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A GIS-based approach for estimating spatial distribution of seasonal temperature in Zhejiang Province, China*

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Abstract: This paper presents a Zhejiang Province southeastern China seasonal temperature model based on GIS techniques. Terrain variables derived from the 1 km resolution DEM are used as predictors of seasonal temperature, using a regression-based approach. Variables used for modelling include: longitude, latitude, elevation, distance from the nearest coast, direction to the nearest coast, slope, aspect, and the ratio of land to sea within given radii. Seasonal temperature data, for the observation period 1971 to 2000, were obtained from 59 meteorological stations. Temperature data from 52 meteorological stations were used to construct the regression model. Data from the other 7 stations were retained for model validation. Seasonal temperature surfaces were constructed using the regression equations, and refined by kriging the residuals from the regression model and subtracting the result from the predicted surface. Latitude, elevation and distance from the sea are found to be the most important predictors of local seasonal temperature. Validation determined that regression plus kriging predicts seasonal temperature with a coefficient of determination (R^2), between the estimated and observed values, of 0.757 (autumn) and 0.935 (winter). A simple regression model without kriging yields less accurate results in all seasons except for the autumn temperature.

Key words: GIS, Multiple regression analysis, Interpolation, Seasonal temperature, Spatial distribution
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INTRODUCTION

Spatial distribution estimates of meteorological data are becoming increasing important as inputs to spatially explicit landscape, regional, and global models. Interpolation is a common method translating for estimated spatial distribution of meteorological data that come from distantly scattered meteorological stations into raster data, which has benefits of simplicity and convenience. The choice of spatial interpolator is especially important in mountainous areas where data collections are sparse and meteorological variables may change over short spatial scales.

Traditionally, the method used to interpolate meteorological variables had been linear interpolation between stations and the drawing of isolines based on the researcher's knowledge of the area under study. With the spread of computers, more interpolation procedures were proposed and implemented. There are more recent works on meteorological interpolation dealing with the factors that model it. Interpolation methods commonly applied for estimating temperature include inverse distance weighting (Eischeid *et al*., 1995; Lennon and Turner, 1995; Willmott and Matsuura, 1995; Ashraf *et al*., 1997; Dodson and Marks, 1997), splines (Hulme *et al*., 1995; Lennon and Turner, 1995) and kriging (Hudson and Wackernagel, 1994; Hammond and Yarie, 1996; Holdaway, 1996; Ashraf *et al*., 1997). There are also studies seeking statistical relationships between geographical

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variables and temperature variables (Benzi *et al.*, 1997; Chessa and Delitala, 1997; Hargy, 1997; Vogt *et al.*, 1997). These studies commonly use variables such as elevation, latitude and longitude as predictors of temperature variables. GIS is an effective tool for data integration and spatial analysis (Rhind, 1991) and has been used to model temperature (Lennon and Turner, 1995; Goodale *et al.*, 1998; Kurzman and Kadmon, 1999; Ninyerola *et al.*, 2000; Agnew and Palutikof, 2000).

This study aims to develop an objective mapping and interpolation method that takes into account geographical variables, and uses GIS techniques to obtain final maps of seasonal temperature over a relatively large area.

The current work uses an empirical and statistical procedure to estimate the spatial distribution of seasonal temperature in Zhejiang Province (southeastern China). This procedure is empirical because it uses data obtained from meteorological stations for building and validating the model, and is also statistical because it is based on a multiple regression modelling followed by kriging of residuals. In regression modelling, as dependent variables, we used seasonal temperature, whereas as independent variables, we used altitude, latitude, longitude, distance to sea, slope, aspect, etc. The variation of temperature with terrain variables is the premise underlying the model formulation.

STUDY AREA AND DATA

Study area

Zhejiang Province (118º00′~123º00′ E and 27º00′~31º30′ N) locates south of the Yangtze River delta in southeastern China, where 71.6% of the land is mountain, 22.0% plain and 6.4% water (Fig.1). The topography is very complicated and variable, including mountains, hills and plains. The province covers an area of 101 800 km^2 and has a population of approximately 45 million. According to the landform structure and ecological environment as well as the characteristics of crop regional distribution, six regions with their own agricultural landform types have been recognized: plain region in northern Zhejiang, mountain and hill region in northwest Zhejiang, hill and basin region in east Zhejiang, hill and basin area in middle Zhejiang, mountain region in south Zhejiang, and island hill and coastal plain region in southeast Zhejiang. Zhejiang Province located in southeastern China belongs to the middle and north subtropical meteorological zone (Zhejiang Statistics Bureau, 1998).

