ASSESSING THE EFFECT OF INCORPORATING TOPOGRAPHICAL DATA WITH GEOSTATISTICAL INTERPOLATION FOR MONTHLY RAINFALL AND TEMPERATURE IN PING BASIN, THAILAND

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Abstract

This paper aims to assess the effect of incorporating topographical data with geostatistical interpolation for monthly rainfall and temperature in Ping Basin, Thailand. The spatial interpolation techniques based on 11 semivariogram models of 4 main sub-types of cokriging with 3 topographical variables: elevation, longitude, and latitude have been applied in this study. The best interpolation models from cokriging technique on mean monthly rainfall and mean monthly temperature are selected by Akaike Information Criterion (AIC) based on partial sill, range and nugget that the best monthly models of kriging technique is operated in same mentioned selection. In addition, an assessment of the effective results of the cokriging interpolation models is performed by 2 approaches: i) comparing the errors of the best results from other interpolations excluding topographic data with the least MAE, MRE and RMSE value and ii) comparing the accuracy of results from Multiple Linear Regression (MLR) with the coefficient of determination (r^2). It was found that cokriging models of mean monthly rainfall and mean monthly temperature have more effectiveness than other interpolations excluding topographic data and MLR including topographic data. Therefore, this study can use the best results of sub-type and semivariogram model from cokriging including topographic variables for mean monthly rainfall and mean monthly temperature surface interpolation.

Keywords: **Rainfall and temperature, topographic data, geostatistical interpolation, cokriging, Ping Basin**

Introduction

Forest rehabilitation plays an important role in forest conservation in Thailand and requires a basic knowledge of the forest ecosystem model. Basically, the forest ecosystem model is quantified into two components: biotic (flora, fauna, microorganism and human) and abiotic (energy and physical environment). Especially physical data (e.g. soil, climate,

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geology, topography, and forest fire) are always used to classify in forest type distribution because it is easy to understand the relationship between them (Aber *et al.*, 2001). Climatic data are essential input variables for ecological modeling and play a significant role in flora and fauna distributions; they are usually a key to understanding the interdependence between environmental and biological factors and are widely used in developing ecological zones and biodiversity assessments (Pearson *et al.*, 2002; Hong *et al.*, 2005). Generally, climatic variables are measured at a few meteorological stations which can be used to interpolate surfaces in unknown locations. In Geographical Information Systems (GIS), statistical interpolation techniques are commonly applied for mapping climatic data. In the field of forest ecological modeling, rainfall and temperature variables are often used for spatial interpolations which usually incorporate 3 topographic variables: elevation, longitude, and latitude. Hutchison (1995) and Trisurat *et al.* (2009) mentioned rainfall and temperature variables that are often highly correlated with topographical variables. Table 1 summarized two main interpolation methods: the deterministic method and the geostatistical method with theirs variants.

This paper intends to apply geostatistical interpolation including additional information, i.e. cokriging for mean monthly rainfall and mean monthly temperature in the long term data (1971-2000). The advantage of cokriging is that it can add correlated information to an interested variable e.g. climatic data. The best interpolation models of cokriging in each month are selected by Akaike Information Criterion (AIC) based on partial sill, range and nugget that is processed for selection of kriging models in each month too. Additionally, cokriging can be applied as a linear model of coregionalization (Boer *et al.*, 2001) with the semivariance and cross-semivariance function as well (Isaaks and Srivastava, 1989). This application of cokriging is used in this study to assess the effect of incorporating the 3-topographical data (elevation, longitude, and latitude) and then it is compared with Multiple Linear Regression (MLR) which is 1 of the linear models that includes various correlated variables. This comparison uses the coefficient of determination (r^2) to investigate the efficient of predicted results from cokriging incorporating the 3 topographical variables. Additionally, deterministic interpolation methods are used to compare with the cokriging method of this study with consideration of Mean Absolute Error (MAE), Mean Relative Error (MRE), and their mentioned RMSE values to check the effectiveness of the measured values and predicted values in the interpolated area.

Actually, this paper is a part of research named ‘Prediction of forest type distribution using ecological modeling in Ping Basin, Thailand’ Such mentioned research has used physical factors (climate, topography and soil) for forest ecological modeling that is modeled by spatial analysis. Interpolation mapping of mean monthly rainfall and mean monthly temperature are totally 24 maps are required in 13 sub-watersheds of Ping Basin where study area sites in the north of Thailand. Additionally, 21 main climate stations of Thailand Meteorological Department (TMD) has been applied for this paper where sparsely locate in northern Thailand (Figure 1) for interpolation surfaces of in study area. Results of the interpolation on mean monthly rainfall and mean monthly temperature in this paper will be used in studying the distribution of forest types in the study area that is analysed by integrating other physical factors.

