

# Combining Numerical Rainfall Forecasts and Realtime Observations to Improve Early Inundation Warnings

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## 1 Introduction

Flooding can cause loss of life and property, and the global flood risk is likely to increase because of frequent extreme weather events [5, 13]. Establishing an early flood warning system is the most cost-effective approach to reducing the impact of flooding among all structural and non-structural measures [1, 4].

High computational costs and substantial data requirements will limit the application of early warning systems for real time operational purposes. Efficiency and accuracy are essential considerations for a well-developed early warning system. Therefore, a variety of easy-to-use models and tools, such as simplified equation-based systems, data-driven models, and rainfall threshold-based approaches, have been developed to increase the operational efficiency of early warning systems [3, 8, 14, 17].

This study used ensemble rainfall forecasts and rainfall thresholds to generate inundation forecasts at the township level. Efficiency is particularly important for an operational early warning system. Thus, in this study, the rainfall threshold-based approach is successfully applied to evaluate landslide risk [11] and flood risk [3, 12]. It is a low data requirement model with high efficiency and stability, and it is easy to maintain. The complexity of the Earth–atmosphere system and the associated physical interactions add uncertainty to ensemble rainfall forecasts. The accuracy of rainfall forecasting is the focus of this study. A study [9] revealed that most numerical global models over predicted or slightly under predicted the rainfall frequency based on various thresholds in Australia. This study used the numerical rainfall forecasts as output data associated with multiple rainfall gauges in the

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rainfall threshold approach to decrease spatial uncertainties. Additionally, a data assimilation technique combining numerical rainfall forecasts and real time observations at rainfall gauges was proposed to decrease temporal uncertainties. The remainder of this paper is organized as follows. Section 2 briefly describes the data and the study area, including the ensemble rainfall forecasts developed in Taiwan. Section 3 includes the details of the methods applied in this study. Sections 4 and 5 present the results and conclusions.

## 2 Study Area and Data

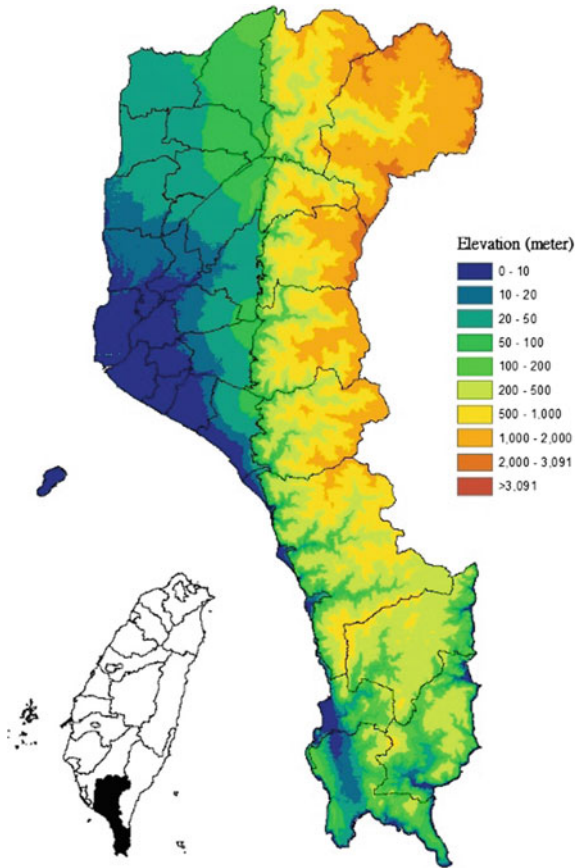
### 2.1 Study Area

Pingtung County, which is located in southern Taiwan (Fig. 1), was selected as the study area. The total area of the county is 2776 km<sup>2</sup>, and its approximate population was 0.83 million in 2016. Agriculture and tourism are the major contributors to the county's economy. The county has a tropical climate and an annual rainfall of 2641 mm, which is not evenly distributed in time and space. Mountainous areas receive more than 4000 mm of precipitation, while plain and alluvial fan areas receive 2000–3000 mm and coastal regions receive 1000 mm. There are 33 townships in Pingtung County, and the elevation decreases from northeast to southwest. The most densely populated townships are in western Pingtung. Typhoons with heavy rainfall impact the county every year from June through October and cause various disasters, such as landslides and flooding. Local subsidence from groundwater overdraft increases the frequency of flooding and worsens the associated effects on local residents.

