Cross Validation of Spatial Interpolated Rain Gage and Satellite-Based Rainfall over Chao Phraya River Basin Thailand

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***Abstract*—** **The availability of satellite-based precipitation products has greatly improved as more organizations and institutions produce these data. However, these datasets contain some bias because it is not a direct measurement of rainfall. Before satellite precipitation data can be bias corrected using rain gage data, the local rain gage data should be able to accurately represent its spatial distribution.~~Before satellite precipitation data can be corrected, the local rain gage data should be able to accurately represent its surrounding area.~~ Using spatial interpolation techniques on these point data would estimate the values where there gaps are found. ~~Using spatial interpolation techniques on these point data would predict and estimate the values where there gaps are found.~~ The study analyzes the results of different spatial interpolation methods namely Inverse Distance Weighting (IDW), Kriging with a Spherical Semivariogram, Kriging with an Exponential Semivariogram, and Kriging with a Gaussian Semivariogram over Chao Phraya River Basin in Thailand with daily rain gage data from 2000 to 2010 from Thai Meteorological Department (TMD) and Royal Irrigation Department (RID). ~~in Thailand with daily rain gage data from 2000 to 2010 from the Thai Meteorological Department (TMD) and Royal Irrigation Department (RID).~~ Subsequently, the correlation coefficient (CORR) of each interpolated dataset to the satellite precipitation estimate of Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network - Cloud Classification System (PERSIANN-CCS) in 2010 would be determined. The cross-validation results show that Kriging generally has a lower root-mean-square-error (RSME) than IDW interpolation. As for the case in Thailand, Kriging with Spherical Semivariogram has the lowest RSME and CORR with respect to the daily rain gage data. The interpolation method with the highest correlation coefficient when compared to the PERSIANN-CCS dataset varied with each month. Overall, the Kriging with Spherical Semivariogram provides a better representative to the rain gage data due to its stochastic characteristic which allows probability and uncertainty in the computation. Applying this technique in adjusting satellite data could improve the correction results.**

Keywords—precipitation data estimation; spatial interpolation; kriging; satellite-based precipitation

I. Introduction

In recent years, the availability of satellite-based precipitation products has greatly improved as more organizations and institutions produce these data. However, these datasets contain some bias when compared to the actual precipitation occurring on the surface of the earth. Therefore, the discrepancies must be corrected using ground-based recordings to improve the accuracy of satellite rainfall [1]. Some literatures used spatially interpolated precipitation estimates from rain gages for the correction of satellite rainfall products [2][3].

Spatial interpolation may show rainfall patterns that could be correlated with the satellite precipitation data. Moreover, the results of these interpolations can be used in various ways. Examples of these are for hydrologic modeling [4][5], estimation of average daily precipitation [6], rainfall network design [7], and others.

However, one interpolation methods may not best represent the rainfall over a certain vicinity in all cases. There are different approaches to conducting spatial interpolation. Deterministic approaches such as Inverse Distance Weighting (IDW) interpolation are simple and do not require elaborate computations but it may not be a good representative if there are only limited number of points. As such, this method has been utilized for its simplicity [8][9][10]. On the contrary, applying geostatistical methods such as Kriging objectively predicts values using parameters relating to the spatial characteristics of the data but the computations are more complex and may require more resources than its counterpart [11][12]. In addition, incorporating more factors complex in the procedures, such as using the elevation, can be used in estimation of the precipitation through stochastic spatial interpolation [13][14][15][16]. Cross validation of the interpolation methods is one of the numerous ways to determine the accuracy of a certain approach.

The aim of this study is to identify the most adequate spatial interpolation method for the Chao Phraya river basin and determine the correlation of the satellite-based precipitation to the interpolation output. Similar comparisons in determining which interpolation approach have been conducted by numerous studies [17][18][19]. The purpose of determining the correlation of the output interpolation data with the satellite date is to identify how significant the bias for correction.

