. The difference in the average values between the two months can explain monthly variations of the MSPE, but cannot explain the rank of estimation methods. The better estimate resulting from the use of universal kriging and cokriging might be closely related to the inclusion of drift terms and correlation relationships between surface air temperature and elevation, respectively. The positive definition conditions allowed the average nugget

Table 1. *Average Nugget Variance and Frequency in Selected Semivariogram Models for Each Geostatistical Technique*

Month		Estimation method				
		SK	UK1	UK2	SC	UC
January	Nugget var. (°C^2)	1.43	1.43	1.42	1.85	2.01
	Sph. model	185	186	168	230	189
	Exp. model	107	107	108	227	250
	Gaus. model	452	451	468	287	305
August	Nugget var. (°C^2)	1.07	1.07	1.06	1.40	1.55
	Sph. model	57	57	56	328	286
	Exp. model	156	154	153	203	202
	Gaus. model	531	533	535	213	256

SK: Simple kriging, UK1: Universal kriging with two-dimensional drifts, UK2: Universal kriging with one-dimensional drifts, SC: Simple cokriging, UC: Universal cokriging with two-dimensional drifts, Nugget var.: Nugget variance, Sph.: Spherical, Exp.: Exponential, Gaus.: Gaussian

variance of cokriging to increase, and affected the selection of semivariogram models.

5.2 *Hourly Change in Prediction Error*

To identify the characteristics of prediction error by displaying diurnal variations of the error, the mean error for each hour was calculated using cross-validation over the 42 sites in a similar manner to MSPE. The mean error hereafter is referred to as HMSPE. Figure 4 shows diurnal variations of HMSPE obtained from the UK1 estimator. The other four techniques, the SK, UK2, SC and UC estimators, showed similar results to those in UK1. HMSPE for both months remained approximately constant from 01:00 (LST) to 07:00, but a different trend can now be found. Values for HMSPE during January decreased from 07:00 to 15:00 and then increased. On the other hand, values for HMSPE during August increased from 07:00 to 15:00 and then decreased.

A diurnal variation of hourly nugget variance was calculated in a similar manner to HMSPE. This variation generally corresponded with that of HMSPE. As indicated in Table 2, the hourly nugget variance for January decreased during the daytime, while that for August increased. Therefore, HMSPE can be considered to depend on the values of nugget variance. The nugget variance includes error in temperature measurements and fluctuation in temperature that occurs over distances shorter than the sampling distance (about 21 km). Since the measurement error was ± 0.15 °C irrespective of the temperature studied, it would not be expected that variations in the nugget

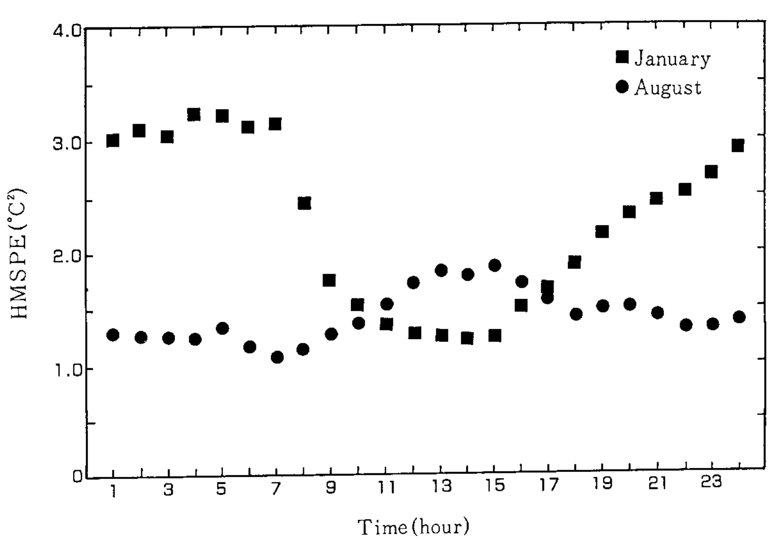


Fig. 4. Diurnal variation of hourly mean squared predicted error (HMSPE) over one month for the UK1 method

variance are strongly affected by the measurement error. This dependence may imply that a different climatic factor, depending on season, becomes dominant, affecting the accuracy of spatial prediction. In winter, since nocturnal cooling is relatively strong, local-scale topographical effects such as wind shelter by small hills and vegetation, which stagnate cold air, have a greater influence on determining surface air temperature at night. A highly variable surface air temperature pattern might be formed within the distance between the stations. In summer, the daytime variation in radiation within the distance of station sites might have an important bearing on the accuracy of spatial prediction. This variation might be due to variations in local cloudiness (e.g., Hoyt, 1977).

