USING COKRIGING TECHNIQUE FOR SURFACE INTERPOLATION OF CLIMATE DATA IN THAILAND

Yaowaret Jantaka[1] , Suwit Ongsomwang[2] and Suriporn Charungthanakij[3]

[1]PhD candidate, School of Remote Sensing, Institute of Science, Suranaree University of Technology,
111 University Avenue. Suranaree Subdistrict, Muang. Nakhon Ratchasima 30000, Thailand;
Tel. (66) 044-224652 and Fax. (66) 044-224316
E-mail: yjantakat@gmail.com

[2]Associate Professor, School of Remote Sensing, Institute of Science, Suranaree University of Technology,
111 University Avenue. Suranaree Subdistrict, Muang. Nakhon Ratchasima 30000, Thailand;
Tel. (66) 044-224652 and Fax. (66) 044-224316
E-mail: yjantakat@gmail.com

[3]Lecturer, Geography Department, Faculty of Arts, Silpakorn University
Sanamchandra Palace Campus, Nakhon Pathom, 73000, Thailand;
Tel. (66) 3425 5840 and Fax. (66) 3425 5794
E-mail: scharung@hotmail.com

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ABSTRACT: This paper required using cokriging technique for spatial interpolation of temperature data in Northern Thailand. The temperature data was used as long-term average climate data (1971-2000) that was recorded from main climate stations of Thailand Meteorological Department (TMD). Such temperature data was used for this study such as mean monthly maximum temperature, mean monthly minimum temperature and mean monthly temperature. These climatic variables were determined as a predicted variable or interested variable while topographic data (elevation, longitude and latitude) were additional covariates for cokriging. Herein, the best results of cokriging on temperature data were considered with the least Root Mean Square Error (RMSE). As a result, the best results of cokriging on all temperature data are preferred to sub type of DCK and semivariogram model of Exp. This study has expected that the proposed cokriging technique will be alternative for spatial interpolation of another climate data in Thailand.

1. Introduction

Climate plays a significant role in flora and fauna distributions; it is usually a key to understand the interdependence between environmental and biological factors and is widely used in developing ecological zones and biodiversity assessments (K¨ oeppen, 1923; Hills, 1960; Bailey, 1985; Woodward, 1987; Hong et al., 2005). Neither the determinant effect of climate on ecosystems nor estimates of the spatial distribution of climatic variables are required more than ever for sustainable management of natural resources. Determining spatial climate conditions, however, is not easy, because long-term average climate observations are sparsely scattered, discrete and irregularly distributed meteorological stations. These discrete data have to be extended spatially to reflect the continuously and gradually changed climate pattern. In particular, climatic dependence on topography must be taken into account when developing reliable climate estimates. This is especially so in Northern Thailand, where more than 60% of its area is covered by mountains and hills (DNP, 2007). In recent years, there are more much attention has been given to the application of interpolation techniques to climatic analysis which are available in geographical information systems (GISs), for example, Ashiq et al. (2010); Trisurat et al. (2009); Watson and Neman (2009); Reich et al. (2008); Benavides et al. (2007); and Vajda (2007). According to these stated papers, cokriging technique is one of them that is preferable, as it takes into account the climatic dependence on topography by using a trivariate function of latitude and longitude as two independent variables and elevation as a covariate (Hong et al., 2005). Therefore, this paper aims to apply cokriging technique for spatial interpolation on long-term temperature data (1971-2000) of Thailand Meteorological Department (TMD). Temperature data, is one of climatic variables, is so important for forest types classification (Young and Giese, 2003). The study area is selected for surface interpolation that is area of Northern region (Figure 1).