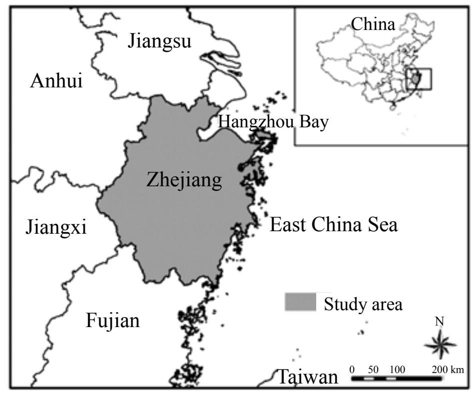

Fig.1 Zhejiang Province and its neighbors in eastern China

Data acquisition and preprocessing

Monthly mean air temperature data were obtained from 59 meteorological stations of the Zhejiang Meteorological Bureau. Because the World Meteorological Organization (WMO) gives 30 years as the optimal length for a series, station data were averaged over the period 1971 to 2000. Only sites with records spanning at least 25 years were retained, except for sites above 200 m for which all records were used. All sites above 200 m have at least 22 years records. Seasonal temperature data from 52 meteorological stations were used to construct the regression model. The data from the other 7 stations were retained for model validation. A point coverage of the meteorological stations used for parameterizing the model was created in Arc/Info (Fig.2). Standard seasons were used: December, January, and February for winter, March, April, and May for spring, June, July, and August for summer, September, October, and November for autumn.

The digital elevation model (DEM) was derived from 1:250000-scale topographic maps at a resolution of 100 m. The DEM was re-sampled to a resolution of 1 km by taking the mean value of the 100 original elevation pixels for each new grid cell (Fig.2). A 1:250000-scale vector coastline of the study area and political boundaries were obtained from National Geomatics Center of China (NGCC). The vector coastline was then converted to raster data at the same resolution as the elevation data, 1 km. Land cells were assigned a value of 1, and sea cells a value of 0.

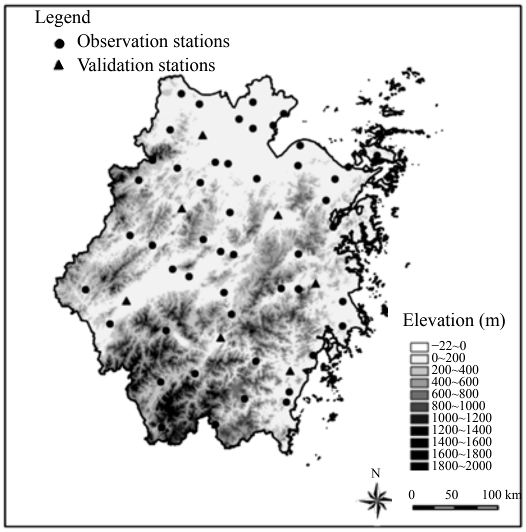

Fig.2 Geographical location of meteorological stations and DEM used in the study

METHOD DESCRIPTION

The method was used to map seasonal temperature, based on regression modelling of the seasonal temperature, which was normalized first with geographic factors as the independent variables, followed by interpolation of the model residuals. This method involves both deterministic and stochastic components. The terrain variables are used to parameterize the regression model and represent the deterministic component of the model. The residuals from the regression model, treated as random spatial variables, represent the stochastic components and are interpolated using kriging method. The regression surface and the interpolated residual surface are added together to get the final grided datasets. The Arc/Info GIS is applied to 4 maps of the seasonal temperature.

Multiple linear regression model

Stepwise multiple linear regression was performed with seasonal temperature as the dependent variable and terrain variables as the predictors. Each variable was tested for normality before building the regression models.

The terrain variables were converted to raster format in Arc/Info. The terrain variables listed in Table 1 served as candidate variables in the regression models and were derived from the 1 km resolution DEM.