The study area is situated between latitudes 15° 22’ 29” and 19° 53’ 10” N and longitudes 14° 04’ 05” and 100° 54’ 37” E where covers 4 provinces of Thailand (Chiang Mai, Mae Hong Son, Lamphun, and Tak) and covers an area of 22,472.23 km^2 or 65% of Ping Basin. Ping Basin is 1 of 3 first-order river system in Thailand where are intensively managed because of severe disturbance of the

Table 1. Studying of spatial interpolation with climate variables for forest ecological modeling; recommended methods are shown in bold

Regions	Variables	Interpolation methods	Sources
Mountain-plain region, Upper Pakistan	1	IDW, LPI, RBF, **OK, OCK**	Ashiq *et al.* (2010)
The northern of Thailand	1,5	TPS	Trisurat *et al.* (2009)
Yellowstone of National Park, USA	1	Trivariate zonal Kriging with fitting the zonal variogram; **OK**, SK, UK, DK Trivariate zonal CoKriging with elevation; **OCK**, SCK, UCK, DCK CoKriging with elevation: OCK, SCK, **UCK**, DCK	Watson and Neman (2009)
Mexico	1,5	Kriging with semi-variograms to evaluate residuals for models	Reich *et al.* (2008)
Mountainous region, Northern Spain	5	OK, **OKxyz, OKED, UK1, UK2**	Benavides *et al.* (2007)
Norway	1	Kriging	Vajda (2007)
British Columbia, USA	5	NN approaches, **Weighted-average approaches with OK, and GIDS integrated Multiple linear regression**	Stahl *et al.* (2006)
China	1,5	TPSS (ANUSPLIN)	Hong *et al.* (2005)
Great Britain	5	Kriging integrated neural network	Pearson *et al.* (2002)
Canada	1,5	**TPSS (ANUSPLIN)** and GIDS	Price *et al.* (2000)
Mountainous region, Scotland	1	OK	Prudhomme and Reed (1999)
The eastern of USA	1,5,7	IDW	Iverson *et al.* (1999)
Ireland	1,3,5	Polynomial regression integrated IDS	Goodale *et al.* (1998)
Australia	1	TPS	Hutchison (1995 and 1998)

1 is rainfall, 2 is relative humidity, 3 is solar radiation, 4 is sunshine duration, 5 is temperature, 6 is wind speed, 7 is evaporation, 8 is vapour pressure, IDW is Inverse Distance Weighted, LPI is Local Polynomial Interpolation, RBF is Radial Basis Functions (e.g. CRS: Completely Regularized Spline, SWT: Spline with Tension, MQ: Multiquadric, IMQ: Inverse Multiquadric, and TPS: Thin Plate Spline), OK is Ordinary Kriging, SK is Simple Kriging, UK is Universal Kriging, DK is Distinctive Kriging, OCK is Ordinary CoKriging, SCK is Simple CoKriging, UCK is Universal CoKriging, DCK is Distinctive CoKriging, IDS is Inverse distance-squared, TPSS (ANUSPLIN) is thin-plate smoothing splines that is analysed in ANUSPLIN program, GIDS is Gradient plus Inverse-Distance-Squared, OKxyz is Ordinary Kriging developed in the XY plane and in the X, Y and Z-axis, OKED is Ordinary Kriging with external drift, UK1 is Universal Kriging, using the ordinary least squares (OLS) residuals to estimate the variogram, UK2 is the generalized least squares (GLS) residuals, and NN is Neareast-Neighbor approaches

forest area. Ping Basin includes lower montane forest and upper montane forest, are highly dominant in the higher altitudes whereas deciduous forest types are in the low and moderate altitudes (DNP, 2007). The topography of Ping Basin including the study area has a mountainous complex and plain area with elevations between 100 and 2500 m. Additionally, the TMD has reported the average annual rainfall and temperature data during 1971-2000 from records of the 21 main stations in northern Thailand. The reporting presented the average annual temperature ranges to be from 23.3 to 28.2°C depending location and the average annual rainfall ranges to be from 962.4 to 1702.2 mm.

Materials and Methods

Materials

This paper had applied the mean monthly rainfall and mean monthly temperature data from the 30-year period (1971-2000) from 21 climate stations of the TMD which are located in the north of Thailand. These climate stations are transformed into points in GIS that, in each point, include climate data and 3 topographic variables (elevation, longitude, and latitude). In this study, climate data is arranged with 2 layers: layer of precipitation and layer of temperature. In each layer, there is attribute data that includes mean monthly climate data and such 3 above topographic variables. The topographic data of 21 climate station is defined with same values (Table 2) and are used for considering monthly relationship with the correlation (Pearson coefficient). This paper had summarized monthly statistics of 30 years (1971-2000) data through correlation (r) is shown in Table 3. From Table 3, correlation of mean monthly rainfall data is higher than 0.5 except May-September in rainy season while correlation of mean monthly temperature data is higher than 0.6 in all months.