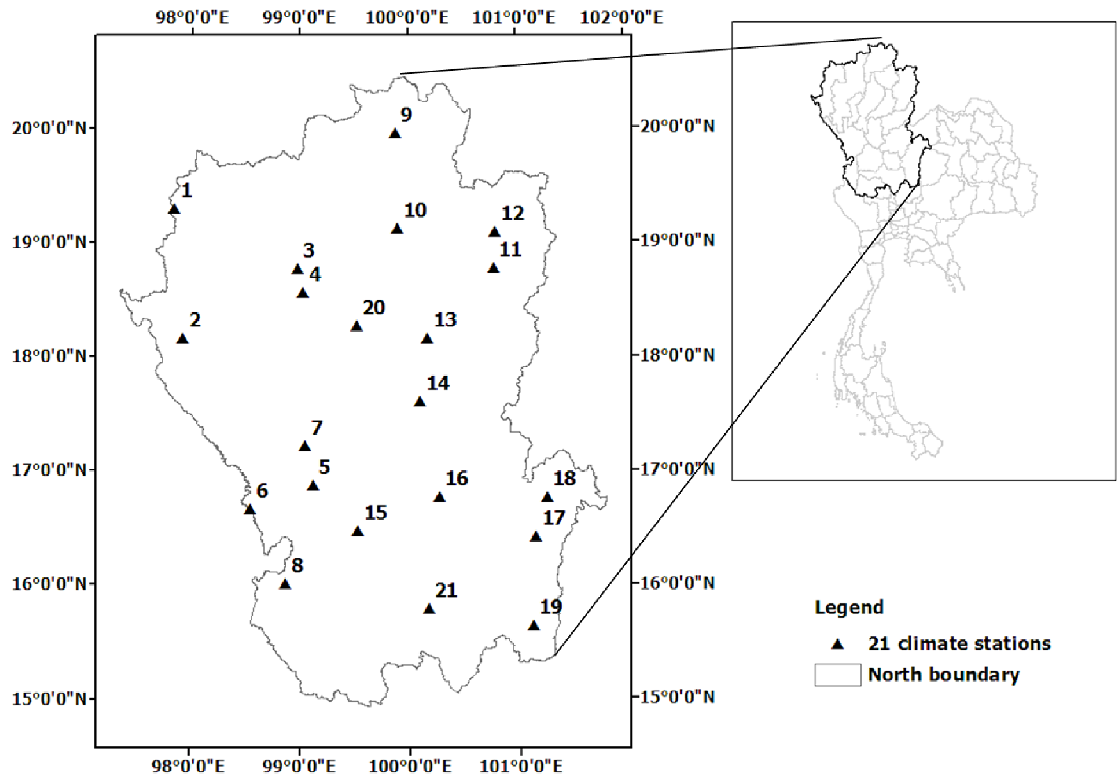

Figure 1 The study area and 12 main climate stations of TMD in Northern region

2. Temperature data

Long-term temperature data (from 1971 to 2000) were recorded from 21 north stations of Thailand Meteorological Department (TMD) (Figure 1). Temperature data were derived for mean monthly maximum temperature (°C), mean monthly minimum temperature (°C) and mean monthly temperature (°C) that were summarized with basic statistics as Table 1.

Table 1 Statistical summarization for monthly mean temperature data of 21 climate stations

Month	Tmax			Tmin			Tmean		
	Range	Mean	SD	Range	Mean	SD	Range	Mean	SD
Jan	28.10-32.70	30.91	1.24	12.10-18.80	15.24	2.15	19.10-25.50	22.32	1.98
Feb	31.00-35.10	33.54	1.07	12.30-21.80	16.93	2.85	24.20-28.20	24.53	2.17
Mar	33.80-37.50	36.01	0.90	15.20-24.50	20.28	2.58	24.20-30.30	27.65	1.73
Apr	34.80-38.40	36.99	1.03	19.20-26.00	23.30	1.76	26.00-31.50	29.54	1.39
May	32.30-36.00	34.80	0.97	21.20-25.60	24.10	1.05	25.60-30.20	28.69	1.05
Jun	29.60-34.80	32.87	1.15	21.70-25.30	24.19	0.80	24.90-29.50	27.89	1.02
Jul	28.90-34.20	32.08	1.24	21.30-24.90	23.90	0.82	24.30-29.00	27.39	1.08
Aug	28.40-33.40	31.66	1.14	21.40-24.60	23.72	0.75	24.10-28.30	27.01	0.98
Sep	29.60-33.10	31.99	0.79	21.00-24.70	23.42	0.80	24.30-28.10	26.93	0.86
Oct	29.90-33.00	31.73	0.81	19.80-24.10	22.33	1.01	23.70-27.70	26.26	0.97
Nov	28.30-32.10	30.69	1.00	16.40-21.60	19.31	1.35	21.70-26.30	24.31	1.30
Dec	26.60-31.20	29.61	1.28	12.50-18.40	15.62	1.77	18.90-24.60	21.86	1.73

