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IMPROVEMENT OF FLOOD EARLY WARNING LEAD TIME TO ENABLE SUFFICIENT COMMUNITY RESPONSES: A CASE STUDY OF HAT YAI CITY, SOUTHERN THAILAND

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Abstract: Flooding is the only type of natural disaster that has significantly affected the way of life of the residents in Hat Yai city in southern peninsular Thailand. Since the large floods in 2010, warning capability by local authorities has been improved by forecasts of water level in the U-Tapao river. This paper describes the procedures used to determine appropriate water-level forecasting approaches and also focuses on improving flood early warning lead time to enable sufficient response. The water level forecasting results showed that the actual lead times of 5, 10 and 10 hours and the lead time errors of 4, 4 and 0 hours for flood routing, unit hydrograph and MIKE 11 DA approaches, respectively. Performance evaluation for the best approach was conducted based on the longest actual lead time and the least lead time error criteria. The best approach was found to be the MIKE 11 DA followed by the unit hydrograph and the flood routing approaches. In addition, increasing the lead time from 5 to 10 hours can be achieved for the Hat Yai flood warning system.

Keywords: Water level forecasting, flood early warning lead time, MIKE 11 DA, unit hydrograph.

Introduction

Floods are natural disasters that cause considerable material, social and environmental losses and frequently result in loss of human lives (Casagrande *et al.,* 2017). Of all natural disasters, floods impact the greatest number people across the world (Moore *et al.,* 2005). In the USA, the Mississippi "Great Flood" in 1993 was the most severe on record, while catastrophic floods in China and Bangladesh are a way of life associated with much human suffering and death (Moore *et al.,* 2005; Fakhruddin *et al.,* 2015). In Thailand, the Bangkok "Great Flood" in 2011 was reported to have caused global economic damage (Swiss Re, 2012).

Flood warning systems are important to mitigate the effects of flooding (Werner *et al.,* 2009), forecasting is an essential tool in the warning process. The aim of flood forecasting is to increase the lead time for a flood warning system (Casagrande *et al.,* 2017). Many flood forecasting approaches are available, such as extrapolation techniques, simple transfer function models, unit hydrograph approaches and hydrodynamic models (Werner *et al.,* 2009). In Nepal, successful forecasting increased lead time from 2-3 to 7-8 hours and reduced the risk of flooding (Smith *et al.,* 2017). In Brazil, flood forecasts can be issued up to 48 hours ahead with a low rate of false warnings, based on a hydrological model for stream-flow forecasting (Casagrande *et al.,* 2017). In Bangladesh, the one-dimensional modeling software MIKE11 was used to simulate water levels and discharges in rivers for deterministic flood forecasting up to 72 hours ahead (Hettiarachchi & Thilakumara, 2015).

Hat Yai city is a center for economics, trade, education and tourism in southern peninsular Thailand and has frequently experienced flooding (Supharatid, 2006; Chalermyanont & Chup-Uppakarn, 2015). The city and its suburban areas are on the floodplains at the downstream of the U-Tapao Basin (Figure 1). Its population exceeds half a million people. In the last three decades, three major floods in 1988, 2000 and 2010, that heavily affected residents and severely damaged the economy of the city (Supharatid, 2006; Kongjun & Noipairoj, 2011). It can be simply said that a major flood occurs about every 10 years. After the 2010 flood, the largest ever recorded, a meeting organized by Prince of Songkla University concluded that because the city is on a floodplain, flooding is unavoidable, but an effective flood warning system should be put in place to minimize damage. In response to this conclusion, a Songkhla Flood-Watch Committee (SFWC) was appointed by the governor of Songkhla province. The SFWC consists of representatives from the Royal Irrigation Department (RID), the Thai Meteorological Department (TMD), the Department of Water Resources (DWR), the Department of Disaster Prevention and Mitigation (DDPM), the Hat Yai Municipality and the Prince of Songkla University (PSU). Its duties were mainly to develop flood forecasting and warning systems.