### 2.2 Data

Accurate flood records, including the time of occurrence, depth, and extent of inundation, are essential to evaluating quantitative analyses. However, data collection during a flood period is challenging. For example, identifying the occurrence time of inundation is challenging because of the lack of in situ monitoring devices. This study used urban inundation alerts issued by the Water Resources Agency (WRA) as a reference for evaluation. All the counties in Taiwan plan their emergency response measures based on the urban inundation alerts of the WRA. During a typhoon, the WRA issues the alerts using the observed rainfall records. The WRA updates its alerts every 10 min and uploads the information to an open-source platform operated by the National Science and Technology Center for Disaster Reduction [7]. The data include observed flood warning information, such as the location and duration of the flood warning. Five typhoons that occurred in

**Fig. 1** Map of Pingtung County

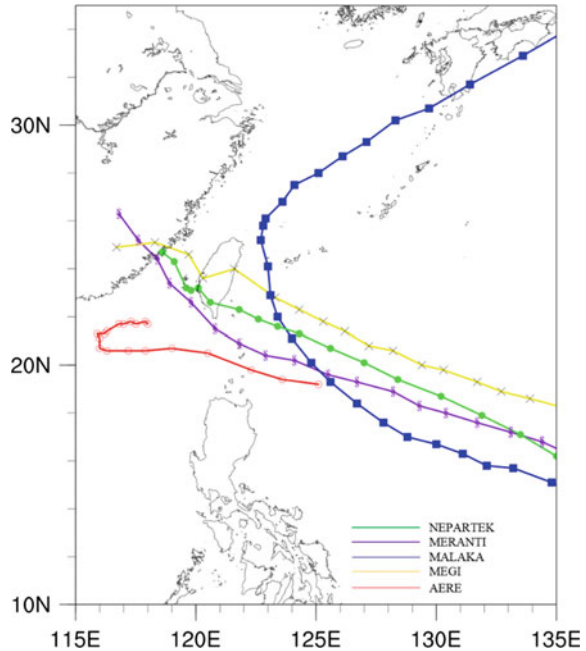


**Table 1** Information from five typhoons in 2016 used to evaluate the system performance

Name	Warning period (LST)
NEPARTAK	07/06 14:30–07/09 14:30
MERANTI	09/12 23:30–09/15 11:30
MALAKAS	09/15 23:30–09/18 08:30
MEGI	09/25 23:30–09/28 17:30
AERE	10/05 11:30–10/06 14:30

2016 were used in the evaluation. Table 1 and Fig. 2 show their warning periods and observed tracks. Typhoons MERANTI and NEPARTARK directly affected Pingtung County and caused considerable damage to the county. Typhoon AERE did not generate damage to the county but was included in this study to evaluate the overall performance of the proposed inundation forecasts, which include correct inundation warnings and false alarms. Decision makers may hesitate to consider the forecast information if a system with a high false alarm rate is used [2].

**Fig. 2** The observed tracks of five typhoons in 2016 used in this study



### 3 Methods

#### 3.1 Ensemble Rainfall Forecasts

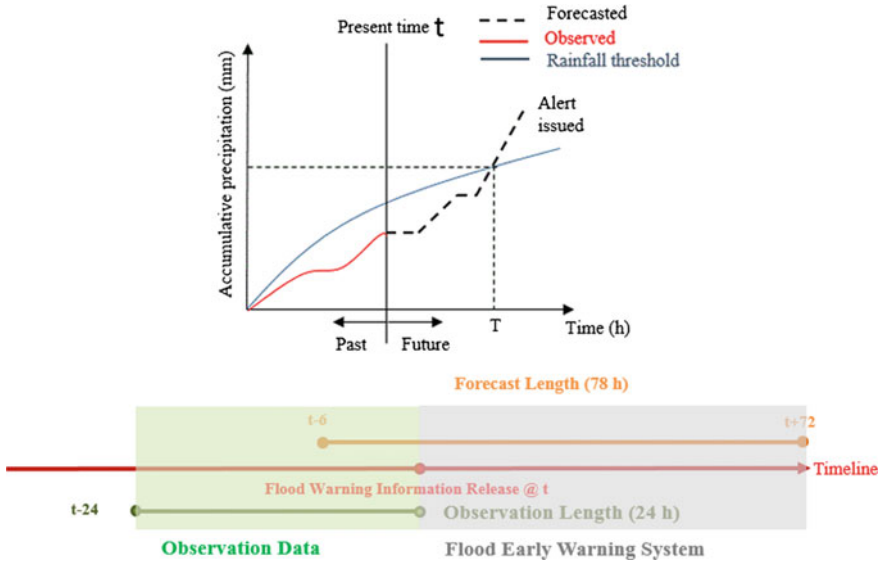
This study used rainfall forecasts from a precipitation ensemble forecasting experiment, namely, the Taiwan Cooperative Precipitation Ensemble Forecast Experiment (TAPEX). TAPEX is a collective effort among academic institutes and government agencies, such as National Taiwan University (NTU), National Central University (NCU), National Taiwan Normal University (NTNU), Chinese Culture University (CCU), the Central Weather Bureau (CWB), the National Center for High-Performance Computing (NCHC), the Taiwan Typhoon and Flood Research Institute (TTFRI), and the National Science and Technology Center for Disaster Reduction (NCDR). The experiment started in 2010 and was the first attempt at designing a high-resolution numerical ensemble weather model in Taiwan. It aims to provide 72-h typhoon precipitation forecasts and generates four runs per day at a 5 km spatial resolution. In this study, 28 ensemble members (28 numerical weather models) were used to provide rainfall forecasts. Additional details regarding TAPEX can be found in previous studies [6].

