Remote Sensing Applications _ Water Resources

Application of Remote Sensing and Gauged Precipitation Information for Improving Hourly Typhoon Rainfall Forecasting of WRF

Author(s): Pao-Shan Yu, Jhong-Wei Chen, Yu-Cheng Lin, Chen-Min Kuo, Tao-Chang Yang, Ze Yuan

Proposed Presenter(s): Pao-Shan Yu, Yu-Cheng Lin, Chen-Min Kuo, Tao-Chang Yang,

Ze Yuan

Department of Hydraulic and Ocean Engineering, National Cheng Kung University

Address: No.1, Daxue Rd., East Dist., Tainan City 701, Taiwan (R.O.C.)

Phone: (+886) 2757575-63248

Email: yups@mail.ncku.edu.tw, yk6z1247@yahoo.com.tw

Preference: Oral Presentation

This study aims at developing a weighted WRF Ensemble Model (WRFEM) based on remote sensing precipitation information to improve the hourly rainfall forecasting of WRFEM during typhoon events. Based on gauged precipitation information, the weighted WRFEM is further coupled with error correction models developed by Random Forests (RFs) and Support Vector Machine (SVM) respectively for increasing the forecasting accuracy of WRFEM.

The remote sensing information used in this work is QPESUMS radar rainfall and PERSIANN-CCS satellite rainfall. First, this study adopts 5 similarity indexes to evaluate the similarity of spatial distribution between QPESUMS radar rainfall and PERSIANN-CCS satellite rainfall in a region covering Taiwan and its nearby ocean. The results show that QPESUMS radar rainfall and PERSIANN-CCS satellite rainfall have similar and reasonable rainfall spatial estimation. Twenty-one forecasts (i.e., ensemble members) by WRFEM are adopted. The 6-hour-behind rainfall forecasts of each ensemble member are compared with the QPESUMS radar precipitation and PERSIANN-CCS satellite precipitation, respectively, to calculate the weight of each ensemble member by different weighting methods. Eight weighting methods are compared to find the best one for giving the weight to the 6-hour-ahead forecasts of each ensemble member for the weighted ensemble forecasting. The results indicate that the weighting method, rank reciprocal method, is the optimal one which makes the weighted WRFEM perform the best based on QPESUMS radar precipitation. Finally, the forecasts of the weighted WRFEM are corrected by two machine learning methods, RFs and SVM, for enhancing the forecasting performance. The results show that RFs has better correction ability than SVM; the RFs improves the 1~2-hour-ahead forecasting and the underestimation, but for the 3~6-hour-ahead forecasting the improvement is not significant.

KEYWORDS: WRF, Rainfall Forecasting, Remote Sensing, Random Forests, Support Vector Machine

Introduction

Short-term quantitative precipitation forecasting is always an important issue in hydrology, especially torrential rainfall caused by typhoons. Typhoon rainfall often results in severe disasters such as flood and landslide in Taiwan. Thus, a disaster warning system is needed to mitigate the damage of disaster. The establishment of a warning system requires an accurate rainfall prediction. Therefore, an accurate typhoon rainfall forecasting is needed.

Numerical weather prediction models (NWP models) are effective tool to forecast short-term quantitative precipitation, and Weather Research and Forecasting model (WRF model) is a next-generation mesoscale numerical weather prediction system currently among NWP models.

The WRF ensemble forecasting provided from Taiwan Typhoon and Flood Research Institute (TTFRI) shows useful information about typhoon rainfall. Thus, WRF ensemble from TTFRI is used in this study. In addition, Shin et al. (2003) explored the impacts of three different ensembles for typhoon precipitation forecasting. The result indicates that a weighted ensemble shows a slightly increase in forecast skills, compared to the bias-corrected ensemble; In order to obtain higher effective forecasting, this study developed a “weighed” WRF ensemble model (W-WRFEM) compared to Average WRF Ensemble Model (A-WRFEM) from TTFRI.

Shin et al. (2003) used the European Center for Medium range Weather Forecasting (ECMWF) numerical weather prediction model to establish two different ensemble forecasting, then create the third one by six different operational forecast models. The author compared the performance of these three ensemble forecasting on typhoon rainfall forecasting, and found not only the ensemble forecasting results that use different models to be established is the best, but can upgrade the capacity of the forecasting locally.

Hsiao et al. (2013) used WRF ensemble forecasting model for compared the typhoon rainfall with ground rainfall stations in Taiwan. The author took Typhoon Nanmadol for example, and applied the rainfall forecasting results to Ilan and Pingtung mountainous watershed for water level forecasting. The result shows that WRF ensemble forecasting can provide effective rainfall and predicted probability of water level, and can control its uncertainty.