This paper describes procedures used by the SFWC to select appropriate water-level forecasting approaches to warn Hat Yai city of floods. Three approaches of water-level forecasting were considered, namely streamflow routing, unit hydrograph and MIKE 11 DA

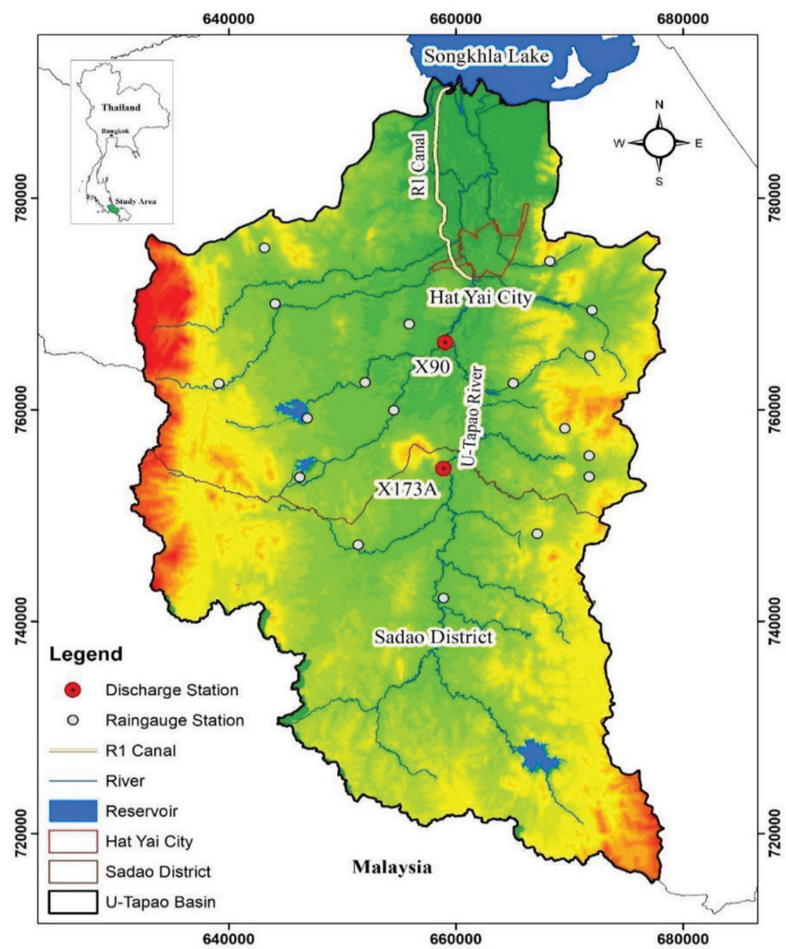

Figure 1: The U-Tapao Basin

modeling. This paper also focuses on improving the flood-warning lead time to provide enough response time.

Study Area

The U-Tapao Basin (Figure 1) is in Songkhla province, in southern Thailand. The basin consists of 10 sub-basins with a drainage area of 2,392 km^2 and is between N718000 to N788000 and E630000 to E682500. It is surrounded by mountainous areas on the eastern and western sides, while the northern and southern boundaries are the Sonkhla Lake and the Thai-Malaysian border, respectively. The U-Tapao river is the main drainage path of the basin with about 102 km in length and average upstream and downstream slopes of 1:10,000 and 1:200, respectively. The river flows from Sadao district in the south through the center of the basin and Hat Yai city and finally drains to the Songkhla Lake (Chalermyanont & Chup-Uppakarn, 2015). The drainage capacity of the river in Hat Yai city is 465 cms (Kongjun & Noipairoj, 2011).