II. Study Area and Data

In this study, the rain gage datasets from the Thai Meteorological Department (TMD) and Royal Irrigation Department (RID) in Thailand ~~are used for the cross validation of the spatial interpolation methods and for comparison with the satellite precipitation data.~~ are tested for consistency and used for the cross validation of the spatial interpolation methods and for comparison with the satellite precipitation data.

A. Study Area

The selected area in this study is the Chao Phraya river basin in Central Thailand as shown in Fig. 1. The country has 25 defined river basins with Chao Phraya being the 9th largest, having an area of 20526.37 km^2. Majority of the country's main productivity are situated in this river basin, which include the agriculture, industry, and service sectors. Moreover, the main water body in the Chao Phraya river basin is the Chao Phraya River, which flows through Bangkok, the capital of Thailand.

B. Rainfall Data

The rain gage datasets used in this study were from TMD and RID. The daily rain gage data used in this study is a collection of multiple rain gage data from 2000 to 2010. The first dataset has 381 stations in Chao Phraya river basin. The second dataset has 12 stations within the study area but only 6 stations have rainfall records.

The satellite-based rainfall dataset were from the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Cloud Classification System (PERSIANN-CCS) developed by the Center of Hydrometeorology and Remote Sensing (CHRS) of University of California, Irvine [1]. The satellite product has a resolution of 0.04 degree by 0.04 degree (approximately 4km by 4km). The satellite data used for the study were all days of the year 2010.

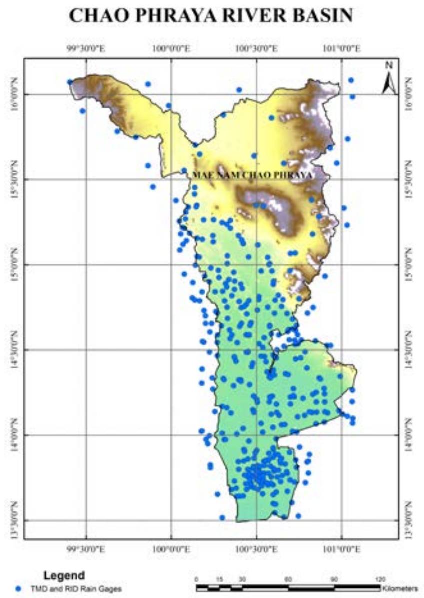


Fig. 1. Chao Phraya River Basin and the Rain Gage Stations within

III. Methodology

The study evaluated the spatial interpolation methods through cross validation. The areal rainfall outputs of each method were then correlated with the satellite precipitation products of PERSIANN-CCS. The interpolation methods were chosen based on the common approaches used in the literatures.

A. Spatial Interpolation

Spatial interpolation can be categorized into two approaches: deterministic and stochastic. These different methods have been mainly used in the estimation of the precipitation [20]. For the deterministic method, the Inverse Distance Weighting (IDW) method would be used. On the other hand, Kriging would be used for the stochastic approach.

1) Inverse Distance Weighing (IDW)

In this approach, values at specific location is computed through weighted average. The weights used in the computation is the inverse of the distance of the target point to each known point. As shown in (1), the prediction value is

$$z^*(u)=\frac{\sum_{i=1}^{n}\frac{z(u_i)}{d(u_i)^k}}{\sum_{i=1}^{n}\frac{1}{d(u_i)^k}} \quad (1)$$

where $z^*(u)$ is the predicted value at the location, u, $z(u_i)$ are the actual values at each known location, u, $d(u_i)$ is the distance of the each known location, u, from the predicated value location, and k is the exponent of the distance. The exponent for the method carry the significance of the known values to the predicted value.

In this study, two IDW interpolations were computed. The difference between the two computations were the value of the exponent, where the first calculation used an exponent value, k, equal to 1, while the second calculation used squared weights where the exponent value of 2.

2) Kriging

This method is similar to IDW to which the weights are defined by the distance of the target point to the known points. However, each weight is determined by a function called a semivariogram.

