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Combining Satellite And Gauge Precipitation Data With Co-Kriging Method For Jakarta Region

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HYDROLOGICAL MODELING USING BLENDED SATELLITE-GAUGE PRECIPITATION DATA FOR JAKARTA REGION

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Jakarta is vulnerable to flooding mainly due to prolonged and heavy rainfall and thus a robust hydrological modeling is called for. In order to obtain a good hydrological model, a high quality of spatial precipitation data is therefore desired. Two types of common rainfall sources are available: satellite and gauge station observations. Gauge data is considered to be a reliable and accurate source of rainfall. However, the limited number of stations makes the spatial interpolation from gauge data not very much appealing. On the other hand, the gridded rainfall nowadays has high spatial resolution and improved accuracy, but still, relatively less accurate than its counterpart. To achieve a better precipitation data set, the study uses cokriging method, a blending algorithm, to yield the blended satellite-gauge gridded rainfall at approximately 10-km resolution. The Global Satellite Mapping of Precipitation (GSMaP, $0.1^{0}\times0.1^{0}$) and daily rainfall observations from gauge stations are used. The blended product is compared with satellite data by cross-validation method. The newly-yield blended product is then utilized to re-calibrate the hydrological model. Several scenarios are simulated by the hydrological models calibrated by gauge observations alone and blended product. The performance of two calibrated hydrological models is then assessed and compared based on simulated and observed runoff.

INTRODUCTION

A high quality of spatial precipitation data is of great importance in hydrological modeling. In rainfall-runoff models, the simulated discharge is highly affected by quality of rainfall observations [1][2]. There are quite a lot of blended algorithms implemented to produce blended gridded product. Rozante *et al.* [7] used Barnes objective analysis method. Each grid is estimated by weighted average of gauge data, in which the weights are estimated by minimizing RMSE between original and corrected satellite data by trial and error. Xie and Arkin applied Reynolds' algorithm [13] to blend gauge-based monthly analyses from Global Precipitation Climatology Centre and three types of satellite estimates by solving the Poisson equation with boundary conditions as gauge data. Xie *et al.* [14][15] recommended optimal interpolation based algorithm. Under the OI framework, the final analysis value (blended value) at a target grid box is defined through modifying the first guess (bias-corrected satellite data) at the grid box using gauge-based observations at and near the targed grid box. Woldemeskel *et al.* [12]

suggested a linearized weighting procedure, in which the gauge data were first interpolated by thin plate smoothing splines and modified invers distance weight; the gridded data is further weighted combined with satellite data, where weights were calculated by minimizing error variance between two gridded data, gauge and satellite. In addition, Li and Shao [5] proposed a kernel-based double-smoothing algorithm. Shen *et al.* [11] proposed a Bayesian optimal blending algorithm.

An ordinary cokriging (OCK) method are applied in this study, which is a linear combination of satellite and gauge data, in which the weighing coefficients are solved by minimizing error variance of true and estimate grid point. Several studies have used OCK to merge rain gauge and radar rainfall: Krajewski [4] and Seo *et al.* [10]. Schuurmans *et al.* [9] applied ordinary collocated cokriging (OCCK) [8] to blend TRMM Multi-satellite Precipitation Analysis (TMPA) and daily precipitation measurements.

Jakarta is vulnerable to flooding mainly due to prolonged and heavy rainfall and thus a robust hydrological modeling is called for. In order to obtain a good hydrological model, a high quality of spatial precipitation data is therefore desired. Two types of common rainfall sources are available: satellite and gauge station observations. Gauge data is considered to be a reliable and accurate source of rainfall. However, the limited number of stations makes the spatial interpolation from gauge data not very much appealing. On the other hand, the gridded rainfall nowadays has high spatial resolution and improved accuracy, but still, relatively less accurate than its counterpart.

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DATA

Rain gauge data

Eighteen stations are available in Jakarta watershed of the total area about 1400 square kilometers. The temporal resolution is daily observations.

Satellite data

Global Satellite Mapping of Precipitation (GSMaP) is a satellite product by Earth Observation Research Center (EORC) at Japan Aerospace Exploration Agency (JAXA) [6]. The spatial resolution of GSMaP is $0.1^0 \times 0.1^0$. The temporal resolution of GSMaP is hourly.

METHODOLOGY

To achieve a better precipitation data set, the study first uses kriging method to obtain a gridded product from rain gauge network; the cokriging method is further applied to yielding the blended satellite-gauge gridded rainfall at approximately 10-km ($0.1^0 \times 0.1^0$.) resolution by blending gridded rain gauge network and satellite precipitation. The blended product is assessed by cross-validation method.

The kriging/cokriging is an interpolation method, which is a linearly weighted combination of multivariable observations. The kriging/cokriging method ensures the estimator is unbiased with minimum error variance.

Variogram is first estimated, which describes in terms of variances how spatial variability changes as a function of distance and direction [3]. The experimental variogram/semivariogram $\gamma(h)$ is calculated as half the average squared difference between the paired data values,

$$\gamma(\mathrm{h}) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [G(x_i) - G(x_i + h)]^2 \quad (1)$$

where $G(x_i)$ is the rain gauge measurements, h is the separation distance and $N(h)$ is the number of point pairs. To assure that the kriging equations have a unique and stable solution (i.e., to force the variogram to be positive definite) we have to fit a suitable variogram model to the experimental variogram. Among several models, we chose linear variogram model, defined as

$$\gamma(h) = C_0 + C_1 \cdot h / a \quad (2)$$

where C_0 is nugget, C_1 is partial sill, and a is range.