Data from 21 raingauge stations, installed after the 2010 flood and two streamflow stations (Figure 1) were used courtesy of the TMD and the RID, respectively. The two main streamflow stations are the upstream station at Maunggong and the downstream station at Bangsala, labeled as X173A and X90, respectively. According to local experience and practices (DDPM, 2015), the water level at X90 station has been used to generate early flood warnings. The city will be flooded within 3-5 hours if the water level at X90 station reaches +9.30 m above mean sea level (msl). However, an early warning lead time of 3-5 hours is not sufficient for various types of responses, such as executive decision making by the governor and dissemination of the flood warning through various methods, including the media. In addition, flood warning acceptance and evacuation of a big city such as Hat Yai takes time. Thus, a longer flood warning lead time is needed.

Methods

In this study, three approaches were used to forecast water level at the X90 station at hourly intervals in order to gain a longer flood warning lead time. Details of streamflow routing, unit hydrograph and MIKE 11 Data Assimilation (DA) approaches are provided below.

Streamflow Routing Approach

A simple streamflow routing method is a lumped method for forecasting downstream water level based on the fact that if a high water level is detected upstream, in time, the water level will also increase downstream. It makes use of measured water levels at upstream and downstream stations and a linear relationship between peak water levels upstream and downstream can be determined. A linear relationship between the flow time (i.e., time difference between peak water levels downstream and upstream) and peak water level at upstream is also determined. These relationships are shown in Equations 1 and 2 (Sukhapunnaphan, 2014).

$$H_d = a_1 H_u + b_1 \tag{1}$$

$$T = a_2 H_u + b_2 \tag{2}$$

where H_d is peak water level downstream, H_u is the peak water level upstream, T is the flow time and a_1, a_2, b_1, b_2 are constants.

In this study, time series data of measured water levels at X173A (upstream) and X90 (downstream) stations from 2005 to 2010 were used to determine the relationships in Equations 1 and 2. The relationships were employed to determine that water level at X173A station that corresponds to a +9.30 m msl water level at the X90 station (i.e., the flood warning criterion adopted in the past). By doing this, the use of water level at X173A station for flood warning could increase flood warning lead time.

Unit Hydrograph Approach

Unit hydrograph is a direct runoff hydrograph resulting from a centimeter of excess rainfall generated over the basin (Chow *et al.,* 1988;

Gribbin, 2007). It is a rainfall-runoff model that provides a transfer function to convert excess rainfall to stream discharge (or water level). In case of several storms, the hydrograph at a location can be computed using the discrete convolution equation shown in Equation 3.

$$Q_n = \sum_{m=1}^{n \leq M} P_m U_{n-m+1} \tag{3}$$

where Q_n is stream discharge, P_m is excess rainfall, U_{n-m+1} is unit hydrograph and subscript m is number of storms (m = 1,2,..., n). For more details on the discrete convolution equation, readers can refer to Chow *et al.* (1988).

In this study, a 3-hour unit hydrograph for the X90 station was developed using the Snyder method (Snyder, 1938; Chow *et al.,* 1988) with the following parameters: basin drainage area (A) = 1524 km^2, length of the mainstream from X90 station to the upstream divide (L) = 88.61 km and distance from X90 station to a point on the stream nearest the centroid of the basin area (L_c) = 50.12 km. For the lag coefficient (C_t) and the peak flow coefficient (C_p), as reported by Mitparian and Klubsong (2012), the respective values used were 3.14 and 0.51.

Mike 11 DA Approach

The MIKE 11 DA model is a numerical model developed by the Danish Hydraulic Institute (DHI, 2011) and is an efficient water level forecasting tool. It makes use of the rainfall-runoff model (RR model) and the hydrodynamic model (HD model), while real-time measured water level data are incorporated into the model to improve the accuracy of forecasts. In this study, the RR and HD models by Chalermyanont and Chup-Uppakarn (2015) were used. For the RR model, the catchment area was set from upstream of the X90 station. The catchment area of the RR model was 1,524 km^2. The Thiessen method was employed to compute the average rainfall. The NAM model (abbreviation for "Nedbør-Afstrømnings-Model" in Danish, meaning a precipitation-runoff-model), which is a lumped system routing model based on spatial averaging, was used in the RR model (DHI, 2011). The calibrated NAM parameters representing basin characteristics such as surface zone root zone, groundwater storages and others were employed in the model. Results from the RR model as time series hydrograph were used as inputs to the HD model.