Elevation (ELEV) is included because it is known to be a strong determinant of temperature. On a global average, vertical lapse rates average 6.5 °C per 1000 m in the free troposphere, although there are seasonal and geographical variations (Lutgens and Tarbuck, 1995). The mean elevation within chosen radii (1, 3, 5, and 10 km) was derived using the FOCALMEAN function in Arc/Info to measure the wider influence of elevation at any one location. The

Table 1 Terrain variables derived from the 1 km resolution DEM and used in the regression models

Terrain variables	Description
LAT	Latitude
LON	Longitude
ELEV	Elevation in meters
ELEV*x*	Mean elevation within *x*, where *x* is a radius of 1, 3, 5 and 10 km
ZX*x*	Max elevation within *x*, where *x* is a wedge with a radius of 1, 3, 5, 10, 20 and 50 km, with direction N, NE, E, SE, S, SW, W, and NW. For example, ZX10SE is the maximum elevation in a SE direction within a 45° wedge with a radius of 10 km
SLOPE	Slope in degrees
ASP_*x*	Aspect in degrees, where *x* is N, NE, E, SE, S, SW, W, and NW. For example, ASP_N is given a value of 1 if the cell slopes to the north, and 0 if the slope of the cell is in any other direction
DISTANCE	Distance to the nearest coast
DIR_*x*	Direction of the nearest coast in 8 compass points, where *x* is N, NE, E, SE, S, SW, W, NW. For example, DIR_N is given a value of 1 if the direction of the nearest coast is to the N, and 0 if the nearest coast is in any other direction
LAN*x*	A land-to-sea ratio within a radius *x*, where *x* is 5, 10, 20, 50, and 100 km

maximum elevation within a wedge of given orientation and radius (ZXx) was included to determine the influence of orographic forcing on temperature. This variable was derived using the FOCALMAX function in Arc/Info.

Longitude and latitude variables (LON and LAT) are included to parameterize large-scale gradients of temperature in Zhejiang Province. The direction in which each cell is facing (aspect, ASP_x) is important because of the effect on the microclimatology of the wind, and its SLOPE will determine the amount of solar radiation received and hence affect temperature. Slope and aspect were derived using functions of the same name in Arc/Info.

Distance to the nearest coastline is included to account for maritime influences and is generated using the NEAR function in Arc/Info. Further measurements of coastality, i.e. the mean number of land cells (LANx) within chosen radii (x=5, 10, 20, 50 and 100 km), were computed using FOCALMEAN function in Arc/Info. When wind is from a clearly defined prevailing direction, only windward coasts should be affected by the maritime influence. To incorporate this effect, the direction of the nearest coast was computed for 8 compass points.

Interpolation of seasonal temperature residuals from regression model

Seasonal temperature was estimated using the multiple linear regression models. The residuals from these regression models were rasterised and subsequently analyzed for spatial autocorrelation using a variogram. The residuals, treated as spatially dependent variables, can be used in a geostatistical sense to partially account for any spatial correlation in the residual temperature field. In fact, the choice of interpolation is considered to be less important when a full set of terrain data is available. The residuals were interpolated using local ordinary kriging and subtracted from the predicted surfaces. Kriging was performed on the data using several different methods (spherical, circular, exponential, Gaussian, and linear) in Arc/Info. The sample variogram was used to select the best variogram model. Where the choice of method was not immediately apparent, the residuals were kriged using several apparently reasonable kriging models, and the most appropriate method was then selected on the basis of the RMSE. The variograms computed from the regression model residuals, revealed smaller values of semi-variance for shorter distances between pairs of sample input points (the lags). This suggests that the temperature residuals are more similar for stations located closer together than for those stations farther apart.

RESULTS AND DISCUSSION

Results of multiple linear regression model

The relationships between the seasonal temperature data and terrain variables have been identified on a seasonal basis and are summarized in Table 2. The correlation with latitude (LAT) and ZX1S are higher. With higher latitudes, temperature decreases, although the strength of the relationship varies from season to season. The relationship is strongest in winter (r=−0.664) and weakest in summer (close to zero).

Elevation is also a strong determinant of temperature. Correlations between seasonal temperature and elevation are negative as expected (r=−0.580 to −0.888), assuming a typical temperature lapse rate (Table 2). The relationship is stronger in summer (r=−0.888) and autumn (r=−0.806) than in winter (r=−0.580) and spring (r=−0.633). The maximum elevation within a wider radius (generally radius of 20 km, ZX20x) has the same influence as site elevation (ELEV). It can also be seen that the correlation with the maximum elevation within a radius of 1 km with direction S (ZX1S) is stronger than the correlation with site elevation (ELEV). In spring, for example, the correlation coefficient is 0.635 with ZX1S and 0.633 with ELEV. Generally there is positive correlation between temperature and the maximum elevation in a wedge of given radius and direction. However, if the radius of the wedge is wider than 20 km, the relationship is negative in spring. The selected direction of maximum elevation, and the sign of the association, should be related to the direction of the prevailing winds.