### 3.2 *Rainfall Thresholds*

The WRA in Taiwan develops rainfall thresholds for all townships [16]. Based on historical flood records, the initial rainfall thresholds can be estimated by determining the cumulative rainfall amounts at nearby rain gauges when an event occurred. The final rainfall thresholds of different townships are based on further investigations of the local drainage capacity and local characteristics (e.g., land subsidence) and the professional judgement of local experts. This study used the WRA warnings records to evaluate the results of this study because local governments and civil agencies take necessary measures, such as evacuating residents and deploying dewatering pumps, based on the WRA warning information. Therefore, an early warning system in Taiwan that can forecast the WRA warning information with an extended lead time can benefit the implementation of precautionary actions. This study uses five duration periods, 1, 3, 6, 12, and 24 h, and two levels of alerts for rainfall thresholds. The two levels of alerts are defined as follows. For a first-level alert, if rain continues, the roads and villages subject to a high risk of flooding in the alerted townships may flood. For a second-level alert, if rain continues, the roads and villages subject to a high risk of flooding in the alerted townships will flood in the next 3 h.

The WRA will issue an inundation alert if a rainfall threshold is met by the observed rainfall. This study used forecasted rainfall to replace observed rainfall for the rainfall thresholds of second-level alerts. Overall, 20 ensemble members were used in this study. Each member generates a 72-h rainfall forecast during each run, and each run requires 6 h of computational time. Therefore, four runs were performed per day. Six separate periods (0–3, 0–6, 0–12, 0–24, 0–48, and 0–72 h) were considered to evaluate the future inundation risk in each township. In any given township, if 10 out of 20 rainfalls forecasted by members exceed the abovementioned rainfall thresholds in the six periods, the event will be identified as a high risk of flooding.

The complexity of the Earth–atmosphere system adds spatial and temporal uncertainties to numerical rainfall forecasts. This study decreased the temporal uncertainty by including real time observation data in the forecasts. Five rainfall thresholds were compared to forecasted rainfall to evaluate the inundation risk. The present time  $t$  in Fig. 3 is the time when a forecast is generated. However, only one rainfall threshold, i.e., the one that covers the 1 h period, can be considered at  $t$ ; thus, forecasts are not available at  $t - 1$  and the preceding hours. This shortcoming results in the underestimation of inundation forecasts. Therefore, this study proposed a mixed data technique that fills the gaps in rainfall forecasts with real time observation data from  $t - 24$  to  $t - 1$  prior to issuing inundation forecasts at  $t$ . All five thresholds representing different rainfall durations then can be considered at any given hour, and alerts are issued if the combination exceeds the rainfall threshold at any given time. For example, a 6-h rainfall threshold is considered to evaluate the flood risk at time  $t + 2$ . The accumulated rainfall for 6-h at time  $t + 2$  is calculated including observations for three hours ( $t - 1$ ,  $t - 2$ ,  $t - 3$ ) and forecasts



**Fig. 3** This study issues an inundation alert when forecasted rainfall meets or exceeds any given rainfall thresholds (top) and the alert is evaluated using a combination of observed records and forecasted results (bottom) [18]

**Table 2** Contingency table used for performance evaluation

	Observed	Not observed
Forecasted	Hit	False alarm
Not forecasted	Miss	No event

for three hours ( $t, t + 1, t + 2$ ). Same steps are applied to other thresholds of different rainfall thresholds. During operation, the failure of obtaining real time observations or forecasts may occur. This study excludes any data failure and reviews the flood risk. A further study needs to be conducted to study the impact to the system performance due to the failure of data communication.