The HD model simulates 1-D flow with the dynamic wave description by solving the vertically integrated equations of conservation of continuity and momentum, the so-called 'Saint Venant' equations (DHI, 2017). These equations are as follows:

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = q \tag{4}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial \left(\alpha \frac{Q^2}{A} \right)}{\partial x} + gA\frac{\partial h}{\partial x} + \frac{gQ|Q|}{C^2 AR} = 0 \tag{5}$$

where Q is discharge, A is flow area, R is hydraulic or resistance radius, h is stage above datum, q is lateral inflow, C is Chezy resistance coefficient and a is momentum distribution coefficient.

For the HD model set up, Chalermyanont & Chup-Uppakarn (2015) used two river networks representing the U-Tapao River and the R1 Canal. Note that the R1 Canal is a flood diversion canal (Figure 1). Lengths of the U-Tapao River and the R1 Canal are 102 and 21 km, respectively. The R-1 canal was linked to the U-Tapao River at N772375 and E661320. Chainages of the river network were assigned every 1,000 m and their corresponding river cross-sections were imported. Open boundary conditions were set for both upstream and downstream boundaries. Parameters of the HD model were calibrated and used in MIKE 11 DA model.

Data assimilation (DA) is a technique for combining measurements of the state of the system with the model dynamics in order to improve knowledge of the system. The data assimilation module in MIKE 11 can be used for assimilating water level and discharge measurements to the DA model. The data assimilation methods implemented in MIKE 11 DA model are sequential algorithms. In this case the sequential updating of the model solution is performed with forward model integration, in which the model forecast and the data are melded by a Kalman filter (DHI, 2017).

In this study, the MIKE 11 DA model was employed for water level forecasting and flood warning lead time determination. Time of forecast, measured rainfall and water level data used as inputs are summarized in Table 1. Time of forecast (TOF) refers to the time that the water level forecast is made using all the rainfall recorded prior to that particular time. The first time of forecast (TOF1) was on January 1st, 2012, at 00.00 am. Other TOFs were made every 3 hours for a total of 6 TOFs.

Performance Evaluation of Water Level Forecasting Approaches

Performance evaluation of the three water level forecasting approaches was conducted based on accuracy of the lead time. The 2012 flood that took place on January 1st and 2nd, 2012 was used in the case study because complete rainfall and discharge data were available. In this event, the rain began falling on December 29th, 2011, while extremely heavy rainfall was observed on December 31st, 2011 and January 1st, 2012. Computed basin average daily rainfalls from December 29th, 2011 to January 1st, 2012 were 5.30, 8.41, 54.87 and 157.52 mm, for the respective days.

In the performance evaluation process, forecast of water level and flow time at X90 station with +9.30 m msl was computed based on the approaches described above, using either the rainfall or water level data of the 2012 flood. Expected and actual lead times were then computed by subtracting a time at which either the computed or measured water level reached +9.30 m msl with the time of forecast. The measured water level data showed that the water level at X90 station reached +9.30 m msl on January 1st at 19:00 while the peak water level of +10.01 m msl was recorded on January 2nd at 2:00. The river started overflowing in low-lying areas of Hat Yai city around midnight to 2:00 of January 2nd and the peak water level was observed at 10:00 on the same day. Among the three approaches, the best approach would provide the longest lead time and the least lead time error (absolute difference of expected and actual lead times).