3 Cokriging technique

Cokriging technique was implemented in ArcGIS 9.2, included the interested variables (3 temperature variables: monthly mean maximum temperature (°C), monthly mean minimum temperature (°C) and monthly mean temperature (°C)) and additional-topographical covariates (elevation (m), longitude (dd) and latitude (dd)). Cokriging includes 4 sub-types: Ordinary CoKriging (OCK), Universal CoKriging (UCK), Simple CoKriging (SCK), and Distinctive CoKriging (DCK) and analysing 11 semivariogram models in each sub-type: Circular (Cir), Spherical (Sph), Tetraspherical (Tsph), Pentaspherical (Psph), exponential (Exp), Gaussian (Gau), Rational Quadratic (RQ), Hole Effect (HE), K-Bessle (K-B), J-Bessel (J-B), and Stable (Stab). Then, the best of sub types and semivariogram model in temperature data will be selected with the least Root Mean Square Error (RMSE). The measurements of cokriging are expressed in 3 mathematical formulas for this study as following:

$$Z(s_i) = f(s_i) + \epsilon(s_i), \qquad i = 1,2,\ldots,n \tag{1}$$

where $Z(s_i)$ is the predicted variable, and then decomposed into a randomly deterministic trend $f(s_i)$ (including 3 covariate functions, and autocorrelated errors form $\epsilon(s_i)$. Herein, 3 correlated variables are defined: elevation is $q_1(s)$, longitude is $q_2(s)$ and latitude is $q_3(s)$ through climatic data being the variable of main interest in the study area. The empirical cross-semivariance function can be estimated as:

$$\hat{\gamma}(h) = \frac{1}{2n(h)}\sum_{i=1}^{n(h)}[z(s_i) - z(s_i + h)][q_1(s_i) - q_1(s_i + h)][q_2(s_i) - q_2(s_i + h)]\,[q_3(s_i) - q_3(s_i + h)] \tag{2}$$

where $n(h)$ is the number of data pairs where four variables are measured at a Euclidean distance h, $z(s_i)$ and $z(s_i + h)$ are data of predicted variable, and $q_{1-3}(s_i)$ and $q_{1-3}(s_i + h)$ are data of covariate. The interpolation value at an arbitrary point s_0 in the study area where there is the realization of the (locally) best linear unbiased predictor can be written as the weighted sum of measurements:

$$\hat{f}(s_0) = \sum_{i=1}^{m_1} w_{1i}z(s_i) + \sum_{j=1}^{m_2} w_{2j}q_1(s_i) + \sum_{j=1}^{m_3} w_{3j}q_2(s_i) + \sum_{j=1}^{m_4} w_{4j}q_3(s_i) \tag{3}$$

where m_1 is still the number of measurements of ($z(s_i)$) at ith location within an automatically defined radius from s_0 (out of the modeling data set), and m_2, m_3, and m_4 is the number of meteorological stations within an automatically defined radius from s_0 (out of the modeling and validation set). The weights w_{1i}, w_{2j}, w_{3j} and w_{4j}can be determined using the semivariance functions and the cross-semivariance function.

4. Results

Results of cokriging technique were analysed with 4 sub types and 11 semivariogram models that one of them was selected as the best of sub type and semivariogram model for mean monthly maximum temperature, mean monthly minimum temperature and mean monthly temperature with the least RMSE (Table 2 – Table 4). From Table 2, the best of sub type on mean monthly maximum temperature is totally account as DCK while the best semivariogram models is severally accounted as Exp for March, April, May, October and November; RQ for June, August and September; K-B for January; Stab for February; Gau for July; and Sph for December, respectively. For mean monthly minimum temperature (Table 3), DCK is mostly accounted for the best sub type except February (SCK) while Exp is mostly accounted for the best semivariogram model except February (Gau) and April (RQ). For mean monthly minimum temperature (Table 4), DCK is mostly accounted for the best sub type except January, November, and December (that are accounted as OCK) while Exp is mostly account for the best semivariogram model except November (Tsph) and December (RQ).