Study area and Dataset

The study area is located in southern Taiwan as shown in Fig. 1. The figure displays the spatial range of remote sensing precipitation information and the location of study catchments. This study uses two kinds of remote sensing precipitation information, that is, the QPESUMS (Quantitative Precipitation Estimation and Segregation using Multiples Sensors) radar rainfall and the PERSIANN-CCS (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Cloud Classification System) satellite rainfall. The QPESUMS radar rainfall is developed by Central Weather Bureau in Taiwan and PERSIANN-CCS satellite rainfall is developed by Center for Hydrometeorology and Remote Sensing. The spatial range of QPESUMS is (E115°~E126.5°, N18°~N29°) with the spatial resolution of 1.25°×1.25° and the time scale of 10 minutes. The spatial range of PERSIANN-CCS is nearly global with the spatial resolution of 4°×4° and the time scale of 30 minutes. TTFRI provides the rainfall forecasts by the WRF ensemble model which comprises 21 WRF ensemble members for this work. Due to the differences of spatial range, resolution and time scale for the three kinds of data (i.e., QPESUMS, PERSIANN-CCS, and WRF ensemble model), these data are transformed into the same spatial range of (E117°~E124°, N20°~N28) with the spatial resolution of 4°×4° and the time scale of 1 hour.

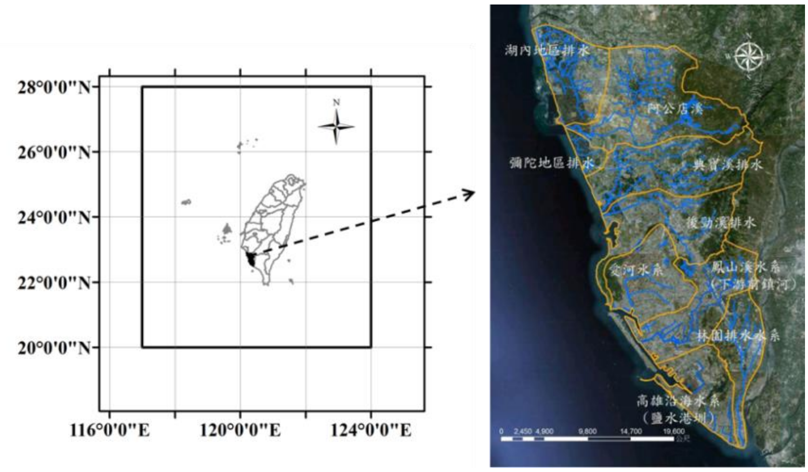

Fig. 1 Spatial range of remote sensing precipitation information and the location of study catchments

Methodology

1. Weighted WRF Ensemble Model

The W-WRFEM gives a weight to the forecast of each WRF ensemble member by using a weighting method, and calculated the weighted mean of forecasts for all WRF ensemble members as the forecast.

The main concept of the W-WRFEM is: if an ensemble member has a higher similarity of spatial rainfall pattern between the present time, 1 to 5-hour-behind (t, t-1, t-2,..., t-5) forecasts of the ensemble member and the present time, 1 to 5-hour-behind (t, t-1, t-2,..., t-5) QPESUMS radar rainfall or PERSIANN-CCS satellite rainfall, then the 1 to 6-hour-ahead (t+1, t+2,..., t+6) forecasts of the ensemble member have a higher weight.

Seven weighting methods are respectively regression coefficient, regression coefficient root, Inverse RMSE, Inverse RMSE root, Rank Sum, Rank Reciprocal and Rank Order Centroid method which the “Rank” is decided by spatial correlation coefficient.

2. Weighting method

The simplest weighting method is to give every ensemble member with the same weight:

$$w_i = \frac{1}{N} \tag{1}$$

The second technique is based on regression coefficient of ensemble members with remote sensing precipitation information, which is proposed by Stefanova and Krishnamurti (2002). The formula is as follows:

$$w_i = \frac{a_i}{\sum_{i=1}^{N} a_i} \tag{2}$$

The best choice for the power of regression coefficient is 0.5 (Stefanova and Krishnamurti, 2002). Therefore, it is also analyzed which is third weighting technique.

The forth method is based on the inverse of root mean square error (RMSE) of ensemble member performance, which is described by Casanova and Ahrens (2009). The formula is as follows:

$$w_i = \frac{r_i}{\sum_{i=1}^{N} r_i} \tag{3}$$

r is the inverse of RMSE, and the power of 0.5 is also analyzed in this study which is fifth method.