Distance from the sea and the land/sea ratio are negatively associated with temperature in winter and autumn, but the relationship is positive in spring and summer (Table 2). In winter and autumn this may be attributed to the warming influence of the sea. In fact, the correlations are lowest in summer. It is possible

Table 2 Temperature correlations with some important terrain variables

Terrain variables	Winter	Spring	Summer	Autumn
LAT	–0.664**	–0.416**	–0.034	–0.386**
LON	0.124	–0.302*	–0.064	0.229
ELEV	–0.580**	–0.633**	–0.888**	–0.806**
ELEV3	–0.425**	–0.473**	–0.801**	–0.689**
ELEV10	–0.036	0.002	–0.429**	–0.329*
SLOPE	–0.423**	–0.548**	–0.775**	–0.633**
DISTANCE	–0.164	0.260	0.056	–0.228
LAN5	–0.187	0.238	0.130	–0.242
LAN50	–0.305*	0.245	0.086	–0.367**
LAN100	–0.329*	0.252	0.106	–0.365**
ZX1S	–0.583**	–0.635**	–0.890**	–0.809**
ZX1SE	–0.580**	–0.633**	–0.888**	–0.806**
ZX1W	–0.538**	–0.602**	–0.874**	–0.774**
ZX3S	–0.477**	–0.533**	–0.819**	–0.725**
ZX3SE	–0.483**	–0.545**	–0.835**	–0.731**
ZX3SW	–0.470**	–0.511**	–0.807**	–0.719**
ZX5S	–0.364**	–0.402**	–0.727**	–0.626**
ZX5SE	–0.260	–0.258	–0.633**	–0.536**
ZX5E	–0.412**	–0.463**	–0.785**	–0.677**
ZX10W	–0.080	–0.076	–0.474**	–0.363**
ZX10E	–0.241	–0.203	–0.570**	–0.510**
ZX10S	–0.206	–0.118	–0.492**	–0.463**
ZX20NW	–0.007	0.099	–0.291*	–0.270
ZX20S	–0.115	0.067	–0.288*	–0.340*
ZX50E	–0.079	0.186	–0.182	–0.289*
ZX50S	–0.053	0.246	–0.050	–0.217
DIR_W	0.119	–0.132	–0.130	0.120
DIR_NW	–0.029	–0.016	0.036	0.007
ASP_SE	0.039	0.101	0.024	–0.008
ASP_S	–0.049	–0.303*	–0.353*	–0.114
ASP_SW	0.245	0.074	0.094	0.242

Correlation significance: * 0.05 level (2-tailed); ** 0.01 level (2-tailed)

that the relationship between latitude and distance to the sea has some influence in this case. Temperature decreases with distance inland in winter and autumn, but increases in summer when convective forcing has a greater role (Table 2). The correlation coefficients are generally small, the largest being the spring value of 0.260. Longitude is not a significant predictor of seasonal temperature on a local scale.

For the regression models (Table 3), outliers with strong influence were removed and the models refined. The amount of variance accounted for by the terrain variables is high for temperature, ranging from 97.0% in winter to 98.2% in summer.

Latitude (LAT) occurs consistently in the regression models, and is the most important predictor of seasonal temperature. Elevation is found to be the second (first in the case of summer temperature) most important predictor variable in 3 of the 4 seasonal temperature models, either the elevation of the grid cell (ELEV) or the maximum elevation within a wedge of some radius and direction (ZX*x*). The most useful radius appears to be 1 km in a southerly direction (ZX1S).

A measure of maritime influence greatly improves the fit of the models, and illustrates the considerable influence of the sea on the Zhejiang temperature. Though distance from the sea (DISTANCE) does not appear in the regression equations for seasonal temperature, the land/sea ratio is associated with temperature in all seasons except autumn. A land/sea ratio within a wider area (generally radius of 100 km, LAN100) is included in all seasonal temperature models except autumn, but is a more powerful indicator of summer, spring and winter temperature (respectively the second, third and third variable entered).

Aspect and direction to the nearest coast are secondary predictors of temperature, but can be important in particular seasons. Aspect is included as a predictor of temperature for every season. Aspect is a more significant predictor in the winter and autumn temperature models than in the spring and summer temperature models. The direction to the nearest coast also has significance in the temperature models, and moreover, the correlations are more significant in summer and autumn, if the direction of the nearest coast is E.

Results of interpolation residuals from regression model

The sample variograms were generated for seasonal temperature in Fig.3. There is positive correlation between semi-variance and separating distances up to a range. The range defines the limit of spatial dependence, and is indicated by the point at which the variogram rises linearly to its upper boundary (sill).