5.3 *Effects of Inclusion of Elevation Data*

HMSPE with cokriging is influenced by effects resulting not only from the spatial auto-correlation for surface air temperature but from the spatial cross-correlation between the air temperature and elevation. In order to evaluate consequences of inclusion of elevation data on the spatial prediction, these effects must be separated. Thus, the ratio of the prediction error obtained by using cokriging to that by kriging was regarded as a measure of the effect of elevation data. The smaller the ratio, the greater the effect of elevation data, and *vice versa*. The mean ratio for each hour was computed in a similar manner to HMSPE. The mean ratio of HMSPE from UC to UK1 estimators is presented in Table 2. Even if the ratio is compared between the SC and SK estimators, the comparison yields a consistent result.

As indicated in Table 2, the decrease in HMSPE due to the effects of the inclusion of elevation data ranged from 23% to 46% and was conspicuous for afternoons in January. A different diurnal pattern for the mean ratio could be found depending on the month. For January, this ratio remained

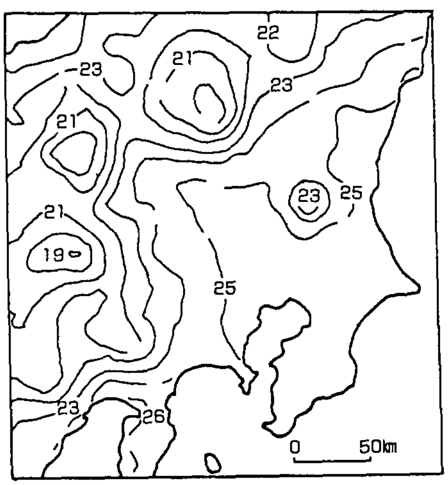
Table 2. *Diurnal Variation of Hourly nugget variance, Mean Ratio of HMSPE from UC to UK1 and Coefficient of Determination*

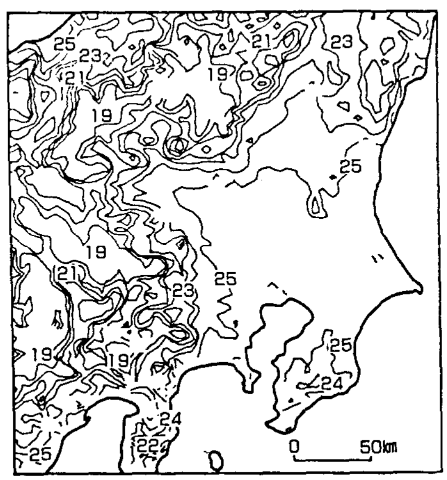
Hour	January			August		
	Nugget var. (°C^2)	Mean ratio	R^2	Nugget var. (°C^2)	Mean ratio	R^2
01:00	1.93	0.72	0.66	0.87	0.66	0.83
02:00	1.95	0.73	0.66	0.85	0.66	0.83
03:00	2.19	0.73	0.65	0.83	0.69	0.83
04:00	2.06	0.72	0.64	0.84	0.69	0.84
05:00	1.98	0.71	0.65	0.77	0.71	0.83
06:00	2.18	0.72	0.64	0.54	0.72	0.84
07:00	1.95	0.74	0.64	0.50	0.69	0.85
08:00	1.53	0.73	0.68	0.79	0.75	0.83
09:00	0.97	0.68	0.71	1.12	0.77	0.78
10:00	0.91	0.62	0.72	1.18	0.76	0.73
11:00	0.91	0.64	0.72	1.27	0.72	0.69
12:00	0.99	0.62	0.72	1.46	0.72	0.65
13:00	0.71	0.59	0.72	1.30	0.71	0.62
14:00	1.01	0.58	0.72	1.33	0.72	0.60
15:00	0.94	0.58	0.74	1.45	0.73	0.60
16:00	1.10	0.54	0.76	1.52	0.72	0.62
17:00	1.11	0.62	0.76	1.59	0.72	0.66
18:00	1.11	0.63	0.75	1.24	0.72	0.73
19:00	1.33	0.69	0.73	1.39	0.68	0.78
20:00	1.43	0.67	0.71	1.24	0.64	0.80
21:00	1.30	0.68	0.70	1.11	0.66	0.81
22:00	1.51	0.72	0.68	0.84	0.69	0.82
23:00	1.39	0.71	0.67	0.77	0.65	0.82
24:00	1.73	0.70	0.66	0.84	0.63	0.83