A semivariogram is the representation of the spatial correlation of every point in a given dataset to each other. With (2), the semivariogram value binned at a specific distance is the mean of the variance of pairs of each data point to every other points,

$$\gamma(h)=\frac{1}{2n(h)}\sum_{i=1}^{n(h)}[z(u_i)-z(u_{i+h})]^2 \quad (2)$$

where γ(h) is the variogram at the lag distance, h, n(h) is the number of data pairs falling in the same lag distance, h, and z(u) is the value at location, u. The semivariogram values would be plotted against the distance. This empirical semivariogram plot would then be fitted in a theoretical semivariogram model in order to have a continuous function to be used for the Kriging weights.

In this study, data values within the same month were binned together in one semivariogram to give consideration to the temporal dimension of the datasets.

Different semivariogram models have been used for Kriging. In this study, the models used were the following:

- Spherical Semivariogram Model

$$\gamma(h)=\begin{cases} c\left(\frac{3h}{2a}-\frac{1h^3}{2a^3}\right), & h\leq a \\ c, & h>a \end{cases} \quad (3)$$

- Exponential Semivariogram Model

$$\gamma(h)=\left\{c\left[1-e^{-\left(\frac{h}{a}\right)}\right], h>0\right. \quad (4)$$

- Gaussian Semivariogram Model

$$\gamma(h)=\left\{c\left[1-e^{-\left(\frac{h}{a}\right)^2}\right], h>0\right. \quad (5)$$

where c is the sill and a is the range. In some studies, parameters and characteristics of different semivariograms have been assessed in order to find the best model to be used in Kriging precipitation interpolation [21][22].

Once the theoretical semivariogram has been prepared, the prediction value can be computed by (6),

$$z^*(u)=\sum_{i=1}^{n}\lambda_i \cdot z(u_i) \quad (6)$$

where λ_i is the Kriging weight for each known value determined from the semivariogram model.

Due to the computational constraints that would arise from large matrices, the study only considered the five nearest points in computing the prediction value.

B. Cross Validation

This study used the leave-one-out cross validation method in the evaluation of the spatial interpolation methods. This cross validation approach removes one point from the dataset and computes the value at the removed point with all the remaining data in the set. This value would then be compared to the actual value. The process continues until every data entry has a corresponding computed value.

The statistical analysis used in the cross validation of the spatial interpolation methods were Mean Absolute Error (MAE) as in (7), Root-Mean-Square Error (RMSE) as in (8), and Correlation Coefficient (CORR) as in (9)

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|z(u_i)-z^*(u_i)\right| \quad (7)$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}[z(u_i)-z^*(u_i)]^2} \quad (8)$$

$$CORR=\frac{\sum_{i=1}^{n}\left[z^*(u_i)-\bar{z}^*\right][z(u_i)-\bar{z}]}{\sqrt{\sum_{i=1}^{n}\left[z^*(u_i)-\bar{z}^*\right]^2}\times\sqrt{\sum_{i=1}^{n}[z(u_i)-\bar{z}]^2}} \quad (9)$$

where $\bar{z}^*$ is mean of the predicted values and $\bar{z}$ is the mean of the actual values. Because there would be large numbers of zero values in the dataset, only days with occurrence of rainfall for both observed and predicted would be considered.

C. Satellite Data Analysis

It is crucial to determine how well the interpolation outputs would be related to the satellite-based precipitation data. Similar to the cross validation, MAE, RSME, and CORR would be computed for each month where the interpolated values would be considered as the known data while the satellite data would be the predicted data.

IV. Results and Discussion

A. Monthly Semivariogram Parameters

The monthly theoretical semivariogram sill and range resulted from the binning of data pairs at the temporal dimension. From January to December, each day of every month was collected into one empirical semivariogram where the theoretical semivariogram parameters was fitted into the model functions. The results of this process for each theoretical semivariogram model is shown in Table 1.

Compared to the usual way of computing the theoretical semivariogram parameters, combining the data pairs of each day into each month produced faster computation. Since the typical manner of Kriging interpolation considers only the currently observed data pairs, theoretical semivariogram parameters would be computed for each day. This would use more resources than simply using one semivariogram model for the whole month.