### 4 Results

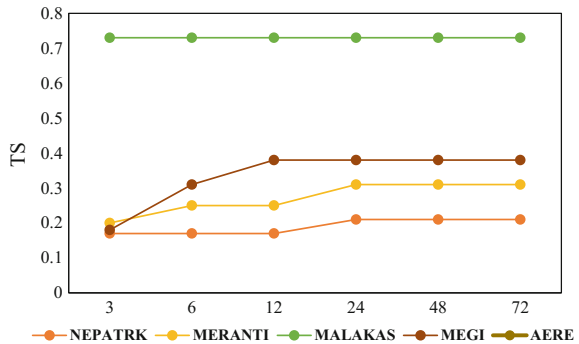
Table 2 is a contingency table that many studies have used to evaluate forecasting performance [10, 19]. This study applied two performance measures to evaluate performance: the accuracy rate (ACC) and threat score (TS). The definitions of these measures are as follows:

$$ACC = \frac{Hit + No\ event}{Hit + Miss + False\ alarm + No\ event}, \tag{1}$$

$$TS = \frac{\text{Hit}}{\text{Hit} + \text{Miss} + \text{False alarm}}, \tag{2}$$

where hits and miss were determined based on whether the forecasts were consistent with the observations. A false alarm was associated with a forecast that did not correlate with observed data. “No event” was assigned when neither the observation nor the forecast indicated flooding. TS ranges from 0 to 1 and is also known as the critical success index (CSI), which generally results in low scores for rare events. The accuracy rate (ACC) of the model, which is shown in Eq. (1), is also called the proportion of correct forecasts [15]. This metric is simple and intuitive, and it served as a valuable reference in this study. Figure 4 shows the TS performance in different periods. Typhoon AERE has no results plotted in Fig. 4 since no alarms were issued from the observations or forecasts. The TS performance without multiple gauges or observations cannot be calculated during all periods. The results show that the performance significantly improved when alerts were issued based on the improved method. Table 3 shows that the ACC performance improved when multiple rainfall gauges and real time observations were considered. There is one exception which is Typhoon MERANTI. A further study

**Fig. 4** Comparison of TS performance in various time periods when most flood alarms were issued



**Table 3** Difference in ACC performance with (ACC\*\*) and without (ACC\*) multiple gauges and observations

ACC** - ACC*	0-3	0-6	0-12	0-24	0-48	0-72
NEPARTAK	0.12	0.12	0.15	0.15	0.15	0.15
MERANTI	0.12	-0.04	-0.04	-0.04	-0.04	-0.04
MALAKAS	0.03	0.03	0.03	0.03	0.03	0.03
MEGI	0.03	0.03	0.06	0.06	0.06	0.06
AERE	-	-	-	-	-	-

regarding why the performance of MERANTI was not improved needs to be conducted in the future. In conclusion, the addition of multiple rainfall gauges and observations decreased the spatiotemporal uncertainties and improved the forecasting performance.

## 5 Conclusions

This study proposed an early inundation warning system that integrates ensemble rainfall forecasts and rainfall thresholds. Five rainfall thresholds with different durations were applied. Five typhoons in 2016 and real inundation alert records issued by the WRA were used to evaluate the performance of the method proposed in this study. Real time observations and multiple rainfall gauges were applied to decrease the temporal and spatial uncertainties associated with numerical rainfall forecasts. The results showed that the proposed method had a high TS score, which is associated with a higher inundation alert detection rate. Numerical weather predictions were the dominant input that influenced the forecast results. The performance of the system varied according to the different typhoons tested. This study developed a data assimilation technique that combined real time observations and forecasted rainfalls to decrease the temporal uncertainty of numerical weather prediction and to improve inundation forecasting. This technique improved the appeal of the early warning system and generated valuable forecasts that allow decision makers to make better choices under various conditions. To further decrease the spatial uncertainty of numerical weather prediction, this study used rainfall forecasts as output data associated with multiple rainfall gauges. The TS score improved when additional gauges and observations were used in comparison with the results from only using one gauge. Decision makers use forecasted rainfall and threshold-based early warning systems for a high-level overview of the flood risk. Given its advantage, including an extended lead time and rapid estimation process, the model presented here is beneficial for emergency deployment and planning in large areas prior to flooding. However, the proposed approach only can provide high-level information instead of detailed forecasts. The system is developed for a rapid review of flood risk at county level based on a threshold concept. The threshold values of a county are needed to update periodically according to most current on site conditions.