Nugget var.: Hourly nugget variance, Mean ratio: Mean Ratio of HMSPE from UC to UK1, R^2: Coefficient of Determination approximately constant from 01:00 to 08:00 and then decreased, but increased from 17:00 as much as to the values obtained during the morning. The effect of including elevation data might be lowered mainly by the topographical effect on a small scale due to strong nocturnal cooling, as described above. The decrease in the mean ratio from 09:00 to 16:00 and the steep increase at 17:00 corresponding to sunset supports the explanation for the decrease. Although it is difficult to interpret the fluctuation in the mean ratio within the daytime in January, the diurnal variation in the mean ratio shows the general tendency that the decrease in the prediction error is more pronounced in the daytime than in the nighttime. This tendency may be attributed predominantly to the mixing of air in the atmospheric boundary layer, because the mixing attenuates fluctuations in surface air temperature due to local-scale environments.

When the positive or negative radiation balance at the surface becomes larger, just as the interdependence between surface air temperatures at other points nearby is highly variable due to the factors mentioned above, the spatial cross-correlation between the air temperature and elevation becomes deteriorated. Therefore, by including elevation data as additional information, the diurnal fluctuation in spatial prediction error becomes widespread so that in summer the prediction becomes more accurate in the nighttime than in the daytime, and *vice versa* in winter.

The coefficients of determination (R-squared), shown in Table 2 were estimated from linear regression of the hourly surface air temperature on elevation data. The R^2 has the diurnal vari-





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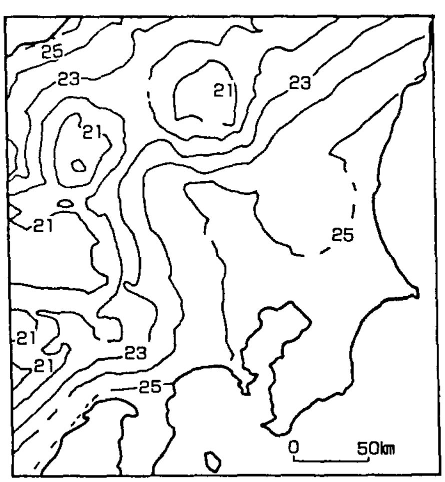

c

Fig. 5. Regional map of surface air temperature at 05:00 on 10 August 1990, produced by the (a) SK, (b) PR and (c) UC methods. Isarithms are at intervals of 1.0 °C. SK: Simple kriging, PR: Polynomial regression, UC: Universal cokriging with two-dimensional drifts