Table 3 Summary multiple linear regression results for temperature

Season	Adjusted R^2	Terrain variables
Winter	0.970	–LAT/–ZX1S/–LAN100/+ELEV5/–ASP_SE/–ASP_W/+ZX3N
Spring	0.977	–LAT/–ZX1S/+LAN100/+ELEV5/+LAN5/+ZX3E/+ZX50SE/–ZX5N/–ZX20W/–DIR_E/–ASP_W
Summer	0.982	–ZX1S/+LAN100/–LAT/–DIR_W/–ZX5NW/+ELEV3/–DIR_E/–DIR_SW/+ASP_NE/+ZX50SE
Autumn	0.971	–LAT/–ZX1S/+ELEV3/–ZX50NW/–ASP_SE/–DIR_E/+ASP_S/+ZX3NE/–ASP_W

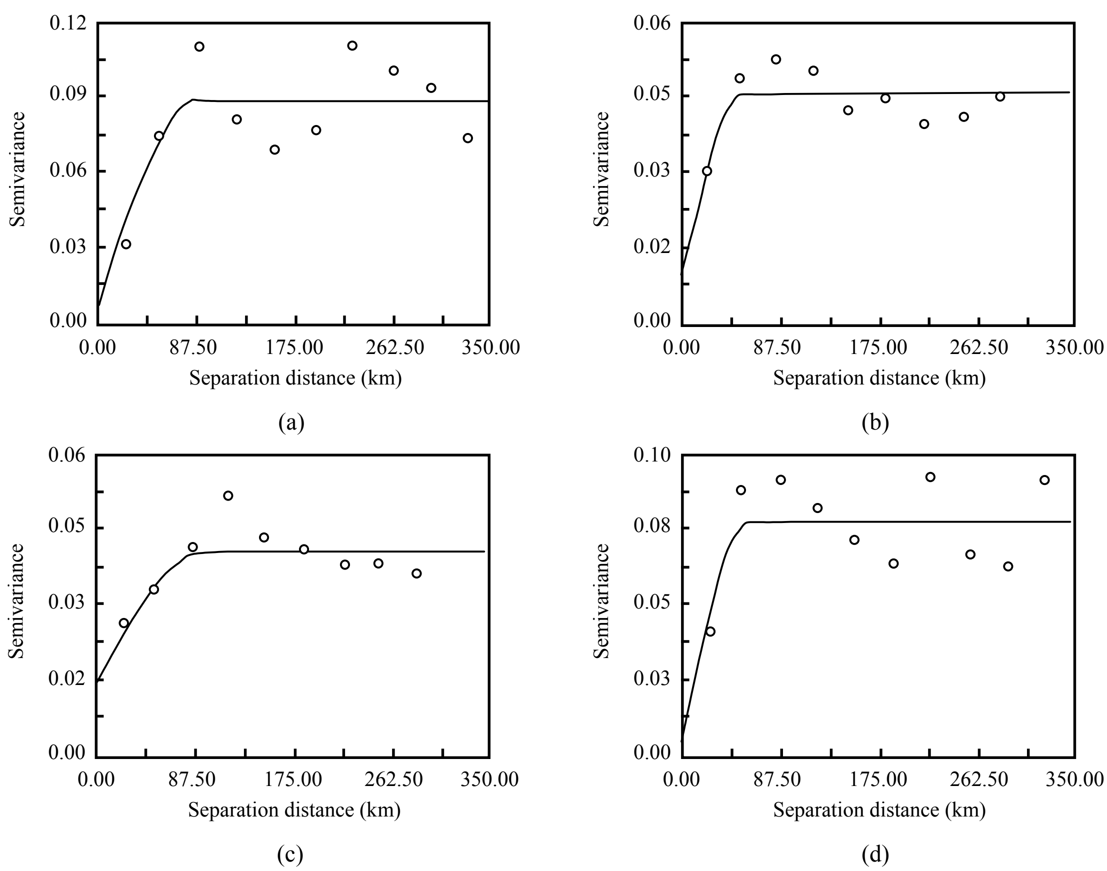

Fig.3 Sample variogram for seasonal temperature (°C^2). (a) Winter; (b) Spring; (c) Summer; (d) Autumn

At distances greater than the range there is no discernible spatial correlation in the residuals. Spherical model of estimated semi-variance provides a reasonable fit to the sample data for seasonal temperature.