Table 1: Time of forecast, measured rainfall and water level data

Number of Forecast	Time of Forecast		Measurement	
	Date	Time	Accumulated Average Rainfall (mm)	X90 Water Level (m msl)
TOF1	01-01-2012	0:00	78.25	+3.34
TOF2	01-01-2012	3:00	145.31	+3.65
TOF3	01-01-2012	6:00	201.34	+4.52
TOF4	01-01-2012	9:00	218.47	+5.60
TOF5	01-01-2012	12:00	224.84	+7.15
TOF6	01-01-2012	15:00	226.08	+8.20

Results and Discussion

Streamflow Routing Results

Analytical results of the simple streamflow routing method in terms of a relationship between the water levels at X173A and X90 stations and the flow time, are shown in Figure 2 and Equations 6 and 7. The H_d seems to be well predicted by H_u, but T is not well predicted. The R^2 values of Equations 6 and 7 are 0.9548 and 0.4922, respectively.

$$H_d = 1.541H_u - 16.06 \quad (6)$$

$$T = -3.425H_u + 65.03 \quad (7)$$

Equation 6, thus, was employed to determine the H_u at X173A station that corresponds to the flood warning water level at X90 station (i.e., $H_d = +9.30$ m msl). Similarly, Equation 7 was used to determine the flow time between these two stations. This flow time T is the expected lead time of the early warning. The computed H_u at X173A station was +16.46 m msl and the computed T was about 9 hrs. However, the observed times of H_u and H_d were respectively 14:00 and 19:00 on January 1st, so the actual lead time was 5 hours or about 4 hours less than the model inferred lead time. Because of the poor relationship of Equation 7, a poor expected lead time was obtained.

Unit Hydrograph Results

A synthetic 3-hour unit hydrograph, developed for the X90 station based on the Snyder method, is shown in Figure 3. It mainly shows that a centimeter of excess rainfall over the catchment area of the X90 station would generate a peak discharge of 74.38 cms within about 30 hours. The discrete convolution technique (i.e., Equation 3) was applied using the unit hydrograph and the rainfall data of the 2012 flood, to forecast the discharge and corresponding water level at the X90 station. A series of plots of computed water level vs time are shown in Figure 4. Note that TOFs details refer to Table 1. Computed water level at X90 station does not reach +9.30 m msl in TOF1 to TOF3 plots. In the TOF3 plot, in particular, the peak water level is +9.16 m msl. In the TOF4 plot, the water level at X90 station reaches +9.30 m msl at 23:00 on January 1st, 2012. Thus, TOF4 can be used for issuing flood early warning with expected lead time of 14 hours. However, the actual lead time observed was 10 hours.

MIKE 11 DA Results

The measured and simulated hydrographs of X90 station from December 2011 to January 2012 were used in the calibration of the RR and HD models, as presented by Chalermyanont