Interpolation Methods

This paper had categorized interpolation methods into 2 main groups: interpolation method including topographic data and interpolation method excluding topographic data as following:

Interpolation Method Including Topographic Data

This method is the cokriging technique that is implemented in ArcGIS 9.2 for this

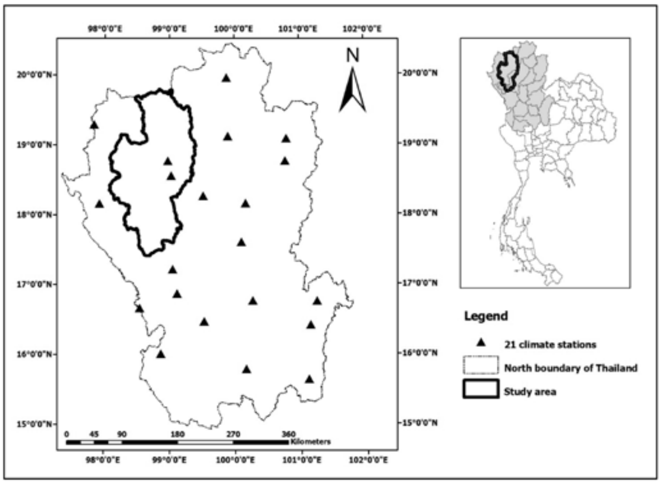

Figure 1. The study area and climate stations in the northern region, Thailand

paper. Cokriging interpolation includes the interested variables (mean monthly rainfall and mean monthly temperature) and additional-topographical covariates (elevation, longitude and latitude). Cokriging is most effective when the covariates are highly correlated (Collins and Bolstad, 1996; Ashrat *et al.*, 1997; Nalder and Wein, 1998; Apaydin *et al.*, 2004). In this study, 4 different cokriging sub-types: Ordinary CoKriging (OCK), Universal CoKriging (UCK), Simple CoKriging (SCK), and Distinctive CoKriging (DCK), are used for interpolating climate data 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). Additionally, cokriging is developed by incorporating 3 correlated variables: elevation, longitude and latitude with climatic data (rainfall and temperature) for surface interpolation. Herein, the actual meteorological measurement is

Table 2. Topographic data of 21 climate stations for this paper

Climate Stations	Elevation (m)	Latitude (dd)	Longitude (dd)
MaeHongSon	800	19.30	97.83
Mae Sariang	208	18.17	97.93
Chaing Mai	308	18.78	98.98
Lamphun	292	18.57	99.03
Tak	123	16.88	99.12
Mae Sot	238	16.67	98.55
Bhumibol Dam	149	17.23	99.05
Umphang	528	16.02	98.87
Chaing Rai	387	19.97	99.88
Phayao	394	19.13	99.90
Nan	205	18.78	100.78
Tha Wang Pha	228	19.10	100.80
Phrae	163	18.17	100.17
Utraradit	69	17.62	100.10
Kamphang Phet	82	16.48	99.53
Phitsanulok	47	16.78	100.27
Phetchabun	122	16.43	101.15
Lom Sak	149	16.77	101.25
Wichiang Buri	77	15.65	101.12
Lampang	255	18.28	99.52
Nakhon Sawan	28	15.80	100.17

m = meter and dd = degree decimal

Table 3. Summary statistics of 30 years (1971-2000) averaged monthly climate data and the correlation (r)

Rainfall (mm)					
Month	**Mean**	**Standard deviation**	**Minimum**	**Maximum**	**r versus elevation, latitude and longitude**
Jan	5.9	2.3	1.8	11.2	0.60
Feb	11.5	4.4	5.0	23.0	0.84
Mar	25.0	9.9	8.7	43.0	0.92
Apr	61.7	21.6	30.0	104.0	0.78
May	172.5	20.2	146.0	233.0	0.13
Jun	149.5	38.3	88.0	235.0	0.30
Jul	177.6	62.7	80.0	319.0	0.40
Aug	223.4	64.3	114.0	378.0	0.40
Sep	212.7	31.3	160.0	271.0	0.23
Oct	123.7	39.0	79.0	206.0	0.58
Nov	34.0	14.7	11.0	61.0	0.58
Dec	8.0	4.3	3.0	19.0	0.79

Temperature (°C)					
Month	**Mean**	**Standard deviation**	**Minimum**	**Maximum**	**r versus elevation, latitude and longitude**
Jan	22.3	2.0	19.1	25.5	0.88
Feb	24.5	2.2	21.0	28.2	0.83
Mar	27.6	1.7	24.2	30.3	0.75
Apr	29.5	1.4	26.0	31.5	0.66
May	28.7	1.0	25.6	30.2	0.66
Jun	27.9	1.0	24.9	29.5	0.69
Jul	27.4	1.1	24.3	29.0	0.69
Aug	0.69	1.0	24.1	28.3	0.67
Sep	26.9	0.9	24.3	28.1	0.70
Oct	26.3	1.0	23.7	27.7	0.71
Nov	24.3	1.3	21.7	26.3	0.78
Dec	21.9	1.7	18.9	24.6	0.84

denoted as z(s_1), z(s_2),..., z(s_n), where s_i = (x_i, y_i) is a point for interpolation, x_i and y_i are the coordinates of point s_i and n is equal to the number of measurement points. The elevation, longitude, and latitude at point s in northern Thailand will be denoted as q_1(s), q_2(s) and q_3(s), respectively. The cokriging technique is similar to kriging in that it relies on the notion of spatial autocorrelation that is well explained elsewhere (Isaak and Srivastava, 1989; Lloyd, 2007). The measurements are expressed in a simple mathematical formula in this study as:

$$Z_1(s_i) = f_1(s_i) + \epsilon(s_i), \quad i = 1, 2,\ldots, n \tag{1}$$

where $Z_1(s_i)$ is the main variable of interest as mean monthly rainfall and mean monthly temperature, and then decomposed into a deterministic trend $f_{1\text{-}4}(s_i)$, and random, autocorrelated errors form $\epsilon(s_i)$. The different cokriging sub-types are: OCK which is the form of an unknown deterministic function, UCK which is the form of linear regression where the regression coefficients are unknown, SCK which is the form of completely known trend, and DCK which is the form of predictors of functions of variables. Each cokriging sub-type includes 11 different semivariogram models (Cir, Sph, Tsph, Psph, Exp, Gau, RQ, HE, K-B, J-B, and Stab) for studying the spatial correlation between measured points and which can be known as basic semivariogram functions (Boer *et al.*, 2001):

$$\gamma(s, h) = \frac{1}{2}\, var[F(s)\text{-}F(s+h)] \tag{2}$$

where the assumption is that h is the Euclidean distance between 2 points, the trend is constant and $\gamma(s, h)$ is independent of s. A parametric function is used to model the semivariance for different values of h. In this paper, 11 semivariogram models (as mentioned above) are used for the interpolated value at an arbitrary point s_0 in the study site where there is the realization of the (locally) best linear unbiased predictor of $F(s_0)$ and can be written as basically the weighted sum of the measurements.

$$\hat{f}(s_0) = \sum_{i=1}^{n} w_i z(s_i) \tag{3}$$

where the weights w_i are derived from the kriging equation by means of the semivariance function; and n is the number of measurement points within a radius from point s_0 (let follows by default). The parameters of the semivariance function and the nugget effect can be estimated by the empirical semivariance function. An unbiased estimator for the semivariance function is ½ the average squared difference between paired data values.

$$\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(s_i) - z(s_i + h)]^2 \tag{4}$$

where $n(h)$ is equal to the number of data pairs of measurement points separated by the Euclidean distance h.

As mentioned Table 1, cokriging integrated elevation was often purposed for several purposes. Herein, the cokriging technique incorporates 3 correlated variables: elevation, longitude, and latitude because they are importantly correlated to study rainfall and temperature data in the field of forest resource. In the cokriging study, 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:

$$\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(s_i) - z(s_i + h)][q_1(s_i) - q_1(s_i + h)][q_2(s_i) - q_2(s_i + h)] [q_3(s_i) - q_3(s_i + h)] \tag{5}$$

where *n(h)* is the number of data pairs where four variables are measured at a Euclidean distance *h*.

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 of *F*(s_0) can be written as the weighted sum of measurements:

$$\hat{f}(s_0) = \sum_{i=1}^{m_1} w_{1i} z(s_i) + \sum_{j=1}^{m_2} w_{2j} q_1(s_i)$$
$$+ \sum_{j=1}^{m_3} w_{3j} q_2(s_i) + \sum_{j=1}^{m_4} w_{4j} q_3(s_i) \quad (6)$$

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.

Interpolation Method Excluding Topographic Data

This method comprises of 5 interpolation techniques: 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, can be summarized with concept in Table 4. The best results of 6 interpolation techniques were compared with the best results of cokriging technique to assess interpolation method incorporating topographic data for mean monthly rainfall and mean monthly temperature.

Cross Validation

Cross validation is used for investigating predicted models to the values at unknown locations. Cross validation uses all of the data to estimate the autocorrelation model. Then it removes each data location, one at a time, and predicts the associated data value. This procedure is repeated for the sample points and so on. For all points, cross validation compares the measured and predicted values. This study used all parameters of methods optimized for the least cross validation error.

Comparison

This step aims to assess effectiveness of cokriging technique that includes additional covariate (elevation, longitude and latitude). Then, there is operation as following:

1) Selecting the best model from cokriging and kriging techniques: this is comparison for selecting the best models of mean monthly rainfall and mean monthly temperature from 4 sub-types (ordinary, universal, simple, and distinctive) and 11 semivariogram models (Cir, Sph, Tsph, Psph, Exp, Gau, RQ, HE, K-B, J-B, and Stab). Cokriging and kriging technique is graphically modeled by 3 values: partial sill, range, and nugget. Partial sill is the sill minus the nugget where the sill is all semivariance values, the nugget is the difference between measurements of semivariance values, and range is distance of the model first flattens out (Figure 2). Moreover, the best models of cokriging and kriging are considered by Akaike Information Criterion (AIC); is a measure of the relative goodness of fit of a statistical model (Akaike, 1974). AIC is implemented in SPSS program.

2) Comparing errors of the predicted result from 6 interpolation techniques: this is comparison between interpolation method including (i.e. cokriging) and excluding (i.e. kriging, IDW, GPI, LPI, and RBF with 5 stated functions) based on topographic data. This comparison is reasonably to assess effectively the different interpolation techniques. Thus, errors were calculated as 'actual minus predicted' and the mean of these errors was calculated in 3 ways: mean absolute error (MAE), providing a measure of how far the

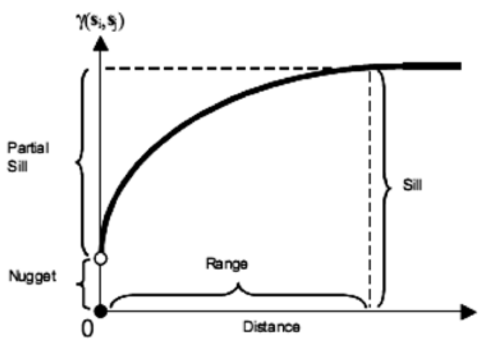

Figure 2. The graphic model of semivariogram with partial sill, range and nugget

estimate can be in error, ignoring its sign; mean relative error (MRE), providing a measure of how far the estimate can be in error relative to the measured mean; root mean square error (RMSE), providing a measure that is sensitive to outliers.