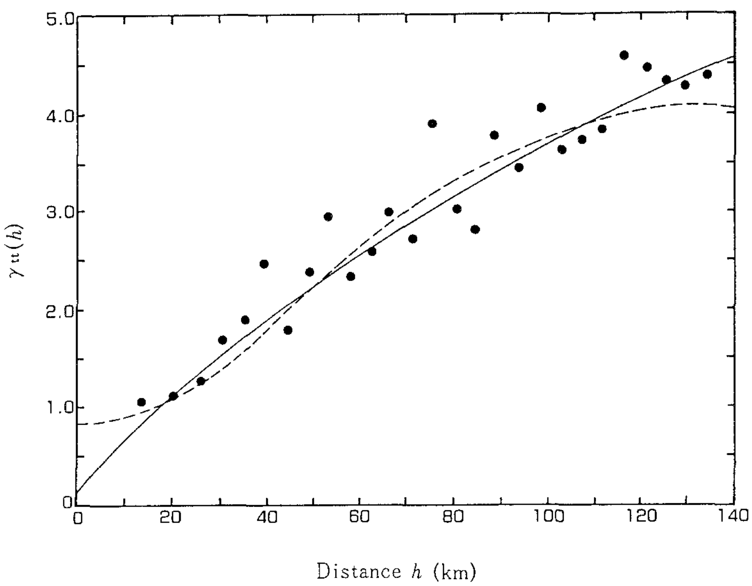

Fig. 6. Experimental auto-semivariogram of surface air temperature at 05:00 on 10 August 1990 with a Gaussian (dashed line) and a exponential (solid line) models fitted

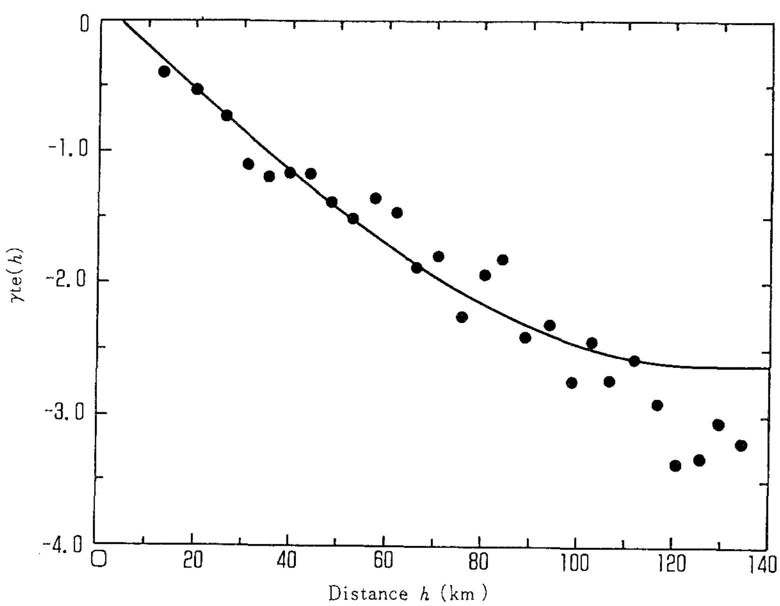

Fig. 7. Experimental cross-semivariogram of surface air temperature and log-elevation at 05:00 on 10 August 1990 with a spherical model fitted

ations wherein the pattern is generally consistent with that of the mean ratio (Table 2). This consistency is reasonable, because the higher value for R^2 ensures more useful application of elevation data as an alternative to surface air temperature data. As a result, we can obtain the intensively measured values of surface air temperature close to locations for which the estimate is required, which lead to improved accuracy of the kriged value which is a local estimate.

5.4 Effects of Inclusion of Drift Terms

An important assumption underlying geostatistical analyses is that expected values at any point are the same throughout the neighborhood, which implies an assumption of zero drift. In practice, however, this assumption is scale-related and may not always be satisfied. The frequency in the optimal number of drift terms for each hourly data set is shown in Table 3 in order to evaluate

Table 3. *Frequency in Optimal Number of Drift Terms over Each Month*

Month	Estimation method	Polynomial order					
		0	1	2	3	4	5
January	UK1	164	93	397	90	0	0
	UK2	146	94	408	96	0	0
	UC	69	74	558	29	14	0
August	UK1	48	130	453	113	0	0
	UK2	47	131	457	109	0	0
	UC	40	86	587	23	8	0

UK1: Universal kriging with two-dimensional drifts, UK2: Universal kriging with one-dimensional drifts, UC: Universal cokriging with two-dimensional drifts

the effect resulting from inclusion of drift terms. The zero order in Table 3 implies that the polynomial drift was not included; that is, the best estimate was obtained by assuming stationary data in a statistical sense. The number of the zero order was much higher in January than in August.

5.5 *Difference in Regional Distribution due to Estimation Method*

Finally, isothermal maps at 05:00 on 10 August were produced using the PR, SK and UC estimators, as shown in Figs. 5(a), (b) and (c), respectively, to obtain information on the difference in the regional distribution of air temperature determined by estimation methods. The time selection was based on the highest value for R^2 ($R^2 = 0.96$). For the SK estimator, the exponential model (Fig. 6) was applied. For UC, the Gaussian (for auto-semivariogram in Fig. 6) and spherical (for cross-semivariogram in Fig. 7) models were applied with drift terms equivalent to a first-degree surface.