5. Conclusion

Temperature data comprises of 3 datasets: (1) mean monthly maximum temperature, (2) mean monthly minimum temperature and (3) mean monthly temperature, are prepared for analysing cokriging technique. The best results of cokriging on all temperature data are preferred to sub type of DCK and semivariogram model of Exp. Sub type of DCK indicates the formed predictors based on various functions of input variables while Exp expresses a relationship in which a constant change in the independent variable gives the same proportional change in the dependent variable (ESRI, 2001).

Additionally, this study recommends that the best results of cokriging should be compare with the best of other interpolations excluding covariate (e.g. Inverse Distance Weighted (IDW), Global Polynomial Interpolation (GPI), Local Polynomial Interpolation (LPI), Radial Basis Functions (RBF) includes 5 functions (Completely Regularized Spline (CRS), Spline with Tension (SWT), Multiquadric (MQ), Inverse Multiquadric (IMQ), Thin Plate Spline (TPS)), and kriging) with the least RMSE. These comparison will helpful confirm the results' effectiveness of cokriging technique.

Table 2 The best semivariogram models of cokriging technique for mean monthly maximum temperature based on the least RMSE

Tmax						
Month	Cokriging Type	Semivariogram Models				RMSE
		Type	Partial sill	Range	Nugget	
Jan	DCK	K-B	0.99	271820	0.08	0.52
Feb	DCK	Stab	0.84	271820	0.29	0.62
Mar	DCK	Exp	0.74	249560	0.38	0.75
Apr	DCK	Exp	1.052	249440	0.078	0.85
May	DCK	Exp	1.14	249470	0.10	0.76
Jun	DCK	RQ	1.11	329730	0.06	0.80
Jul	DCK	Gau	1.10	329150	0.07	0.87
Aug	DCK	RQ	1.05	327040	0.13	0.85
Sep	DCK	RQ	1.07	324670	0.12	0.64
Oct	DCK	Exp	1.12	249370	0.10	0.62
Nov	DCK	Exp	1.08	251030	0.10	0.58
Dec	DCK	Sph	1.08	304590	0.10	0.61

Table 3 The best semivariogram models of cokriging technique for mean monthly minimum temperature based on the least RMSE

Tmin						
Month	Cokriging Type	Semivariogram Models				RMSE
		Type	Partial sill	Range	Nugget	
Jan	DCK	Exp	1.08	253350	0.10	1.07
Feb	SCK	Gau	10.165	254870	0.01	1.20
Mar	DCK	Exp	1.10	252340	0.10	1.38
Apr	DCK	RQ	1.12	330380	0.07	1.26
May	DCK	Exp	1.13	251570	0.10	0.63
Jun	DCK	Exp	1.13	250370	0.10	0.50
Jul	DCK	Exp	1.10	249760	0.10	0.51
Aug	DCK	Exp	1.08	250200	0.10	0.45
Sep	DCK	Exp	1.11	251250	0.10	0.49
Oct	DCK	Exp	1.12	251620	0.10	0.56
Nov	DCK	Exp	1.13	250710	0.10	0.66
Dec	DCK	Exp	1.10	251260	0.10	0.84

Table 4 The best semivariogram models of cokriging technique for mean monthly temperature based on the least RMSE

Tmean						
Month	Cokriging Type	Semivariogram Models				RMSE
		Type	Partial sill	Range	Nugget	
Jan	OCK	Exp	1.08	253350	0.10	1.07
Feb	DCK	Exp	10.165	254870	0.01	1.20
Mar	DCK	Exp	1.10	252340	0.10	1.38
Apr	DCK	Exp	1.12	330380	0.07	1.26
May	DCK	Exp	1.13	251570	0.10	0.63
Jun	DCK	Exp	1.13	250370	0.10	0.50
Jul	DCK	Exp	1.10	249760	0.10	0.51
Aug	DCK	Exp	1.08	250200	0.10	0.45
Sep	DCK	Exp	1.11	251250	0.10	0.49
Oct	DCK	Exp	1.12	251620	0.10	0.56
Nov	OCK	Tsph	1.13	250710	0.10	0.66
Dec	OCK	RQ	1.10	251260	0.10	0.84

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