TABLE I. Monthly Semivariogram Parameters

MON	2000 - 2009					
	SPHERICAL		EXPONENTIAL		GAUSSIAN	
	RANGE	SILL	RANGE	SILL	RANGE	SILL
JAN	0.02033	2.56	0.00662	2.56	0.00877	2.56
FEB	0.12217	8.10	0.04941	8.12	0.04867	8.09
MAR	0.20371	20.46	0.10798	20.72	0.06924	20.35
APR	0.08366	38.18	0.05352	38.47	0.02984	38.10
MAY	0.14748	59.27	0.12965	60.72	0.05586	59.11
JUN	0.32412	61.89	0.95885	84.74	0.10901	61.32
JUL	0.17929	47.79	0.09810	48.36	0.06445	47.60
AUG	0.26584	54.26	0.14834	55.29	0.09059	53.87
SEP	0.22198	108.11	0.32225	117.20	0.06145	107.12
OCT	0.05289	62.95	0.77177	81.79	0.01868	62.88
NOV	0.02484	12.77	0.01074	12.78	0.00921	12.77
DEC	0.00658	2.54	0.00138	2.54	0.00313	2.54

B. Cross Validation for 2000 to 2009 Dataset

The dataset from the year 2000 to 2009 was cross validated using the interpolation methods considered in this study. Each month was evaluated using the statistical ~~parameters MAE, RMSE, and CORR as shown in Table 2. It can be observed that Kriging with daily Spherical semivariogram model has the highest correlation to the actual rainfall data and the lowest out of all the interpolation methods. This is followed by Kriging with monthly Spherical and Exponential semivariogram which did not vary too much in comparison to the previous method.~~

TABLE II. CROSS VALIDATION RESULTS FOR DATASET 2000 TO 2009

MONTH	IDW			IDW (2nd Power)			Daily Semivariogram from 2000 - 2009									Monthly Semivariogram from 2000 - 2009								
							Kriging (Spherical)			Kriging (Exponential)			Kriging (Gaussian)			Kriging (Spherical)			Kriging (Exponential)			Kriging (Gaussian)		
	MAE	RMSE	CORR	MAE	RMSE	CORR	MAE	RMSE	CORR	MAE	RMSE	CORR	MAE	RMSE	CORR	MAE	RMSE	CORR	MAE	RMSE	CORR	MAE	RMSE	CORR
JAN	9.2	16.9	0.41	8.6	15.9	0.47	8.5	13.3	0.59	12.1	18.2	0.35	12.6	19.0	0.33	8.7	13.7	0.56	8.6	13.6	0.56	8.7	13.7	0.56
FEB	10.4	17.9	0.57	10.0	16.7	0.61	10.2	16.0	0.66	13.9	22.2	0.43	13.5	21.4	0.44	10.2	16.1	0.66	10.3	16.3	0.65	12.7	23.3	0.49
MAR	10.4	17.6	0.42	9.9	16.5	0.49	10.2	16.5	0.51	13.6	20.7	0.36	13.7	20.6	0.36	10.3	16.5	0.51	10.2	16.5	0.51	20.1	72.3	0.19
APR	12.3	20.0	0.49	11.7	19.0	0.53	12.3	19.5	0.53	17.1	25.7	0.32	16.9	25.5	0.33	12.4	19.6	0.53	12.3	19.4	0.53	16.2	42.3	0.26
MAY	9.4	15.3	0.46	8.9	14.6	0.51	9.4	15.0	0.51	13.0	20.0	0.31	12.9	19.7	0.32	9.4	15.0	0.51	9.4	15.0	0.51	18.1	103.0	0.09
JUN	8.9	14.9	0.45	8.5	14.3	0.51	8.9	14.6	0.51	12.0	19.2	0.31	12.1	19.4	0.31	9.0	15.0	0.49	9.0	14.9	0.50	28.0	214.7	0.06
JUL	8.3	14.6	0.47	7.8	13.8	0.53	8.2	13.8	0.54	11.1	17.5	0.36	11.1	17.7	0.36	8.3	13.8	0.54	8.2	13.7	0.55	13.1	41.9	0.20
AUG	8.9	14.8	0.50	8.4	14.1	0.54	8.9	14.6	0.54	12.4	19.3	0.35	12.4	19.3	0.35	9.0	14.7	0.53	8.9	14.5	0.54	17.5	66.2	0.16
SEP	10.9	18.9	0.53	10.4	18.2	0.57	10.9	18.2	0.58	15.0	25.2	0.38	15.0	25.4	0.38	11.0	19.0	0.56	11.0	19.0	0.56	25.8	150.6	0.11
OCT	10.3	16.9	0.46	9.7	16.0	0.52	10.2	16.4	0.53	14.1	21.6	0.35	14.1	21.6	0.35	10.2	16.3	0.53	10.4	16.8	0.52	34.6	232.8	0.07
NOV	10.5	17.0	0.51	9.9	16.1	0.55	10.2	16.2	0.55	14.3	21.7	0.38	14.4	21.9	0.38	10.2	16.1	0.56	10.1	16.0	0.56	10.2	16.5	0.54
DEC	9.1	15.7	0.38	8.7	14.7	0.43	8.2	13.8	0.50	10.7	16.4	0.35	11.0	17.1	0.32	8.5	14.2	0.47	8.5	14.2	0.47	8.5	14.2	0.47