**Acknowledgements** The authors would like to thank the Water Resources Agency, Taiwan, for providing the rainfall threshold values and the Central Weather Bureau, Taiwan, for providing rainfall observation data. The study was supported by the Ministry of Science and Technology of Taiwan under Research Grant MOST 105-2625-M-492-017.



## References

1. Alfieri, L., Salamon, P., Pappenberger, F., Wetterhall, F., & Thielen, J. (2012). Operational early warning systems for water-related hazards in Europe. *Environmental Science & Policy*, 21, 35–49.
2. Coughlan de Perez, E., van den Hurk, B., van Aalst, M. K., Amuron, I., Bamanya, D., Hauser, T., et al. (2016). Actionbased flood forecasting for triggering humanitarian action. *Hydrology and Earth System Sciences*, 20, 3549–3560.
3. Gourley, J. J., Flamig, Z. L., Hong, Y., & Howard, K. W. (2014). Evaluation of past, present and future tools for radar-based flash-flood prediction in the USA. *Hydrological Sciences Journal*, 59, 1377–1389.
4. Hallegatte, S. (2012). A cost effective solution to reduce disaster losses in developing countries: hydro-meteorological services, early warning, and evacuation. *World Bank Policy Research Working Papers*.
5. Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., et al. (2013). Global flood risk under climate change. *Nature Climate Change*, 3(816–821), 2013.
6. 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.
7. Lee, C., Wu, S., & Chang, T. (2014, June and 25–27). Implementing common alerting protocol for disaster reduction in Taiwan, 2014 TGIS GeoInformatics—UGIS Joint International Conference, Kaohsiung, Taiwan.
8. Lin, G. F., & Jhong, B. C. (2015). A real-time forecasting model for the spatialdistribution of typhoon rainfall. *Journal of Hydrology*, 521, 302–313.
9. McBride, J. L., & Ebert, E. E. (2000). Verification of quantitative precipitation forecasts from operational numerical weather prediction models over Australia. *Weather Forecast*, 15, 103–121.
10. Nguyen, P., Thorstensen, A., Sorooshian, S., Hsu, K., & AghaKouchak, A. (2015). Flood forecasting and inundation mapping using HiResFlood-UCI and near-real-time satellite precipitation data: the 2008 Iowa flood. *Journal of Hydrometeorology*, 16, 1171–1183.
11. Posner, A. J., & Georgakakos, K. P. (2015). Soil moisture and precipitation thresholds for real-time landslide prediction in El Salvador. *Landslides*, 12, 1179–1196.
12. Raynaud, D., Thielen, J., Salamon, P., Burek, P., Anquetin, S., & Alfieri, L. (2015). A dynamic runoff co-efficient to improve flash flood early warning in Europe: Evaluation on the 2013 central European floods in Germany. *Meteorological Applications*, 22, 410–418.
13. Sampson, C. C., Smith, A. M., Bates, P. D., Neal, J. C., Alfieri, L., & Freer, J. E. (2015). A high-resolution global flood hazard model. *Water Resources Research*, 51, 7358–7381.
14. Shao, Q., Weatherley, D., Huang, L., & Baumgartl, T. (2015). Run CA: Acellular automata model for simulating surface runoff at different scales. *Journal of Hydrology*, 529, 816–829.
15. Wilks, D. (2005). *Statistical methods in the atmospheric sciences* (2nd ed., p. 2005). Burlington: Elsevier.
16. Wu, D. S., & Wang, Y. F. (2009, December and 19). A research on using critical precipitation value for taiwan inundation warning system. In *Proceedings of the 2009 Conference for Disaster Management in Taiwan*, Taipei, Taiwan.
17. Yang, T. H., Chen, Y. C., Chang, Y. C., Yang, S. C., & Ho, J. Y. (2015). Comparison of different grid cell ordering approaches in a simplified inundation model. *Water*, 7(2), 438–454.

18. Yang, T. H., Hwang, G. D., Tsai, C. C., & Ho, J. Y. (2016). Using rainfall thresholds and ensemble precipitation forecasts to issue and improve urban inundation alerts. *Hydrology and Earth System Sciences*, *20*, 4731–4745.
19. Zhang, Y., Reed, S., Gourley, J. J., Cosgrove, B., Kitzmiller, D., Seo, D., et al. (2015). The impacts of climatological adjustment of quantitative precipitation estimates on the accuracy of flash flood detection. *Journal of Hydrology*, *541*, 387–400.