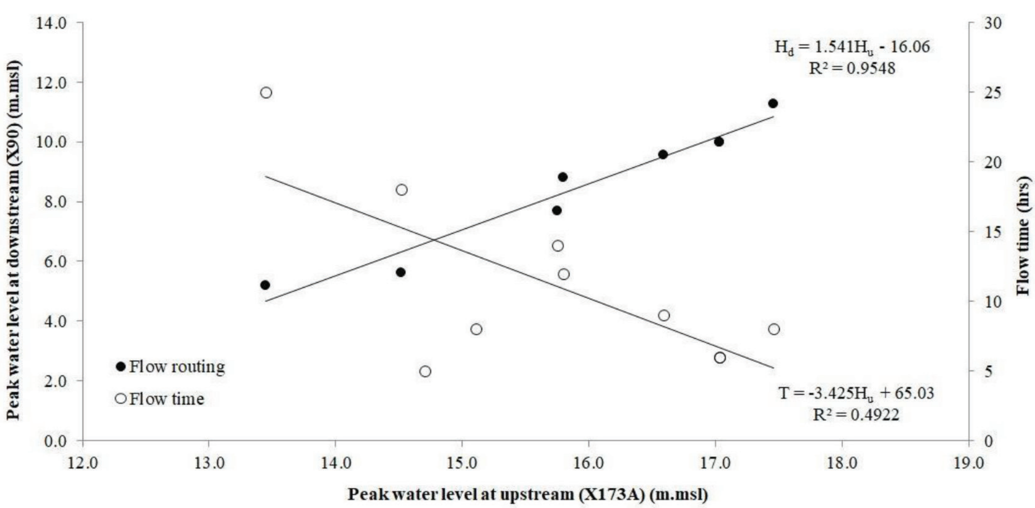

Figure 2: Relationships between peak water level and flow time

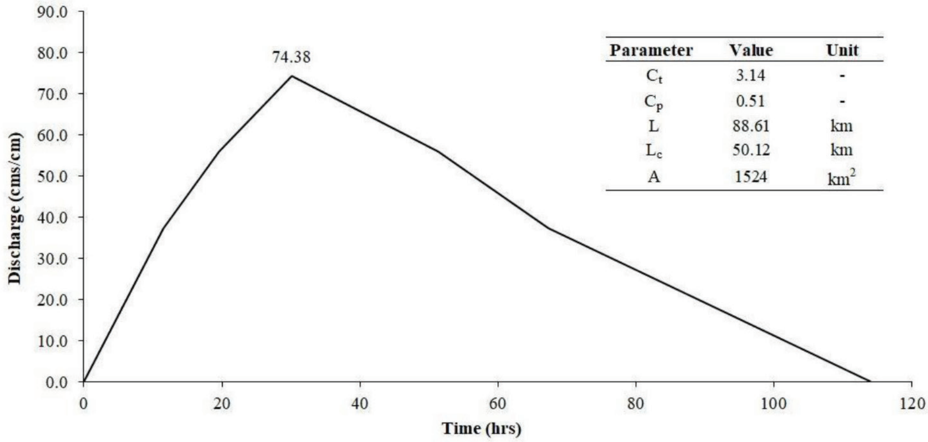

Figure 3: Snyder's 3-hour unit hydrograph for X90 station

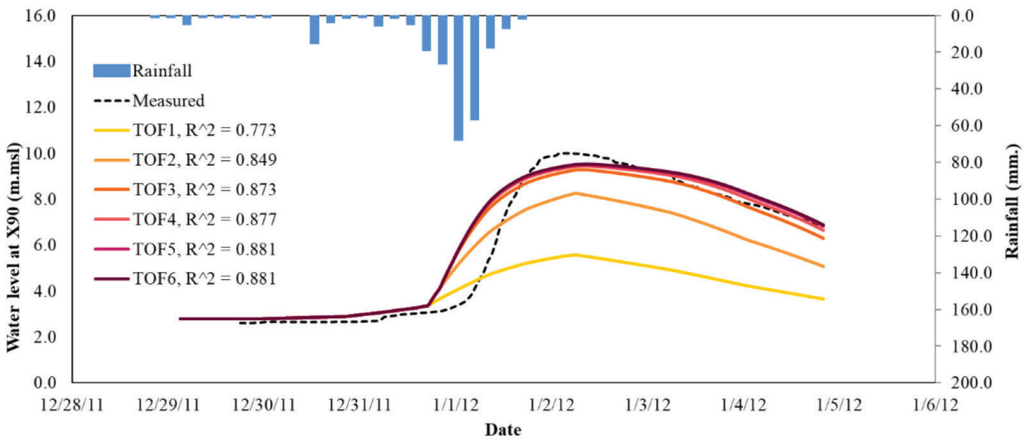

Figure 4: Water level forecasting results from unit hydrograph approach

and Chup-Uppakarn (2015). These two models were calibrated separately by changing related parameters repeatedly until the measured and simulated hydrographs were matched. The calibration results are shown in Figure 5. The best R^2 values obtained from the calibration were 0.919 and 0.959 for the RR and HD models, respectively. The calibrated models were then validated using another set of the X90 hydrographs from November to December 2013. The R^2 values obtained from the validation were 0.854 and 0.870 for the RR and HD models, respectively. The calibration and validation of the models were conducted effectively, hence; the models were ready for forecasting water level at the X90 station.