3) Comparing the accuracy of the predicted results between cokriging technique and Multiple Linear Regression (MLR): this is comparison of statistical techniques with same concept. The best of cokriging interpolation had been compared with MLR that is one popular technique including multiple variables. This paper used the coefficient of determination (r^2) to compare and evaluate relationship of measured values and predicted values at same location. Data, is used for MLR, is defined as same as cokriging technique and is implemented in SPSS program.

Results and Discussion

The Best Cokriging Models and Kriging Models

Best models of mean monthly rainfall and mean monthly temperature from cokriging and kriging techniques had been selected on the basis of AIC (Table 5 and Table 6). The selected interpolation models with the minimum AIC value. From Table 5 and 6, this study found that the monthly interpolation models from cokriging technique gave lower AIC values than kriging technique. Consequently, cokriging models will be selected to interpolate the surface for mean monthly rainfall and mean monthly temperature (Table 5). As mentioned Table 5, the selected-best results of rainfall reveal cokriging sub-type and

Table 4. Summary of interpolation method excluding topographic data

Method	Concept
1. Inverse Distance Weighted (IDW)	IDW assumes that each measured point has a local influence that diminishes with distance.
2. Global Polynomial Interpolation (GPI)	GPI fits a smooth surface that is defined by a mathematical function to the input sample points.
3. Local Polynomial Interpolation (LPI)	While GPI fits a polynomial to the entire surface, LPI fits many polynomials, each within specified overlapping neighborhoods. The search neighborhood can be defined using the search neighborhood dialog.
4. Radial Basic Function (RBF)	Radial basic function (RBF) methods include Completely Regularized Spline (CRS), Spline with Tension (SWT), Multiquadric (MQ), Inverse Multiquadric (IMQ), and Thin Plate Spline (TPS). RBFs are conceptually similar to fitting a rubber membrane through the measured sample values while minimizing the total curvature of the surface. The selected basic function determines how the rubber membrane will fit between the values.
5. Kriging technique	Kriging is similar to cokriging, except that it cannot use additional covariates, e.g. the climatic variable and topographic data. Kriging forms weights from surrounding measured values to predict values at unmeasured locations. Kriging weights come from a semivariogram developed from the spatial structure of the data. To create a continuous surface or map of the phenomenon, predictions are made for locations in the study area based on the semivariogram and the spatial arrangement of nearby measured values. Four different cokriging types similar to the kriging types were used in this study: ordinary (KO); simple (KS); universal (KU); and disjunctive (KD).

semivariogram model as Simple CoKriging with Rational Quadratic (SCK_RQ), on the other hand, Distinctive CoKriging with Exponential (DCK_Exp) is fitted models for monthly mean temperature. These means characteristic of monthly mean rainfall (1971-

Table 5. The best semivariogram models of cokriging method for mean monthly rainfall and mean monthly temperature data based on AIC

Rainfall						
Month	Cokriging Type	Semivariogram Models				AIC
		Type	Partial sill	Range	Nugget	
Jan	SCK	RQ	2.08	330040	3.94	153.10
Feb	SCK	J-B	16.19	451280	3.66	120.25
Mar	SCK	RQ	88.18	451280	15.82	167.07
Apr	SCK	RQ	567.38	325050	0.57	167.07
May	DCK	RQ	0.32	329920	0.74	150.51
Jun	SCK	RQ	767.06	323490	847.99	160.10
Jul	SCK	RQ	3730.70	320260	864.86	160.10
Aug	SCK	RQ	3514.50	321160	1240.90	167.07
Sep	SCK	HE	142.59	471210	869.82	167.07
Oct	SCK	RQ	1870.50	323420	1.87	148.02
Nov	SCK	RQ	253.82	322570	0.25	152.10
Dec	SCK	HE	10.68	471210	10.78	40.20
Temperature						
Month	Cokriging Type	Semivariogram Models				AIC
		Type	Partial sill	Range	Nugget	
Jan	OCK	Exp	4.85	471210	0.01	160.01
Feb	DCK	Exp	1.08	252830	0.01	152.03
Mar	DCK	Exp	1.11	251550	0.01	152.03
Apr	DCK	Exp	1.15	249710	0.01	138.80
May	DCK	Exp	1.10	327190	0.09	134.20
Jun	DCK	Exp	1.11	250600	0.01	140.32
Jul	DCK	Exp	1.11	250630	0.01	145.00
Aug	DCK	Exp	1.10	250120	0.01	135.02
Sep	DCK	Exp	1.13	249850	0.01	140.01
Oct	DCK	Exp	1.12	250750	0.01	140.96
Nov	OCK and UCK	Tsph	2.40	471210	0.01	140.78
Dec	OCK and UCK	RQ	3.67	471210	0.01	160.10

