The Newest Technology on Short-term Flood Forecast

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Outline

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2. Motivation
3. Methodology
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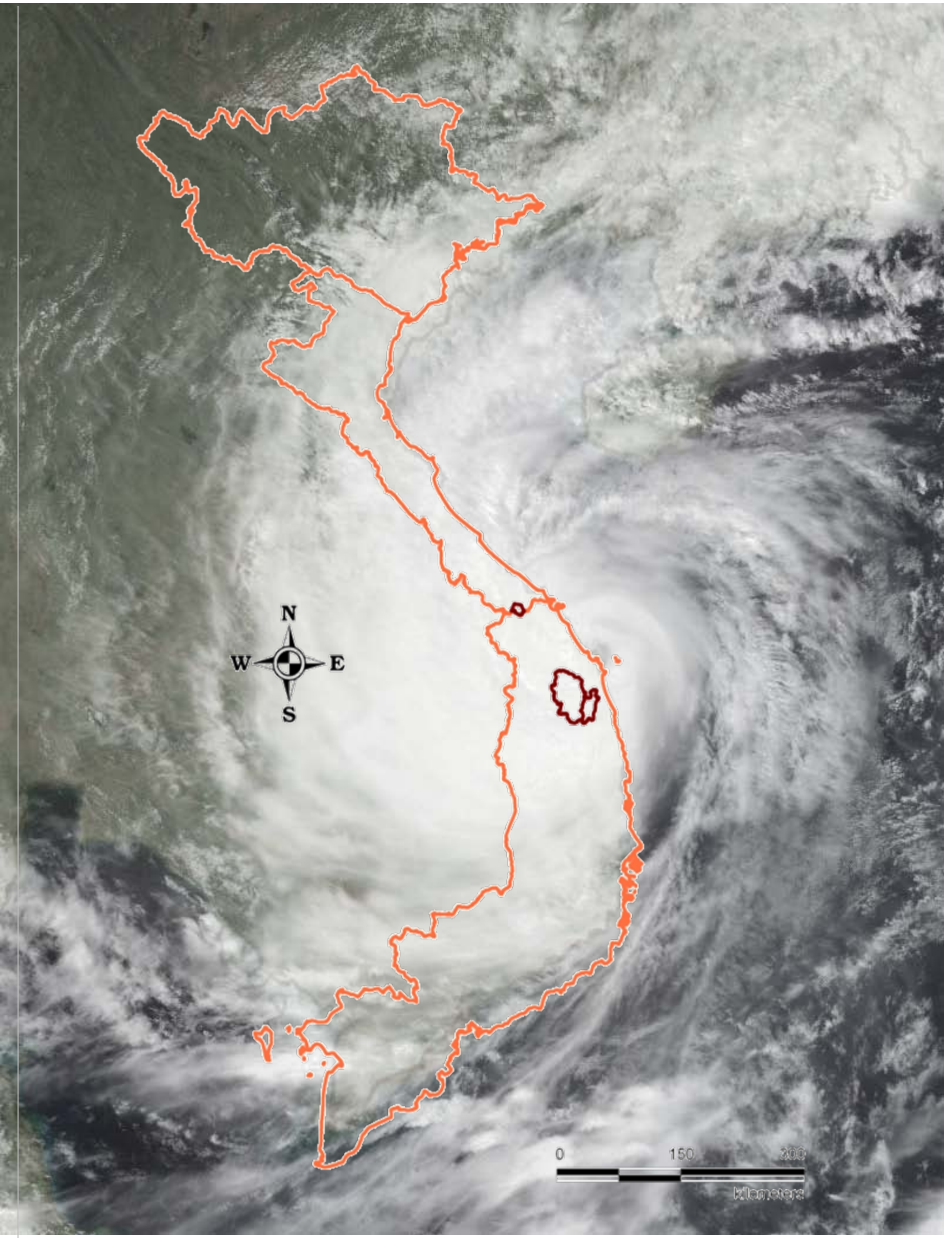
Background

- Floods are the most common climate-related disaster in the world. Frequency and destructive power of floods have been observed increasing, due to:
  - Intensity of precipitation events is projected to increase in most tropical areas, IPCC (2007).
  - Rapid urbanization process has led to shorter response and greater peak of discharge in rivers.