The kriging variance surfaces produced can be used to assign a degree of certainty to the kriged seasonal temperature surfaces. Lower values indicate higher degree of confidence in the interpolated residual, although this also depends on the accuracy of the variogram model. Table 4 suggests that more certainty can be attached to the interpolated summer temperature surface (mean kriging variance of 0.04 °C^2) than the autumn temperature surface (mean kriging variance of 0.06 °C^2).

Table 4 Descriptive statistics for the kriging variance surfaces (°C^2)

	Winter	Spring	Summer	Autumn
Minimum	0.01	0.02	0.02	0.01
Maximum	0.13	0.07	0.08	0.11
Mean	0.05	0.05	0.04	0.06
Standard deviation	0.02	0.01	0.01	0.02

The spatial distribution in the variance for seasonal temperature is shown in Fig.4. Kriging variance is higher where there are few meteorological stations, and around the edges of the domain beyond which there are no stations from which to interpolate. Kriging variance is lower where the density of meteorological stations is higher.

Validation of the seasonal temperature surfaces

Seven validation stations were randomly selected to cover a wide range of Zhejiang Province (Fig.2). The observation surfaces for seasonal temperature were generated using regression alone, and regression followed by kriging of residuals. Then, the estimated values of seasonal temperature at the locations of the validation stations were extracted for comparison with observations. The two methods were compared by the root mean square error (*RMSE*) and determination coefficients (R^2) between the estimated and observed stations. The results of the validation are shown in Table 5. Kriging the residuals improves the *RMSE* and R^2 in all seasons except autumn. As for

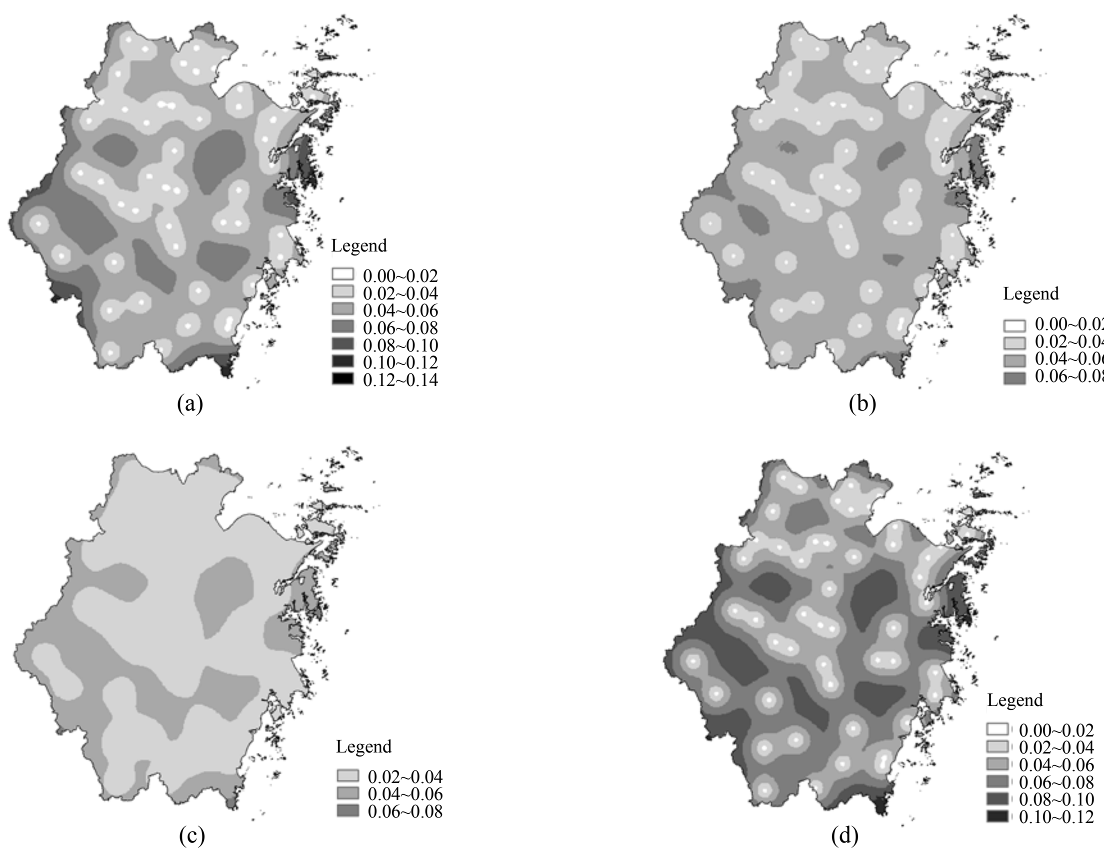

Fig.4 Sample variogram for seasonal temperature (°C^2). (a) Winter; (b) Spring; (c) Summer; (d) Autumn

RMSE, the improvement varies from a decrease of 0.03 in winter to a decrease of 0.06 in spring and summer. As measured by R^2, the improvement varies from an increase of 0.02 in winter to an increase of 0.23 in summer.