2000) data correlated to topographic data tends to completely known trend with RQ semivariogram model. Whereas characteristic of monthly mean temperature (1971-2000) data correlated to topographic data tends to the form of studied variable function with Exp

Table 6. The best semivariogram models of kriging method for mean monthly rainfall and mean monthly temperature data based on AIC

Month	Cokriging Type	Semivariogram Models				AIC
		Type	Partial sill	Range	Nugget	
Rainfall						
Jan	DK	Gau	0.72	471210	0.64	153.55
Feb	UK	Sph	28.02	471210	0.79	126.55
Mar	SK	Cir	158.79	471210	4.12	167.87
Apr	SK	RQ	571.29	448720	42.19	167.87
May	DK	Tsph	0.88	167070	0.23	152.51
Jun	SK	J-B	1506.20	164940	75.46	163.10
Jul	SK	J-B	3200.40	111400	0.01	163.10
Aug	SK	HE	3114.80	111150	650.82	167.87
Sep	DK	HE	0.73	106490	0.01	167.87
Oct	SK	Gau	1702.30	143480	70.23	148.78
Nov	SK	Gau	211.29	147060	14.02	153.55
Dec	SK	K-B	0.01	451280	16.89	41.26
Temperature						
Jan	OK and UK	Gau	6.97	426830	0.11	163.10
Feb	SK	K-B	6.51	451280	0.01	153.55
Mar	SK	RQ	3.66	413840	0.07	153.55
Apr	SK	Psph	1.86	471210	0.01	138.89
May	SK	J-B	0.48	323300	0.51	134.46
Jun	DK	RQ	1.12	408800	0.09	141.23
Jul	DK	Exp	1.36	471210	0.01	146.01
Aug	DK	RQ	0.97	347410	0.13	135.42
Sep	DK	Psph	1.07	301600	0.05	144.01
Oct	DK	RQ	1.31	471210	0.01	142.96
Nov	SK	J-B	1.94	451280	0.25	148.78
Dec	SK	Cir	4.80	471210	0.01	163.10

semivariogram model.

Assessing the Results of Cokriging Incorporating Topographic Data

This assessment is considered by 2 approaches: the error of result and the accuracy of result as follows:

- Comparing the errors of the predicted result between cokriging technique and other interpolation techniques.

Since cokriging is geostatistical model including additional covariates (elevation, longitude, and latitude) that differs from another modeling (kriging, IDW, GPI, LPI, RBF with 5 functions (CRS, SWT, MQ, IMQ and TSP) excluding additional covariates. Therefore, the best model sets of mean monthly rainfall and mean monthly temperature are evaluated separately for their interpolation performance as shown in Table 7 and Table 8

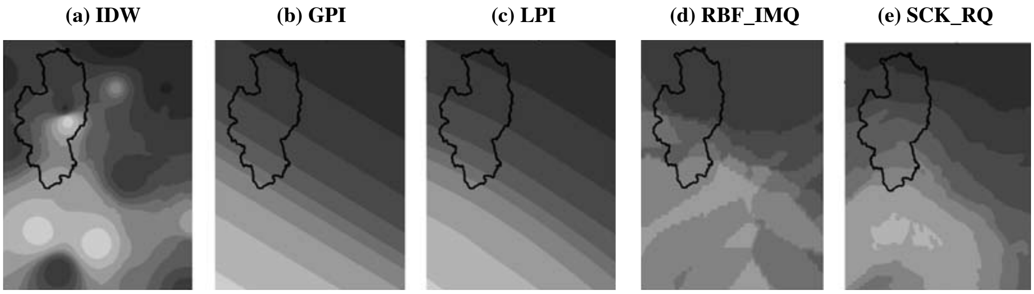

Figure 3. Comparison of rainfall interpolation of January using various deterministic and cokriging methods: (a) Inverse Distance Weighted (IDW), (b) Global Polynomial Interpolation (GPI), (c) Local Polynomial Interpolation (LPI), (d) Radial Basis Function with Inverse Multiquadric (RBF_IMQ), (e) Ordinary Cokriging with Exponential (SCK_RQ) including topographic variables

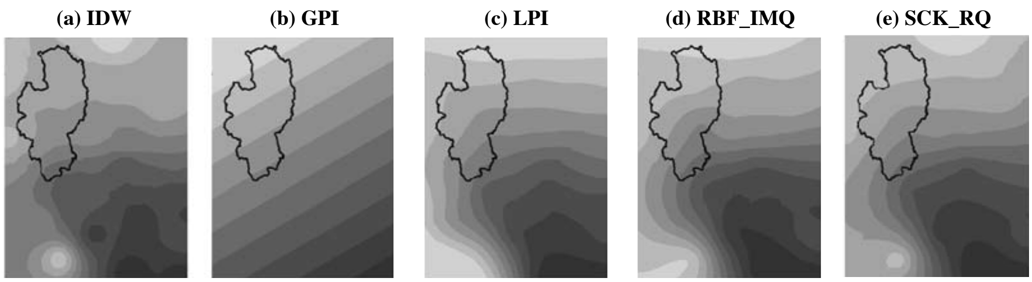

Figure 4. Comparison of temperature interpolation of January using various deterministic and cokriging methods: (a) Inverse Distance Weighted (IDW), (b) Global Polynomial Interpolation (GPI), (c) Local Polynomial Interpolation (LPI), (d) Radial Basis Function with Multiquadric (RBF_MQ) (e) Ordinary Cokriging with Exponential (OCK_Exp) including topographic variables