- Inadequate information on river flow has limited ability to put in place effective river management and flood mitigation plans.

Background

Satellite image of the Typhoon Ketsana
9:00 AM, September 29, 2009



Rural flood

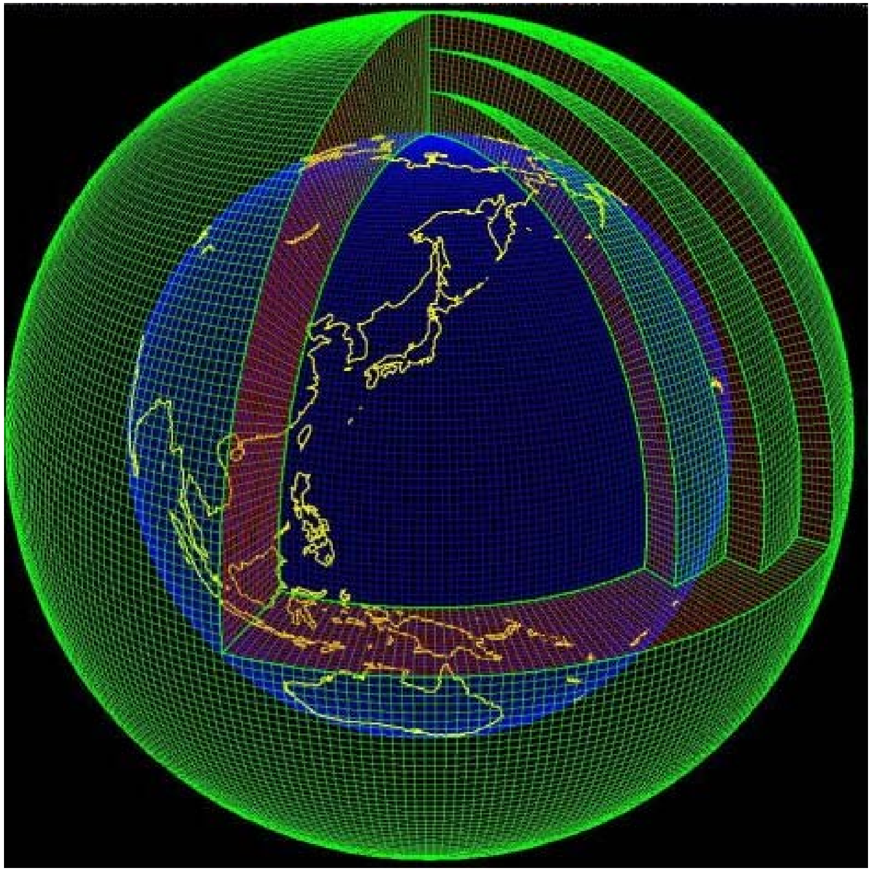
Urban flood

Motivation

"Propose of short-term flood forecast model by coupling the relatively high resolution NWP model with the hydrological model"