The sixth, seventh and eighth methods are based on the rank of every ensemble member performance. The rank is decided by the spatial correlation coefficient (SCC):

$$\mathrm{SCC} = \frac{S_{xy}}{S_x S_y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4}$$

According the research of Byeong Seok (2011), there are three weighting method of rank:

$$w_i = \frac{N+1-i}{\sum_{j=1}^{N} \mathrm{j}} = \frac{2(N+1-i)}{n(n+1)} \tag{5}$$

$$w_i = \frac{\frac{1}{i}}{\sum_{j=1}^{N} \frac{1}{j}} \tag{6}$$

$$w_i = \frac{1}{N}\sum_{j=i}^{N} \frac{1}{j} \tag{7}$$

This study compares W-WRFEMs built by above eight weighting respectively and selects the best W-WRFEMs.

3. **Random Forest**

Random Forest (RF) is a concept of “ensemble learning”, which is through procedure of “random resampling” to build many decision trees (generally 500) for classification and regression.

4. **Support Vector Machine**

The main concept of Support Vector Machine (SVM) is mapping the input vector x to a high dimensional feature space by a non-linear function $\boldsymbol{\phi}$ to solve the non-linear problem:

$$y = f(x) = w^T \phi(\mathrm{x}) + b \tag{1}$$

RF and SVM are adopted to construct the error correction models using the forecasted and gauged rainfall information. Four typhoon events (i.e., Morakot, Fanapi, Nanmandol and Saola) are used for the case study.

Case Study

The W-WRFEM with different weighting methods based on QPESUMS and PERSIANN-CCS, respectively, is used to forecast rainfalls for one to six hours ahead. Fig.2 shows the Root Mean Square Errors (RMSE) between the gauged and forecasted rainfalls by the W-WRFEM with different weighting methods based on QPESUMS and PERSIANN-CCS, respectively, for one to six hours ahead. In the left plot of Fig.2, the W-WRFEM based on

QPESUMS with the Rank Reciprocal Method shows the best performance. In the right plot of Fig.2, the W-WRFEM based on PERSIANN-CCS with the Inverse RMSE Method performs the best. The W-WRFEM based on QPESUMS with the Rank Reciprocal Method is better than the one based on PERSIANN-CCS with the Inverse RMSE Method. Moreover, the W-WRFEMs based on QPESUMS with the 7 weighting methods are better than A-WRFEM with the ensemble mean method.

The W-WRFEM based on QPESUMS with the Rank Reciprocal Method is adopted to forecast 1- to 6-hour-ahead rainfalls which are further corrected by the error correction models developed by RF and SVM, respectively. Fig. 3 shows the percentage changes (or say, improvements) of Correlation Coefficient (CC), RMSE and relative Bias (BIAS) after error correction. The improvements of CC and RMSE reveal that RF improves the 1- and 2-hour-ahead forecasts and SVM shows no improvement for all the lead times. The improvements of BIAS indicate that RF performs better than SVM except for the 4-hour lead time. Overall, RF improves the forecasts of W-WRFEM better than SVM especially for the 1-hour and 2-hour lead time.