Estimated values (as estimated by Method 2) were plotted against observed values for validation sample. The figures for all seasons are shown in Fig.5. The sample points cluster more closely along the diagonal for winter temperature than for other season temperature.

Table 5 Validation of the observed temperature values for the validation sample

Season	Method 1: regression		Method 2: regression+kriging	
	RMSE (°C)	R^2	*RMSE* (°C)	R^2
Winter	0.43	0.914	0.40	0.935
Spring	0.52	0.689	0.46	0.766
Summer	0.28	0.524	0.22	0.762
Autumn	0.57	0.777	0.59	0.757

Map generation of seasonal temperature surfaces

To assess the model behavior, maps were generated for seasonal temperature. Fig.6 shows the temperature surfaces for each season generated by the estimating the temperature for each cell using the terrain-temperature model (terrain regression followed by kriging of residuals). Mountainous areas are clearly depicted due to the strong negative relationship between elevation and temperature. The south of Zhejiang, for example, is shown to be considerably colder than the lower elevation regions.

The spatial descriptive statistics shown in Table 6 are computed for seasonal temperature surface on a cell-by-cell basis. Mean seasonal temperature ranges from 5.38 °C in winter to 25.27 °C in summer, with spatial variance being greatest in autumn.

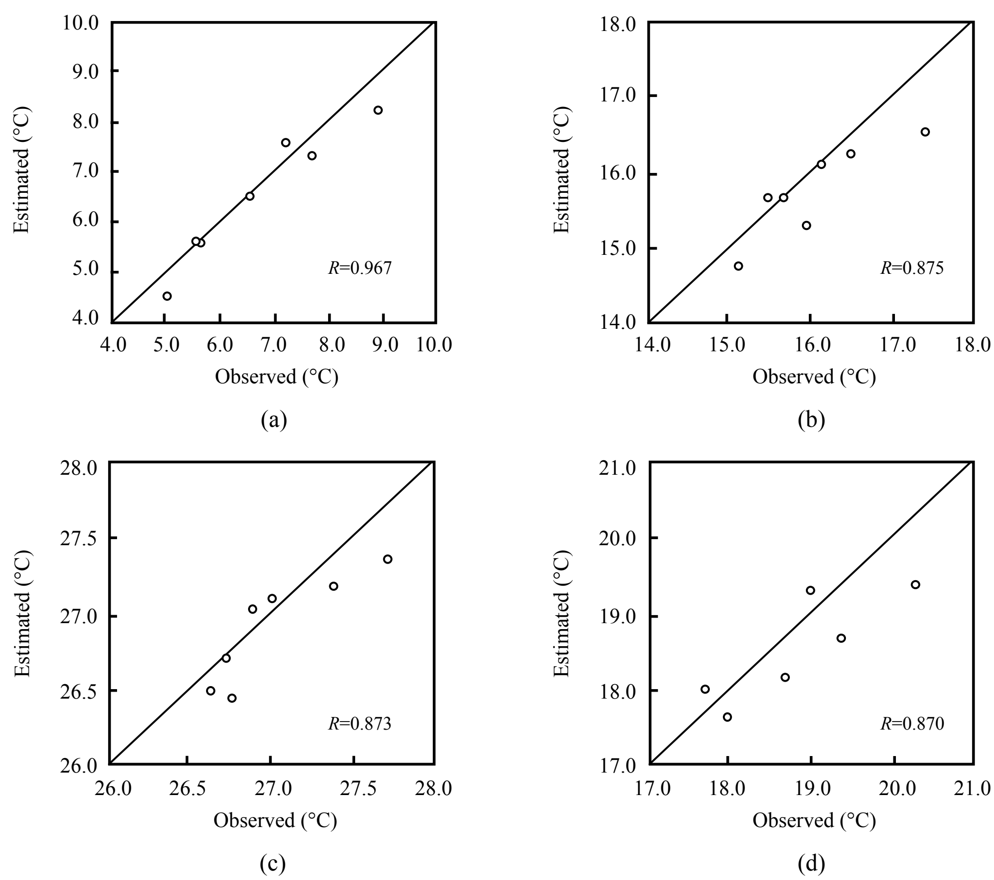

Fig.5 Scatterplots of estimated and observed values for the validation sample. (a) Winter; (b) Spring; (c) Summer; (d) Autumn