Table 7. Summary of error estimators for prediction of mean monthly rainfall

	IDW			GPI			LPI			RBF			Kriging			Cokriging		
Month	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**
Jan	1.87	36.28	2.44	1.82	34.77	2.24	1.79	36.72	2.40	1.78	31.11	2.22 (IMQ)	1.68	29.67	2.20 (DK_Gau)	**1.54**	**28.38**	1.90 (SCK_RQ)
Feb	2.07	19.45	2.49	2.42	22.46	2.86	2.00	18.70	2.38	1.96	18.81	2.39 (IMQ)	2.13	19.71	2.52 (UK_Sph)	**1.93**	**18.26**	**2.36** (SCK_J-B)
Mar	**3.85**	17.09	40.05	4.20	28.78	32.34	4.07	19.91	34.26	4.01	18.63	31.43 (IMQ)	4.00	18.48	5.18 (SK_Cir)	14.29	**8.26**	**4.86** (SCK_RQ)
Apr	12.19	20.78	16.35	13.78	24.79	18.78	14.45	26.98	19.58	11.47	19.97	**15.82** (IMQ)	11.39	20.27	16.23 (SK_RQ)	10.19	**0.20**	16.02 (SCK_RQ)
May	14.51	**0.08**	19.81	17.03	9.90	21.87	17.36	10.39	22.16	14.66	8.47	19.73 (SWT)	14.82	8.40	19.57 (DK_Tsph)	**14.29**	**8.26**	**19.09** (DCK_RQ)
Jun	32.49	22.96	40.99	35.22	23.86	42.44	31.69	21.39	40.14	22.14	14.58	29.72 (MQ)	29.06	19.75	37.41 (SK_J-B)	**29.08**	**0.21**	**37.24** (SCK_RQ)
Jul	44.74	28.19	61.63	52.67	30.70	68.71	45.20	25.07	60.56	42.54	25.42	55.89 (MQ)	**32.14**	19.04	55.75 (SK_J-B)	38.47	**23.17**	**55.62** (SK_RQ)
Aug	47.65	23.76	63.66	53.16	24.98	68.41	47.67	22.07	63.86	**42.66**	20.77	58.79 (CRS)	44.76	21.48	60.66 (SK_HE)	**43.18**	**20.66**	**57.80** (SCK_RQ)
Sep	24.47	11.62	32.21	27.61	13.14	35.58	27.53	13.64	36.58	24.49	11.52	31.60 (IMQ)	24.00	11.97	39.76 (DK_HE)	**23.41**	**11.03**	**30.31** (SCK_HE)
Oct	19.71	14.79	25.85	29.43	23.68	37.18	22.75	17.67	30.51	14.60	11.01	**21.58** (CRS)	12.54	9.70	28.91 (SK_Gau)	17.60	**0.13**	25.66 (SCK_RQ)
Nov	8.48	23.82	11.00	8.48	23.82	14.12	7.09	26.11	9.32	5.03	18.62	**6.57** (SWT)	**0.53**	2.14	10.72 (SK_Gau)	6.18	**0.16**	9.77 (SCK_RQ)
Dec	44.74	28.19	3.81	2.53	38.69	3.17	3.81	28.70	2.60	2.12	25.54	3.13 (MQ)	3.14	39.29	3.24 (SK_K-B)	**2.11**	**27.87**	**1.90** (SCK_HE)