Water level forecast results for X90 station calculated using the MIKE 11 DA approach are shown in Figure 6. For TOF1 to TOF3, the accumulated rainfalls were 78.25, 145.31 and 201.34 mm, respectively, while the measured water levels at X90 station updated to the model were +3.34, +3.65 and +4.52 m msl, respectively (Table 1). In these TOFs, clearly, the water level does not reach +9.30 m msl and no early warning can be issued. However, for TOF4 (i.e., January 1st, 09:00) with accumulated average rainfall of 218.47 mm and measured water level at X90 station of +5.60 m msl, the forecasted water level reached +9.30 m msl at 19:00 on the same day. If based on this result, an early warning was issued, a lead time of 10

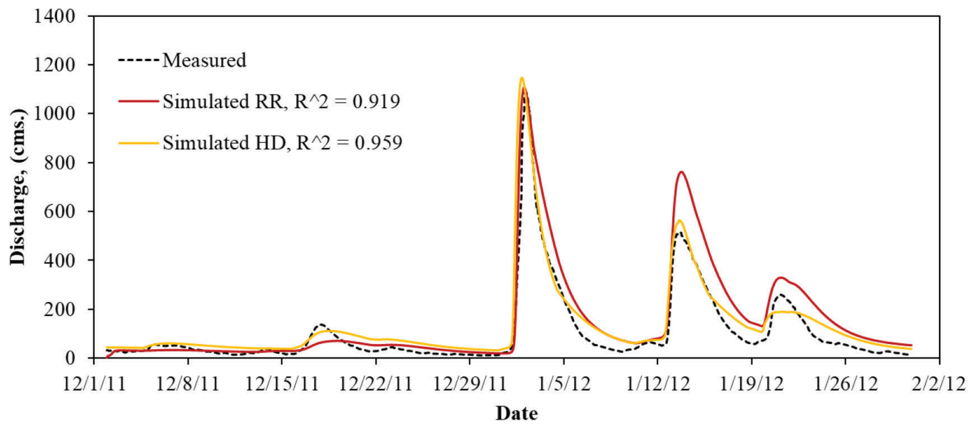

Figure 5: Simulated and measured hydrographs of X90 station used in the calibration of the RR and HD models (from Chalermyanont & Chup-Uppakarn, 2015)

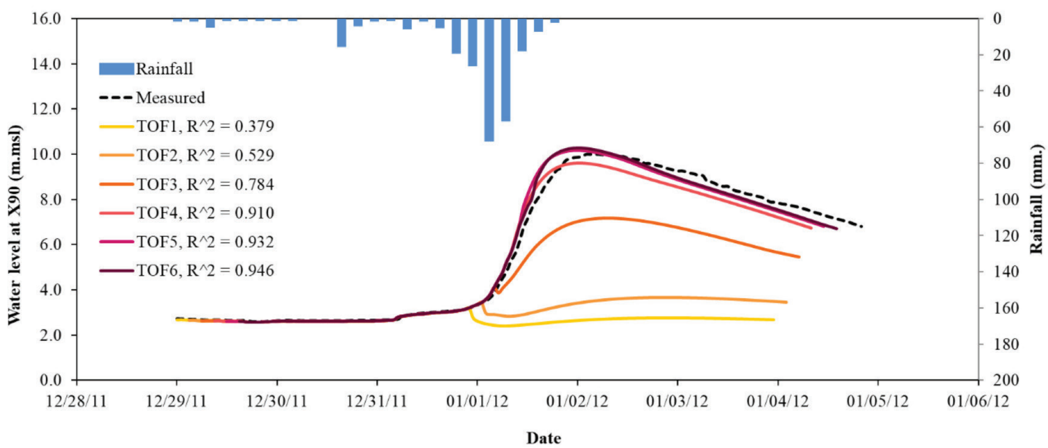

Figure 6: Water level forecasting results from MIKE 11 DA

hours would be expected. This expected lead time is exactly correct and matches the actual lead time.