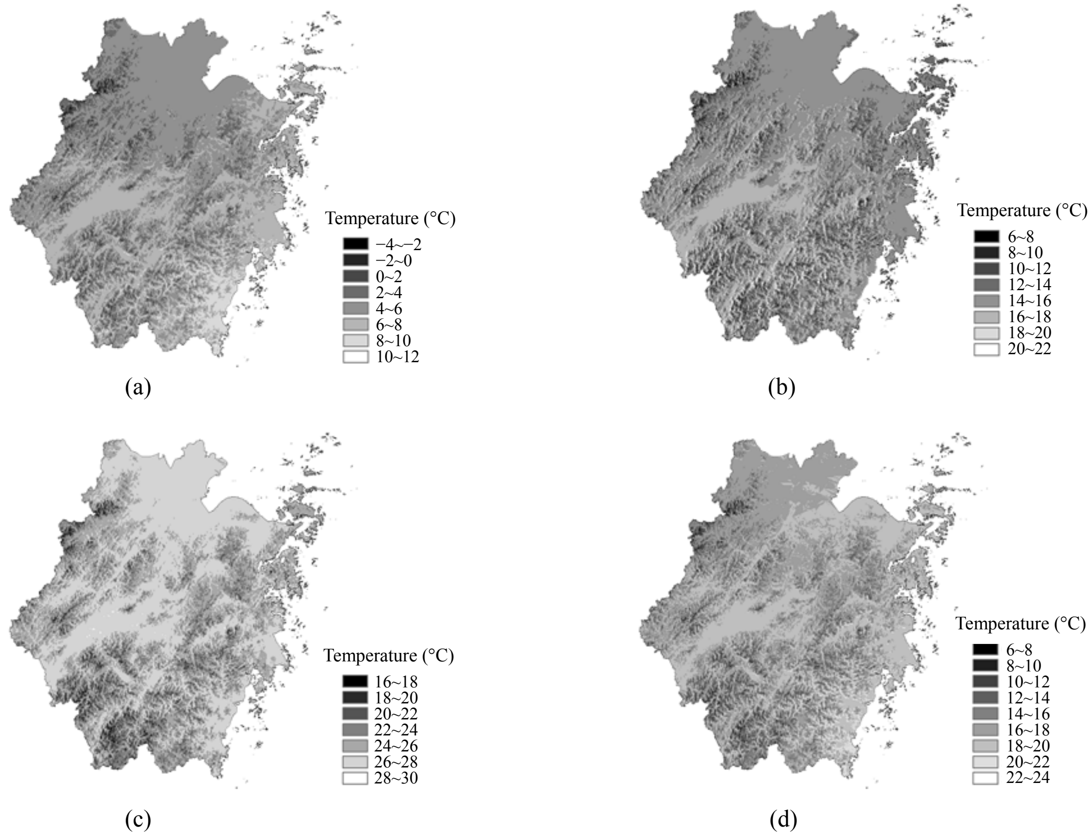

Fig.6 Grided seasonal temperature surfaces, resolution 1 km×1 km. (a) Winter; (b) Spring; (c) Summer; (d) Autumn

Table 6 Descriptive statistics for seasonal temperature surfaces (°C)

	Minimum	Maximum	Mean	Standard deviation
Winter	–2.57	10.39	5.38	1.50
Spring	6.82	21.46	14.78	1.59
Summer	16.80	29.28	25.27	1.72
Autumn	7.91	22.42	17.08	1.81

SUMMARY AND CONCLUSION

This work investigates the application of a GIS to construct DEM-derived terrain variables that are used to interpolate seasonal temperature data for every 1 km×1 km grid cell in Zhejiang Province in southeastern China. The validation results suggest that terrain-temperature model building using terrain variables, followed by kriging of the regression residuals, is useful for interpolating seasonal temperature data. Interpolation results can be transferred to any grid point in the domain for which the characteristics of the terrain variables are known. Latitude, the maximum elevation within a radius of 1 km in a southerly direction (ZX1S), and the land-to-sea ratio within a radius of 100 km (LAN100) are found to be the most powerful predictors of local seasonal temperature. Aspect and maritime influence also improves the model fit, a reflection of the importance of oceanic effects in Zhejiang Province. Validation demonstrates that kriging the residuals improves the *RMSE* for 3 out of the 4 models developed.

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