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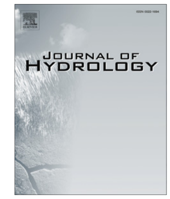

Improvement of watershed flood forecasting by typhoon rainfall climate model with an ANN-based southwest monsoon rainfall enhancement

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SUMMARY

This paper improves the typhoon flood forecasting over a watershed in a mountainous island of Taiwan. In the presence of the stiff topography in Taiwan, the typhoon rainfall is often phased-locked with terrain and the typhoon rainfall in general is best predicted by the typhoon rainfall climate model (TRCM) (Lee et al., 2006). However, the TRCM often underestimates the rainfall amount in cases of slowing moving storms with strong southwest monsoon supply of water vapor flux. We apply an artificial neural network (ANN) based southwest monsoon rainfall enhancement (AME) to improve TRCM rainfall forecasting for the Tsengwen Reservoir watershed in the southwestern Taiwan where maximum typhoon rainfall frequently occurred. Six typhoon cases with significant southwest monsoon water vapor flux are used for the test cases. The precipitations of seven rain gauge stations in the watershed and the southwest monsoon water vapor flux are analyzed to get the spatial distribution of the effective water vapor flux threshold, and the threshold is further used to build the AME model. The results indicate that the flux threshold is related to the topographic lifting of the moist air, with lower threshold in the upstream high altitude stations in the watershed. The lower flux threshold allows a larger rainfall amount with AME. We also incorporated the rainfall prediction with a state space neural network (SSNN) to simulate rainfall-runoff processes. Our improved method is robust and produces better flood predictions of total rainfall and multiple rainfall peaks. The runoff processes in the watershed are improved in terms of coefficient of efficiency, peak discharge, and total volume.

1. Introduction

There are three to five typhoons each year influencing Taiwan with torrential rainfall. Flood forecasting is one of the critical issues of reservoir operations, especially for those reservoirs built in watershed with stiff topography. The stream in the mountainous watershed is rapid and the time of concentration is approximately 3–5 h. The very short concentrated time pose serious challenges for flood forecasting and reservoir operation during typhoon landfall periods. The Taiwan typhoon rainfall is often phased-locked with the Central Mountain Range, with maximum rainfall often occurring on the windward side of the topography. Thus knowing the position of typhoon allows the forecasting of a precipitation pattern and the amount of rainfall from the typhoon climatology history. The quantitative typhoon rainfall prediction in Taiwan is often used with a statistical approach based on the relation between the observed rainfall pattern and the tracks of typhoon in the climatology model (e.g., Lee et al., 2006; the Typhoon Rainfall Climate Model, TRCM). The TRCM used 371 stations over Taiwan during 1989–2001. The model often gives reasonable precipitation estimates on each rain gauge station for 24–36 h time scale by a given typical cyclone center.

Typhoon Morakot 2009, with significant southwest monsoon flow, produced a record-breaking rainfall of 2361 mm in time spans of 48 h in the upstream of the Tsengwen Reservoir watershed (Alishan station). The extreme rainfall event is caused by the very slow moving of Typhoon Morakot and also the significant southwest monsoon water vapor supply (Chien and Kuo, 2011). The importance of the monsoon flow water vapor supply for the typhoon heavy rainfall is recognized in many of the recent studies (Chien et al., 2008; Lee et al., 2008; Ge et al., 2010; Hong et al., 2010). Because TRCM is based on the typhoon climatology of all scenarios, it may underestimate the typhoon rainfall in the presence of strong

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southwest monsoon flow. The southwest monsoon flow is a large scale meteorological feature that is well observed, thus it is possible to improve the typhoon flood forecasting with monsoon flow water vapor enhancement over a watershed.

The artificial neural network (ANN) algorithm is useful in rainfall forecasting, as the algorithm is flexible and data-driven learning in building model without prior assumptions concerning the data distribution and also takes into account the nature of nonlinearity (Gardner and Dorling, 1998). In order to achieve an accurate rainfall forecasting, many meteorological factors are selected as the inputs, including past observed rainfall, typhoon's characteristics, and satellite data (French et al., 1992; Olsson et al., 2004; Lin and Chen, 2005; Lin et al., 2009; Hsu et al., 1997; Bellerby et al., 2000; Hong et al., 2004; Chen et al., 2008).

The ANN approach is also useful in the rainfall-runoff processes (Whitley and Hromadka, 1999; Anctil et al., 2005; Chang and Chen, 2003; Cigizoglu, 2005; Hu et al., 2005; Imrie et al., 2000; Wang et al., 2009; Deka and Chandramouli, 2005; Lange, 1999; El-Shafie and El-Manadely, 2011). In these studies, the feedforward neural network (FNN) is adopted to perform rainfall-runoff processes. There may be some limitations of model calibration and simulation for a dynamical system, including using an inefficient process of trial and error to determine the optimum structure with appropriate number and configuration of its neurons in hidden layers (Imrie et al., 2000) and no dynamics involved due to the static structure of FNN (Chiang et al., 2004). This deficiency in flood forecasting may be remedied by a state space neural network (SSNN) with dynamics (Pan and Wang, 2004). Furthermore, Pan et al. (2007) demonstrated that DLRNN (one type of SSNNs) only needs the current rainfall as the input to get a satisfactory hydrograph while an FNN, which has the same input and number of weights as the DLRNN, performs rainfall-runoff processes poorly.