As mentioned, kriging/cokriging is a generalized least squares regression technique that allows one to account for the spatial dependence between observations, as revealed by the variogram, in spatial prediction. Kriging/cokriging is a linearly weighted combination of single-/multi-variable observations. The ordinary kriging prediction of rainfall R at location x_0 can be defined as

$$R(x_0) = \sum_{i=1}^{n_G} \lambda_i G(x_i) \quad (3)$$

The ordinary cokriging prediction of rainfall R at location x_0 can be defined as

$$R(x_0) = \sum_{i=1}^{n_G} \lambda_i G(x_i) + \sum_{j=1}^{n_S} \xi_j S(y_j) \quad (4)$$

where n_G is number of grids of kriging product from rain gauge network, n_S is number of grids of satellite data GSMaP, $G(x_i)$ is the gridded rain gauge value at location x_i, $S(y_j)$ is the gridded value of GSMaP, λ_i and ξ_j are the weight of each variable which are obtained by solving kriging/cokriging equation.

The newly-yield blended product is then utilized to re-calibrate hydrological model MIKE 11 for Ciliwung River. Each centre point of grid is considered as an artificial rainfall station. The rain events from Feb to Mar 2006 are selected to assess the performance of two hydrological models with different rainfall products by comparing simulated and observed discharge.

RESULTS AND DISCUSSIONS

Three pairs of observed discharges are compared along the Ciliwung River. They are Katulampa, Ratujaya and Sugutamu from upstream downwards. The preliminary results in terms of correlation coefficients are tabulated as below.

Table 1. Comparison between gauge data and blended product

Station	Correlation coefficient	
	STN	OCK
Katulampa	0.775	0.813

Ratujaya	0.816	0.892
Sugutamu	0.522	0.754

REFERENCES

[1] Bárdossy A. and Das T., “Influence of rainfall observation network on model calibration and application”, *Hydrol. Earth Syst. Sci*., Vol. 1, No. 1, (2008), pp 77-89.

[2] Duncan M. R., Austin B., Fabry F. and Austin G. L., “The effect of gauge sampling density on the accuracy of streamflow prediction for rural catchments”, *Journal of Hydrology*, Vol. 142, No. 1-4, (1993), pp 445-476.

[3] Isaaks E. H. and Srivastava R. M., “*Applied geostatistics*”, Oxford University Press, (1989)

[4] Krajewski W. F., “Cokriging radar-rainfall and rain gage data”, *Journal of Geophysical Research: Atmospheres*, Vol. 92, No. D8, (1987), 9571-9580.

[5] Li M. and Shao Q. “An improved statistical approach to merge satellite rainfall estimates and raingauge data”, *Journal of Hydrology*, Vol. 385, No. 1-4, (2010), pp 51-64.

[6] Okamoto K., Iguchi T., Takahashi N., Iwanami K. and Ushio T., “The Global Satellite Mapping of Precipitation (GSMaP) project”, *25th IGARSS Proceedings*, (2005), pp. 3414-3416.

[7] Rozante J. R., Moreira D. S., de Goncalves L. G. G. and Vila, D. A., “Combining TRMM and Surface Observations of Precipitation: Technique and Validation over South America”, *Weather and Forecasting*, Vol. 25, No. 3, (2010), pp 885-894.

[8] Scheel M. L. M., Rohrer M., Huggel C., Santos Villar D., Silvestre E., and Huffman G. J., “Evaluation of TRMM Multi-satellite Precipitation Analysis (TMPA) performance in the Central Andes region and its dependency on spatial and temporal resolution”, *Hydrol. Earth Syst. Sci.*, Vol. 15, No. 8, (2011), pp 2649-2663.

[9] Schuurmans J. M., Bierkens M. F. P., Pebesma E. J. and Uijlenhoet R., “Automatic Prediction of High-Resolution Daily Rainfall Fields for Multiple Extents: The Potential of Operational Radar”, *Journal of Hydrometeorology*, Vol. 8, No. 6, (2007), pp 1204-1224.

[10] Seo D.-J., Krajewski W. F. and Bowles D. S., “Stochastic interpolation of rainfall data from rain gages and radar using cokriging: 1. Design of experiments”, Water Resources Research, Vol. 26, No. 3, (1990), pp 469-477.

[11] Shen S. S. P., Lee J.-Y. and Lau W. K. M., “BAYESIAN OPTIMAL BLENDING AND CREDIBLE INTERVAL ESTIMATION FOR SATELLITE AND GROUND RAINFALL OBSERVATIONS”, *Advances in Adaptive Data Analysis*, Vol. 5, No. 2, (2013), pp 1350006.

[12] Woldemeskel F. M., Sivakumar B. and Sharma A., “Merging gauge and satellite rainfall with specification of associated uncertainty across Australia”, *Journal of Hydrology*, Vol. 499, (2013), pp 167-176.

[13] Xie P. and Arkin P. A., "Analyses of Global Monthly Precipitation Using Gauge Observations, Satellite Estimates, and Numerical Model Predictions", *Journal of Climate*, Vol. 9, No. 4, (1996), pp 840-858.

[14] Xie, P., Chen M., Yang S., Yatagai A., Hayasaka T., Fukushima Y., Liu C., “A Gauge-Based Analysis of Daily Precipitation over East Asia*”. J. Hydrometeor*, 8, (2007), pp 607–626.

[15] Xie P. and Xiong A.-Y., “A conceptual model for constructing high-resolution gauge-satellite merged precipitation analyses”, *Journal of Geophysical Research: Atmospheres*, Vol. 116, No. D21, (2011), pp D21106.