The map obtained from the PR estimator directly reflects the complicated terrain (Fig. 1). On the other hand, the maps drawn using the SK and UC estimators have similar broad patterns of variation. The map drawn using UC is more intricate, however, because the elevation data was collected on a finer grid. Figures 8(a) and (b) show the squareroot of kriging and cokriging variance, respectively. The comparison of results between Figs. 8(a) and (b) indicates that most of the errors at the level of 0.8 °C disappeared with the inclusion of the elevation data as an additional variable. For agricultural applications, tolerance limits for estimation errors of hourly air temperature are about 0.5 °C to 1.0 °C, depending on the kind of practical purpose, such as prediction of frost damage. Therefore, results in Fig. 8(b) indicate the feasibility of using cokriging for agricultural applications.

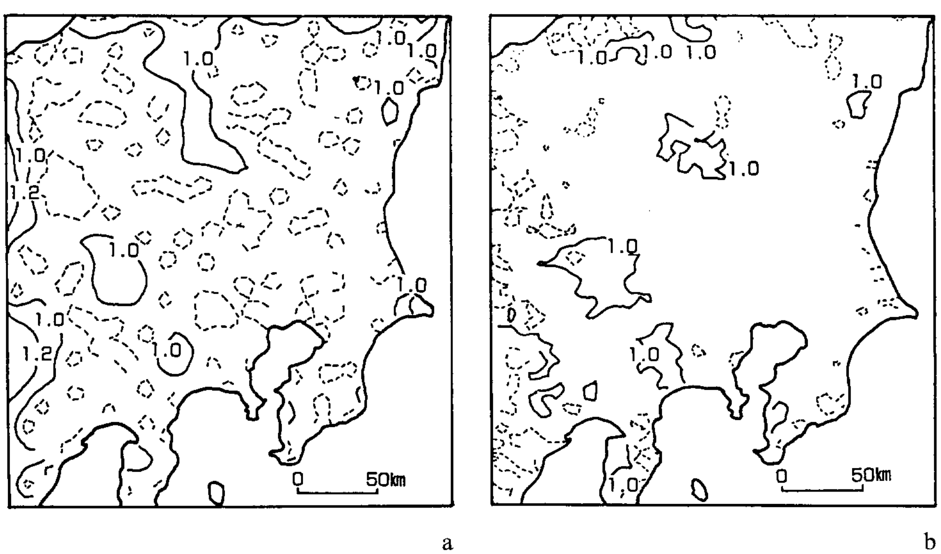

Fig. 8. Error map of surface air temperature at 05:00 on 10 August 1990, produced by the (a) SK and (b) UC methods. Isarithms are at intervals of 0.2 °C. Dashed lines represent isarithms of 0.8 °C. SK: Simple kriging, UC: Universal cokriging with two-dimensional drifts

6. Conclusions

Geostatistical analyses, kriging and cokriging, were applicable to the interpolation of hourly surface air temperature. In particular, cokriging was more useful than kriging and a conventional least-squares procedure relying only on local correlation between air temperature and elevation. The lowering in the accuracy of spatial prediction occurred due to two causes. One was related to a high variation in the air temperature within the distance of the station sites, and the other was related to a distortion of linear relationships of the air temperature with elevation. Both the variation and distortion were ascribed to predominantly the same climatic factors, which were strong sunshine in summer and strong nocturnal cooling in winter. Therefore, the difference in improvement of spatial prediction was widespread between daytime and nighttime. Also, an improvement in prediction accuracy was achieved by incorporating drift terms into the equations regarding the kriging or cokriging estimate.

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Authors' addresses: Dr. Tomoyuki Ishida, Department of Agricultural Engineering, Faculty of Agriculture, Iwate University, Morioka, Iwate, 020 Japan, and Dr. Shigeto Kawashima, Project Research Team, National Agriculture Research Center, Tsukuba, Ibaraki, 305 Japan.