parameters MAE, RMSE, and CORR as shown in Table 2. It can be observed that Kriging with daily Spherical semivariogram model has the highest correlation to the actual rainfall data and the lowest errors out of all the interpolation method. This is followed by Kriging with monthly Spherical and Exponential semivariogram which did not vary too much in comparison to the previous method. Subsequently, both IDW interpolation methods resulted in correlation coefficient and errors lower than the stated Kriging method but were not the worst interpolation for the dataset. The approach with the lowest correlation coefficient and error values is monthly Kriging with Gaussian semivariogram which reach very low CORR values especially in months with higher occurrence of rainfall.

In terms of complexity of computation, IDW interpolation methods were the simplest and the fastest. Kriging using the monthly semivariogram was more complicated than IDW but since there were already defined semivariogram parameters, the computation did not take a significant number of resources to accomplish. On the other hand, Kriging using the daily semivariogram took twice as long as using the monthly semivariogram since the parameters would be computed for each day.

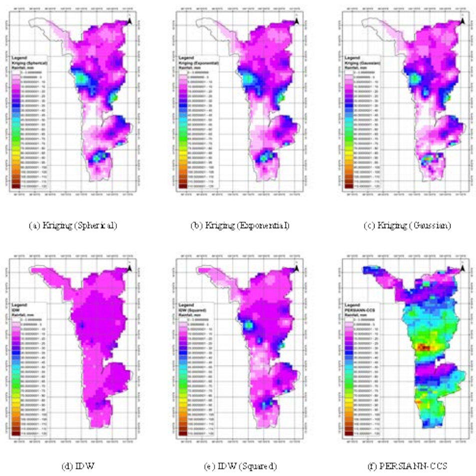
C. Cross Validation for 2010 Dataset

In addition to the 10 year data of 2000 to 2009, the data from year 2010 were also interpolated and cross validated. These two datasets share the same stations. However, in this computation, three different semivariogram parameters were used. These parameters were from the daily semivariogram of dataset 2010, the monthly semivariogram of dataset 2010, and the monthly semivariogram of dataset 2000 to 2009.

Similar to the previous case, all cases of Kriging with Spherical semivariogram overall provided the higher correlation coefficient and relatively lower error values than other Kriging methods. Comparing the results of using these three different semivariogram, the outcome did not vary much. Although the CORR and RMSE values were less favorable during months with less rainfall, Kriging using monthly Spherical semivariogram of 2000 to 2009 had better results than the other interpolation approaches. In this regard, using the semivariogram parameter of a dataset with the same stations as the one being evaluated may be used for the interpolation approach. Fig. 2a to Fig. 2e visually represent the result of the interpolation.

