Reply to comments on hessd-8-4229-2011

Reviewer 1:

The manuscript (hessd-8-4229-2011) aim at devising a weighted average semivariogram (WAS) model instead of using the best-fit theoretical semivariogram (TS) models which is less time consuming and more accurate. The manuscript is very well-written and concise and contribute to the related literature by demonstrating the merit in order to reduce uncertainties associated with the selection of best-fit TS models and their parameters.

In conclusion, the manuscript should be accepted for publication after the below comments are addressed.

1. I would suggest testing whether or not the difference among the model results based on WSVM and TSVM is statistically significant?

Ans: Since the proposed WSVM primarily take the average of the estimated semivariograms by the TSVMs with the corresponding weights based on the objective function value (see Eqs.(10) and (11)), the WSVM should be, in theory, highly statistically dependent on the TSVMS. However, this is a good future work that the statistical test, such as ANOVA, for the WSVM and TSVM would be implemented for quantifying the degree of difference.

2. A few minor comments: Page 4240; 3.2.1 identification of best-fit TSVM; line 10: "… Ertekin, 2007" mistakenly reads "Frtekin, 2007". Page 4245; Conclusions: WSVM and TSVMs do not to be re-abbreviated.

Ans: The typing error for the author's name of the reference "… Frtekin, 2007…" would be corrected and the proposed weighted semivariogram and traditional semivariogram models can be not abbreviated again in the conclusions.

Reviewer 2:

The paper proposes a weighted semivariogram to deal with the determination of the variogram parameters and aimed at improving the quality of estimation models. Although the paper relatively clear, I am concerning about the methodology they propose and the idea of combining basic variogram structures to “optimize” the fitting.

1. Improvement in results is simply consequence of adding flexibility to the minimization of the misfit, by adding several structures of different types. However, this approach lacks a reasonable interpretation of the resulting model. Furthermore, no nugget effect is considered.

   Ans: Generally speaking, the nugget effect represents variability at distances smaller than the typical sample spacing, such as the measurement error; thus, the nugget model accounts for the discontinuity at the origin attributed to small-scale variation. However, the sort of semivariograms provide continuous and smoothen estimation near the known position, whereas the estimation from semivariogram models with the nugget effect significantly differ from the known value even at short distances (Saveliev et al., 1998). Therefore, the proposed WSVM is based on TSVMs without the nugget effect in this study. The above description would be added in the section 2.1.

   - Saveliev, A.A., Mucharamova, S.S., and Piliugin, G.A., 1998. Modeling of the daily rainfall values using surface under tension and Kriging. Journal of Geographic Information and Decision Analysis, 2(2), 52-64.

2. Cross validation as a method to optimize variogram parameters is quite sensitive to the search parameters considered. Results could change significantly with other

search parameters.

Ans: In this study, the cross validation is majorly used in the selection of the best-fit TSVM, and the associated parameters are calibrated by means of the sensitivity-parameter-based genetic algorithm developed by Wu et al., (2011), using the observed rainfall amount of rainstorm event in which the number is specified by the cross validation. Surely, the uncertainty in the optimal parameters should be caused by the number of rainstorms used in the parameter calibration. Therefore, this uncertainty may be reduced using the other optimization method, which is another future work.

- Wu. S.J., Lien, H.C., and Chang, C.H., 2011. Calibration of Conceptual Rainfall-Runoff Model using Genetic Algorithm Integrated with Runoff Estimation Sensitivity to Parameters. *Journal of Hydroinformatics* (*in press*).

3. The authors should discuss the issue of stationary in the determination of the variogram parameters and selection of populations to be modeled.

Ans: In general, the traditional Kriging model is hypnotized to be a spatial random process with a stationary covariance function, namely, the semivariogram model (Xiong et al., 2007). The stationary covariance implies that the smoothness of a response is fairly uniform in each region of the input space (Paciorek, 2003), and this is easy to simplify the analysis and reduce the amount of prior information, which should be given in advance (Currin et al., 1991). Nevertheless, the assumption of a stationary covariance structure underlying Kriging does not deal with these situations which the degree of smoothness of a response obviously varies (Xiong et al., 2007). Since the proposed WSVM is composed of the various types of TSVM, in which the associated weights of TSVM could be varied with different situations and regions, in the future, the application of WSVM could be validated on reducing the uncertainty in the assumption of the stationary and enhancing reliability and accuracy of the estimated semivariograms. The above description would be added in the conclusion.