Table 8. Summary of error estimators for prediction of mean monthly temperature

	IDW			GPI			LPI			RBF			Kriging			Cokriging		
Month	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**	**MAE**	**MRE**	**RMSE**
Jan	0.91	4.01	2.44	0.91	4.01	2.24	0.82	3.72	1.02	0.78	3.19	1.03 (MQ)	0.77	3.40	0.99 (OK/ UK_Gau)	**0.71**	**0.03**	**0.95** (OCK_Exp)
Feb	1.13	4.51	2.49	1.19	4.74	2.86	0.98	4.08	1.20	0.89	3.67	1.254 (CRS)	1.08	4.35	1.29 (SK_K-B)	**0.80**	**0.03**	**1.13** (DCK_Exp)
Mar	1.02	3.64	40.05	1.13	4.02	32.34	0.91	3.36	1.21	0.89	3.69	1.23 (CRD)	0.84	3.06	1.20 (SK_RQ)	**0.82**	**3.01**	**1.01** (DCK_Exp)
Apr	0.84	2.83	16.35	1.04	3.49	18.78	0.83	2.85	1.09	0.81	2.77	1.16 (CRS)	0.79	3.03	1.14 (SK_Psph)	**0.77**	**2.62**	**0.93** (DCK_Exp)
May	0.64	2.23	19.81	0.84	2.90	21.87	0.56	1.98	0.80	0.54	1.91	0.84 (SWT)	14.51	9.02	0.80 (SK_J-B)	**14.29**	**8.26**	**0.74** (DCK_Exp)
Jun	0.63	2.27	40.99	0.78	2.78	42.44	0.49	1.78	0.67	0.46	1.66	0.67 (SWT)	0.51	1.82	0.75 (DK_RQ)	**0.48**	**1.74**	**0.64** (DCK_Exp)
Jul	0.68	2.48	61.63	0.85	3.09	68.71	0.68	2.48	0.67	0.46	1.72	0.68 (SWT)	0.53	1.92	0.80 (DK_Exp)	**0.49**	**1.83**	**0.65** (DCK_Exp)
Aug	0.60	2.22	63.66	0.60	2.22	68.41	0.45	1.71	0.62	0.42	1.56	0.63 (SWT)	0.54	1.99	0.76 (DK_RQ)	**0.46**	**1.73**	**0.62** (DCK_Exp)
Sep	0.51	1.89	32.21	0.51	1.89	35.58	0.44	1.65	0.61	0.36	1.35	0.57 (SWT)	0.38	1.42	0.61 (DK_Psph)	**0.33**	**1.25**	**0.51** (DCK_Exp)
Oct	0.53	1.99	25.85	0.53	1.99	37.18	0.50	1.91	0.78	0.43	1.65	0.72 (CRS)	0.41	2.02	0.65 (DK_RQ)	**0.32**	**1.26**	**0.52** (DCK_Exp)
Nov	0.61	2.48	11.00	0.61	2.48	14.12	0.59	2.42	0.91	0.54	2.19	0.88 (SWT)	0.53	2.14	0.85 (SK_J-B)	**0.33**	**1.25**	**0.83** (OCK/ UCK_Tsph)
Dec	0.72	3.24	3.81	0.90	4.09	3.17	0.74	3.39	1.00	0.64	2.87	0.95 (SWT)	0.62	2.76	0.95 (SK_Cir)	**0.61**	**2.75**	**0.89** (OCK/ UCK_Tsph)

respectively. Results of Table 7 presented that mean monthly rainfall in term of the least MAE, MRE and RMSE is mostly appeared in cokriging technique such as January, February, May, June, August, September and December. On opposite, results of Table 8 presented that mean monthly temperature in term of the least MAE, MRE and RMSE is appeared in all cokriging technique. As a consequence, results of cokriging technique including additional covariates have more effectiveness than results of other interpolation techniques excluding additional covariates. Additionally, this paper had example of rainfall and temperature interpolation of January based on cokriging interpolation including topographic data (elevation, longitude and latitude) and other interpolations excluding topographic data (Figure 3 and Figure 4).

- Comparing the accuracy of the predicted results between cokriging technique and Multiple Linear Regression (MLR)

In this paper, cokriging is applied as a linear model of coregionalization that is similar to the concept of MLR. However, MLR cannot interpolate surfaces; it can predict values at specific (measured) locations. Both cokriging and MLR are compared with the coefficient of determination (r^2) to evaluate the efficient of results (Table 9). Results show that the r^2 values of cokriging interpolation on mean monthly rainfall are equally or slightly lower than r^2 of MLR on January, February, March, April, September, and December. On opposite, r^2 of mean monthly temperature in cokriging is slightly higher than r^2 of MLR on March-October and December.

Conclusions

Assessing the effect of cokriging incorporating the topographic variables of elevation, longitude, and latitude are analysed based on mean monthly rainfall and mean monthly temperature

Table 9. Comparison of r^2 values for cokriging models with additional information for various months

Month	rainfall		Temperature	
	r^2 of Cokriging[1]	r^2 of MLR[2]	r^2 of Cokriging[1]	r^2 of MLR[2]
Jan	0.28	0.36	0.76	0.78
Feb	0.71	0.71	0.72	0.69
Mar	0.75	0.85	0.65	0.57
Apr	0.47	0.61	0.60	0.44
May	0.07	0.02	0.50	0.43
Jun	0.47	0.09	0.61	0.48
Jul	0.19	0.16	0.63	0.47
Aug	0.17	0.16	0.61	0.46
Sep	0.03	0.06	0.67	0.49
Oct	0.57	0.33	0.70	0.50
Nov	0.55	0.34	0.57	0.60
Dec	0.60	0.62	0.72	0.71

1 is the coefficient of determination of Cokriging, and 2 is the coefficient of determination of Multiple Linear Regression

data during 30 years (1971-2000). The best interpolation models have been selected by the AIC value for mean monthly rainfall and mean monthly temperature. In this study, cokriging models are selected for mean monthly rainfall interpolation surface and mean monthly temperature surface (Table 5). Then this paper had evaluated the effectiveness of selected cokriging models in mean monthly climate data by comparing with other interpolations excluding additional covariates (i.e. kriging, IDW, GPI, LPI, and RBF with 5 functions (CRS, SWT, MQ, IMQ, and TPS)) and the linear model technique as MLR. As a consequence, the cokriging technique provides more effectiveness than other interpolations excluding additional covariates (Table 7 and Table 8) and MLR (Table 9) on mean monthly rainfall data and mean monthly temperature data. As stated Table 7-Table 9 above, this study can use the best results of sub-type and semivariogram model from cokriging including topographic variables for mean monthly rainfall and mean monthly temperature surface interpolation.

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