~~*D. Comparison of PERSIANN-CCS Data with Interpolated Data*~~

~~As shown in Table 3, the interpolation data with the highest correlation to the satellite data of PERSIANN-CCS differed with each month. However, the IDW interpolation had the most consistent correlation coefficient and did not have any negative values. It might depend on each month whether an~~



(a) Kriging (Spherical) (b) Kriging (Exponential) (c) Kriging (Gaussian)

(d) IDW (e) IDW (Squared) (f) PERSIANN-CCS

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Fig. 2. Interpolation Results for day of August 10, 2010; (a) Kriging with Spherical Semivariogram, (b) Kriging with Exponential Semivariogram, (c) Kriging with Gaussian Semivariogram, (d) IDW Interpolation, (e) IDW (Squared) Interpolation, and (f) PERSIANN-CCS data.

~~Fig. 2.~~

MONTH	IDW	IDW (2nd Power)	Monthly Semivariogram from 2000 - 2009		
			Kriging (Spherical)	Kriging (Exponential)	Kriging (Gaussian)
	CORR	CORR	CORR	CORR	CORR
JAN	0.11	-0.10	-0.03	0.11	-0.11
FEB	0.21	0.05	0.30	-0.04	0.12
MAR	0.44	0.45	0.32	0.43	0.44
APR	0.21	0.15	0.05	0.26	0.23
MAY	0.20	0.34	0.15	0.27	0.16
JUN	0.18	0.16	0.10	0.13	0.08
JUL	0.22	0.19	0.06	0.10	0.06
AUG	0.25	0.16	0.15	0.04	0.01
SEP	0.30	0.36	0.24	0.06	0.21
OCT	0.20	0.12	0.05	0.08	0.04
NOV	0.60	-0.03	-0.35	-0.19	0.15
DEC	0.37	0.32	0.16	0.11	-0.06

~~V.~~ Correlation of Satellite Data to Each Interpolation Method Output

TABLE III.

D. Comparison of PERSIANN-CCS Data with Interpolated Data

As shown in Table 3, the interpolation data with the highest correlation to the satellite data of PERSIANN-CCS differed with each month. However, the IDW interpolation had the most consistent correlation coefficient and did not have any negative values. It might depend on each month whether an interpolation method would be suitable for correcting the satellite data. Moreover, since PERSIANN-CCS utilizes a cloud classification system for its estimation of precipitation, there might be some discrepancies with the interpolated data as the methods used in this study did not consider factors such as wind direction and ground elevation which affects the actual precipitation on the surface of the earth. As such, this result has shown the need for the correction of the PERSIANN-CCS data in order to fully utilize its potential in hydraulic and hydrologic analyses.

~~VI.~~V. Conclusion and Recommendations

Overall, Kriging with Spherical semivariogram showed the best performance among the interpolation methods for this study. The approach resulted with the highest correlation coefficient and lowest error values. The IDW interpolation methods provided better and more consistent results than the other two Kriging methods.

Among the three semivariogram models, the Spherical model gave the best results. On the other hand, the Gaussian model showed the worst results with correlation coefficients reaching almost zero values.

Moreover, the results showed that using the monthly semivariogram could improve the interpolation in some ways. Comparing the computational resources, the Kriging monthly computation took less than half the time it would for the daily semivariograms. The results also showed that the monthly semivariogram can only be used for datasets sharing the same stations.

As for the comparison of the PERSIANN-CCS data with the interpolation output, the correlation is quite low. The correlations during dry season (Nov – Mar) are generally higher than wet season. The highest correlation of 0.60 is in November with the IDW interpolation. The IDW interpolation had the most consistent correlation coefficient. The results demonstrate the needs of bias correction of the satellite data before applying them and also the improvement in developing the near-real-time satellite rainfall.

Further study of the concept of spatial interpolation would improve the areal representation of precipitation. Furthermore, accounting the temporal characteristic of rainfall in the interpolation would be recommended. As such, these improvements may also lead to more accurate bias correction of satellite precipitation products.

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~~As for the comparison of the PERSIANN-CCS data with the interpolation output, the method with the highest correlation coefficient value varied each month. Including more parameters in the interpolation method such as wind direction and ground elevation may improve the relationship of the datasets. In addition, this may lead to the cross validation having better and more accurate results.~~

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