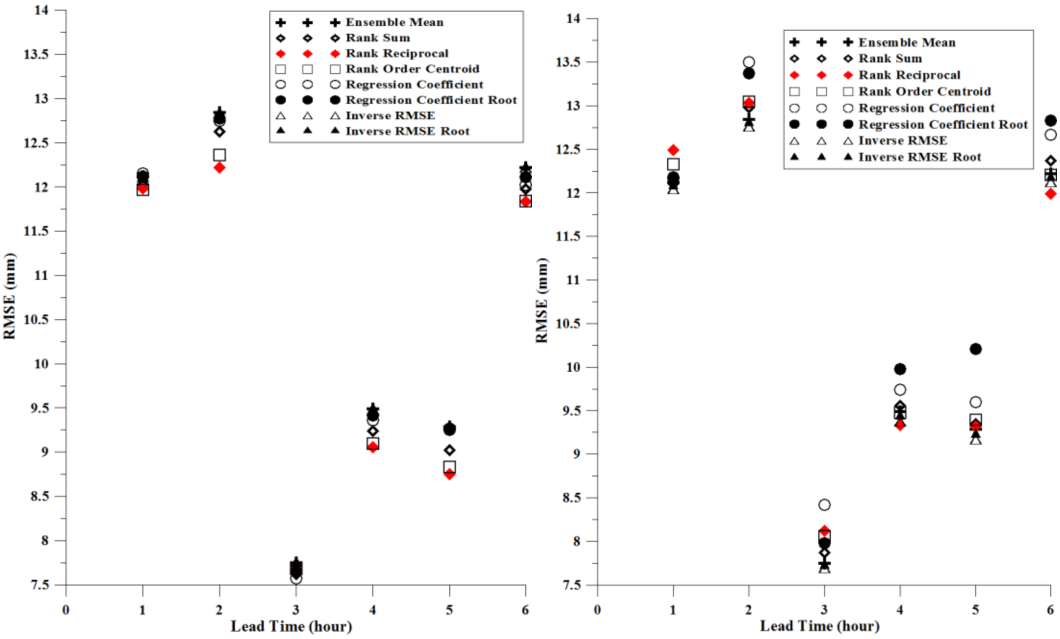

Fig.2 RMSEs between the gauged and forecasted rainfalls for different weighting methods based on QPESUMS (left) and PERSIANN-CCS (right), respectively, for one to six hours ahead

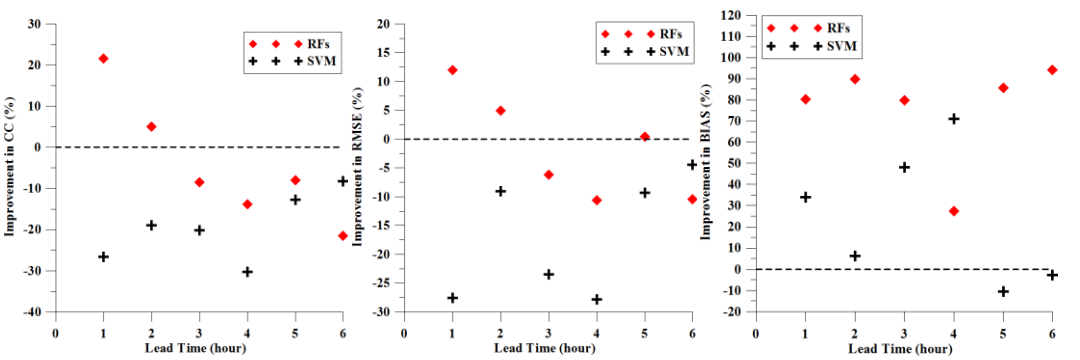

Fig. 4 Improvements of CC, RMSE and BIAS after error correction

Conclusions

This study proposes the W-WRFEM based on two kinds of remote sensing precipitation information (QPESUMS and PERSIANN-CCS) for improving hourly typhoon rainfall forecasting by the WRF ensemble model. Based on gauged precipitation information, the W-WRFEM is further coupled with two error correction models developed by RF and SVM, respectively, to increase the forecasting accuracy of W-WRFEM. The conclusions are addressed as follows.

The W-WRFEM based on QPESUMS with the Rank Reciprocal Method is better than the one based on PERSIANN-CCS with the Inverse RMSE Method. Moreover, the W-WRFEMs based on QPESUMS with the 7 weighting methods are better than A-WRFEM with the ensemble mean method.

RF improves the forecasts of W-WRFEM better than SVM especially for the 1-hour and 2-hour lead time.

In addition to RF and SVM, the other machine learning techniques (e.g., artificial neural networks) can be tried to develop the error correction models in the future work.

References

Shin, D. W., Cocke, S., & Larow, T. E. (2003). Ensemble Configurations for Typhoon Precipitation Forecasts. *Journal of the Meteorological Society of Japan, 81*(4), 679-696.

Hsiao, L. F., Yang, M. J., Lee, C. S., Kuo, H. C., Shih, D. S., Tsai, C. C., et al. (2013). Ensemble Forecasting of Typhoon Rainfall and Floods over a Mountainous Watershed in Taiwan. *Journal of Hydrology, 506*, 55-68.

Stefanova, L., & Krishnamurti, T. N. (2002). Interpretation of Seasonal Climate Forecast Using Brier Skill Score, the Florida State University Superensemble, and the Amip-I Dataset. *Journal of Climate*, *15*(5), 537-544.

Casanova, S., & Ahrens, B. (2009). On the Weighting of Multimodel Ensembles in Seasonal and Short-Range Weather Forecasting. *Monthly Weather Review, 137*(11), 3811-3822.

Byeong Seok, A. (2011). Compatible Weighting Method with Rank Order Centroid: Maximum Entropy Ordered Weighted Averaging Approach. *European Journal of Operational Research*, *212*(3), 552-559.