Pan et al. (2011) used an ANN-based southwest monsoon rainfall enhancement (AME) to improve TRCM rainfall forecasting for two mountain stations Alishan and Yushan with cumulative rainfall over 400 mm. Their result suggested that AME improves TRCM rainfall predictions significantly in both mountain stations. In this paper, we update the database of TRCM to include recent typhoons with strong southwest monsoons. We extend the previous work to investigate the impacts of the southwest monsoon on typhoon rainfalls in the Tsengwen Reservoir watershed by TRCM with AME. The rainfall-runoff processes are simulated with the SSNN from the improved TRCM rainfall predictions. Based on the SSNN, a short term rainfall-runoff forecasting for direct runoff of time $t+1 \sim t+3$ could be performed from the observed rainfall and an experiential phi index of time t for operational flood forecasting work (Pan and Wang, 2004). Therefore, the forecasting is performed in this study because the hydrological responses of time $t+1 \sim t+3$ are carried out based on the observed rainfall of time t and more rainfall predictions of time $t+1 \sim t+3$ via TRCM with AME. Consequently, we evaluate the performance of hydrological models for 1–3 h ahead flood forecasting. The descriptions of methods and data are in Section 2. The results and conclusions are in Sections 3 and 4, respectively.

2. Methods and data

2.1. Study area and European Centre for Medium-Range Weather Forecasts-Tropical Ocean Global Atmosphere (CMWF-TOGA) data

We select the Tsengwen Reservoir watershed as our study area. Located in southern Taiwan, the Tsengwen Reservoir watershed is on the upstream of the Tsengwen creek with an area of 481 km^2, a mean annual precipitation of 2700 mm approximately, and a mean annual stream flow of 29.0 m^3 s^{-1}. The elevation of the watershed ranges from 232.5 m to 2609.0 m and average slope is 54.4%. The Tsengwen Reservoir is located in the downstream of the watershed elevated at 133 m altitude. The topography, location of hydrological and rain gauge stations in the Tsengwen Reservoir watershed is shown in Fig. 1(a). The geographic orientation of the Tsengwen Reservoir watershed implies favorable condition for heavy precipitation, especially in the west half (windward side in general) of the watershed, where most of the rain gauge stations and the hydrological station are located. The stations are in the northeastern–southwestern orientation with the highest station Alishan (2413 m) and the lowest station Tsengwen (207 m).

To quantify the southwest monsoon water vapor flux (SWFlux), we use six hourly (at 0000, 0600, 1200 and 1800 Coordinated Universal Time (UTC)) advanced gridded operational analyses from European Centre for Medium-Range Weather Forecasts-Tropical Ocean Global Atmosphere (ECMWF-TOGA) with 1.125° × 1.125° resolution on 925 h Pa. We compute the SWFlux at each grid with the total wind and the specific humidity. Fig. 2 shows the differences of 925 h Pa wind speed and SWFlux between the six typhoons during the post-landfall period and the averaged pattern calculated from June to August during 2004 to 2009. Fig. 2 illustrates significant SWFlux for these typhoon cases, and the SWFlux provides the needed water vapor for post-landfall extreme rainfall. Although the SWFlux of Typhoon Kalmaegi is the weakest, but it is still stronger than climatology. The green rectangular region (16.875–22.5°N, 110.25–120.375°E with totally 60 grids near Taiwan) in Fig. 2 is used for detecting the SWFlux (Pan et al., 2011). The averaged SWFlux in the green region is computed as equation

$$\overline{Flux} = \frac{\sum_{i=1}^{60} (u_i^2 + v_i^2)^{1/2} \times q_i}{60} \tag{1}$$

where q_i is the specific humidity of the ith grid, and u_i and v_i are zonal and meridional velocity (m s^{-1}) of the ith grid, respectively. With southwesterly flow in mind, the $\overline{Flux}$ is calculated only when $u > 0$ and $v > 0$. Because the water vapor flux is estimated from ECMWF wind field and humidity field, the major possible errors are come from temporal and spatial resolution and the lack of the observed data over ocean. The temporal and spatial resolutions are 6 h and 1.125°, respectively. On the other hand, the data sets are based on quantities analysis or computed within the ECMWF data assimilation scheme. This method has reduced the error of few observed ocean data because satellite data has included.

2.2. Typhoon rainfall climate model (TRCM) and typhoon cases

Lee et al. (2006) developed the TRCM, which used 371 stations during 1989–2001. The domain of TRCM is confined from 19°N to 27°N and from 118°E to 126°E, which is divided by 256 sub grids (0.5° × 0.5°). The TRCM model comprises of a set of rainfall climatology maps, which is for each rainfall station. When the typhoon center is located at any grid box, the climatology hourly rainfall values for 371 stations could be estimated from the maps. Thus, knowing the typhoon tracks can estimate an hourly precipitation pattern and amount from climatology history. The coefficient of determinations (R^2) between model estimated and observed cumulative rainfall are 0.7 and 0.81 for Dan-Shui (DSH) River and Kao-Ping (KPS) River basins, respectively. Moreover, The R^2 are 0.69 and 0.73 if the hourly rainfall individual stations in DSH and KPS were considered. This model often gives reasonable typhoon precipitation estimates on 371 rain gauge stations cumulus rainfall and rainfall intensity (mm h^{-1}) for 24–36 h. In particular, the performance is very well in KPS basins (Lee et al., 2006) near the Tsengwen Reservoir watershed at southwest Taiwan.

To make TRCM more reliable to our study, we update the TRCM database from 1989 to 2008. However, we find that the predicted