Discussion

Expected and actual lead times for flood early warnings derived from three alternative water level forecasting approaches are shown in Table 2. The expected lead time ranges from 9 to 14 hours. The actual lead time, however, ranges from 5 to 10 hours. Unit hydrograph and MIKE 11 DA approaches gave similar actual lead times of 10 hours, while the streamflow routing approach gave the least actual lead time of 5 hours. In addition, performance evaluation of the approaches using the actual lead time and the lead time errors shown in Table 2 reveal that the best approach is the MIKE 11 DA approach (i.e., actual lead time = 10 hours and lead time error = 0 hour) while the worst approach is the streamflow routing approach (i.e., actual lead time = 5 hours and lead time error = 4 hours).

For the streamflow routing approach, it is relatively the simplest approach and can be done at community level but it has some disadvantages such as low lead time and high lead time error. In this approach, the water level was used for flood warning, as water level rises after a certain time following the rain; thus, the resulting lead time was naturally less than that of other approaches, where rainfall information

Table 2: Expected and actual lead times for flood warning derived from three water level forecasting approaches

Approach	Warning Time		Lead Time (hours)		Lead Time Error (hours)
	Date	Time	Expected	Actual	
Streamflow routing	01-01-2012	14:00	9	5	4
Unit hydrograph	01-01-2012	9:00	14	10	4
MIKE 11 DA	01-01-2012	9:00	10	10	0

was used. Besides, the poor goodness of fit (i.e., R^2 of 0.4922) of Equation 7 indicates low accuracy in the prediction of the flow time. Moreover, rainfall information was not considered in this approach and in such a case, if a high concentration of rainfall taking place in areas close to the location was considered; it would affect both flow and lead times and in turn, decrease the accuracy of the forecast.

According to the results of the actual lead time and the lead time error, the unit hydrograph approach was the second-best approach for providing early flood warning. Since its actual lead time is similar to that of MIKE 11 DA approach, the unit hydrograph approach (which is much simpler than MIKE 11 DA approach) could be employed practically. The lead time error could be reduced with proper modifications and calibration. Compared to the measured water level plot (Figure 4), the plots of TOFs show the early rising curves and lower peak water levels than the measured one, thus recalibration of the Snyder's parameters C_t and C_p is recommended if further work is pursued.

The MIKE 11 DA approach is the most complex and expensive approach and was the best approach based on results of this case study. It provided the longest lead time with lowest lead time error. Furthermore, its water level forecasts of TOF4 and beyond essentially matched the recorded measurements as the corresponding R^2 values, as shown in Figure 6, are close to unity. Consideration of the spatial rainfall distribution, the rainfall-runoff model and the hydrodynamic flow, along with updated water levels up to the time of forecast, altogether make this approach robust and accurate in water level forecasting.

Accurate flood forecasting remains difficult to achieve due to uncertainties in many components along the computational chain, especially in rainfall measurement/estimation, rainfall-runoff modeling, flood routing and hydrodynamic modeling. Since issuing a false early warning would cause lots of difficulties and loss of credibility, the SFWC decided not to solely use the MIKE 11 DA approach for flood forecasting and warning. Currently, forecasts by unit hydrograph and MIKE 11 DA approaches are used. The streamflow routing approach is still officially used for flood early warning despite its lesser lead time.

Conclusion

Three water level forecasting approaches were tested to determine a suitable approach for improving lead time of flood warnings to Hat Yai city. The testing was based on one case of severe flooding, with available records of relevant data. Based on a performance evaluation, the approaches rank in order of performance are MIKE 11 DA, unit hydrograph and streamflow routing. In addition, increasing the lead time from 5 to 10 hours can be achieved. In the flood routing approach, in which flood warning is based on the measured water level at an upstream station, the lead time is 5 hours while the other two approaches that utilize measured rainfall give longer lead times of 10 hours. The increased lead time is sufficient for flood responses based on local practice.

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