- Xiong, Y., Chen, W., Apley, D., and Ding, X., 2006. A non-stationary covariance-based Kriging method for metamodelling in engineering design. I*nternational Journal for Numerical Methods in Engineering*, 72, 733-756.
- Currin, C., Mitchell, T., Morris, M., and Ylvisaker, D., 1991. Bayesian prediction of determination functions with applications to the design and analysis of computer experiments. Journal of the American Statistical Association, 86,953-963.
- Paciorek, C.J., 2003. *Nonstationary Gaussian processes for regression and spatial modeling*. Ph.D Dissertation, Carnegie Mellon University, Pittsburgh, PA, U.S.A.

Reviewer 3:

This paper proposes the use of a linear combination of semivariogram models as a way to account for uncertainty attached with semivariogram parameters in spatial prediction (i.e. kriging). In a case-study, the so-called weighted semivariogram model fitted using cross-validation. I have several concerns regarding this approach:

1. It is purely empirical and the mixture of semivariogram models, albeit permissible, has no physical meaning, violates the parsimony rule and unnecessarily increase the CPU time of the kriging algorithm.

   Ans: The proposed WSVM intends to combine the TSVMs by taking into account the fitness to experimental semivariogram and its advantage is without determining the best-fit model, which is generally accomplished using the cross-validation, in order to save computational time. Thus, in theory, the WSVM is an empirical model and the corresponding weights to the TSVMs desired can vary with various observation or regions. However, since this study adopts the conventional Kriging method associated with a basic assumption of the stationary covariance function, a future work on the WSVM is to demonstration its applicability in non-stationary situation.

2. Cross-validation is a hazardous way to estimate the parameters of a semivariogram model since results depend on many implementation parameters, such as the search strategy, in addition to the semivariogram model itself. In addition, results can be very unstable when few observation are available. The statement on Page 4240, line8 that cross-validation is widely used for semivariogram modeling is misleading.

   Ans: In this study, the cross validation is majorly used in the selection of the best-fit TSVM, and the associated parameters are calibrated by means of the sensitivity-parameter-based genetic algorithm developed by Wu et al., (2011), using the observed rainfall amount of rainstorm events. And, on Page 4240, line8, the sentence would be amended as "cross-validation is widely used for the identification of the best-fit semivariogram model".

- Wu. S.J., Lien, H.C., and Chang, C.H., 2011. Calibration of Conceptual Rainfall-Runoff Model using Genetic Algorithm Integrated with Runoff Estimation Sensitivity to Parameters. *Journal of Hydroinformatics* (**in press**).

3. The case-study is based an unrealistically small number of observation, which likely creates very unstable semivariogram and prediction error statistics. Surprisingly, this manuscript does not include any figure with experimental semivariograms and some models fitted using cross-validation. The main conclusion might just be that the average of poorly fitted semivariogram models provides slightly more accurate prediction than each individual. My advice would be to increase the number of observation and replace the black-box cross-validation approach by a graphical modeling strategy that allows one to incorporate any auxiliary information available about the study area (e.g. semivariogram elevation) and phenomenon. An alternative is to use a ML and REML approach that requires fewer observation to estimate reliable semivariograms (Pardo-Iquzquiza, 1997; Lark, 2000; Kerry and Olivar, 2007).

Kerry, R. and Oliver, M.A., 2007. Sampling requirements for variograms of soil properties computed by the method of moments and residual maximum likelihood. Geoderma, 140, 383-396.

Lark, R.M., 2000. Estimating variogram of soil properties by the method-of-moments and maximum likelihood. European Journal of Soil Science. 51, 717-728.

Pardo-Iguzquiza, E., 1997. MLREML: a computer program for the inference of spatial covariance parameters by maximum likelihood and restricted maximum likelihood. Computer and Geosciences, 23, 153-162.

Ans: This study select the Shinmen Reservoir watershed as the study area, because the associated 14 rainfall gauges is approximately uniformly distributed throughout the watershed (see Figure 2), where this is hardly found in Taiwan. In fact, the more observation can obtain more accurate parameters. In addition, the uncertainty in the optimal parameters should be caused by the number of rainstorms used in the parameter calibration. Therefore, this uncertainty may be reduced using the other optimization method, such as the ML and REML approach, and this is another future work. Eventually, since this studys focuses on the comparison of estimated rainfall amount by the WSVM and TSVM, we only show and discuss the difference of the estimations of rainfall amount.

5. Technical corrections

a) Page 4233, line 7. N(h) is the number of observation separated by a distance h.

b) Page 4234. Interestingly, the nugget effect is missing from the list of models. Of course, nugget effect cannot be estimated by cross-validation!

c) Page 4234, line 13. Use the expression “lags” instead of “distance ranges.”

d) Page 4235, line 14. The correct reference is Equation (9).

e) Page 4234, line 15. The notation rm,i(h) is inconsistent with the notation in Equation.

<u>Ans:</u> The abovementioned errors would be corrected in the revision version of our manuscript.