Previous studies

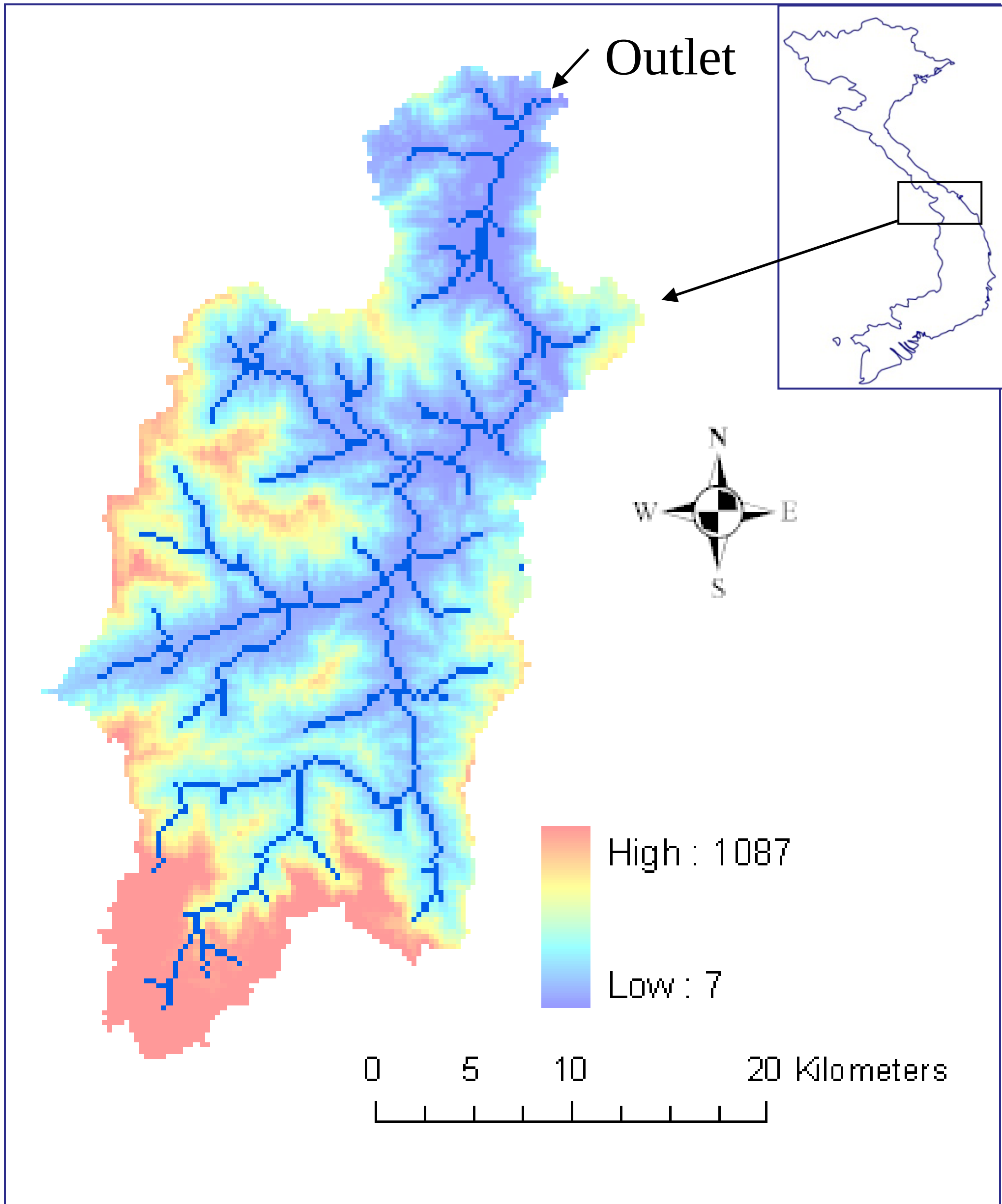
- Kardhana *et al.* (2008) examined the combination of NWP (*mesoscale model*) and distributed rainfall runoff model for flood forecast.
- Younis *et al.* (2008) used *limited area* NWP for flash flood forecasting in France.
- Collischonn *et al.* (2004) introduced flood forecast based on rainfall forecast from a *regional scale* NWP for Uruguay river basin.
- Jens *et al.* (2005) coupled meteorological model (ECMWF, *global scale*) with hydrological model for flood forecasting.



Case study

❖ Ve River Basin, medium size, area of about 750km^2.

❖ Channel networks are delineated based on sub-basins of 500m grid cell size (original DEM-90m).

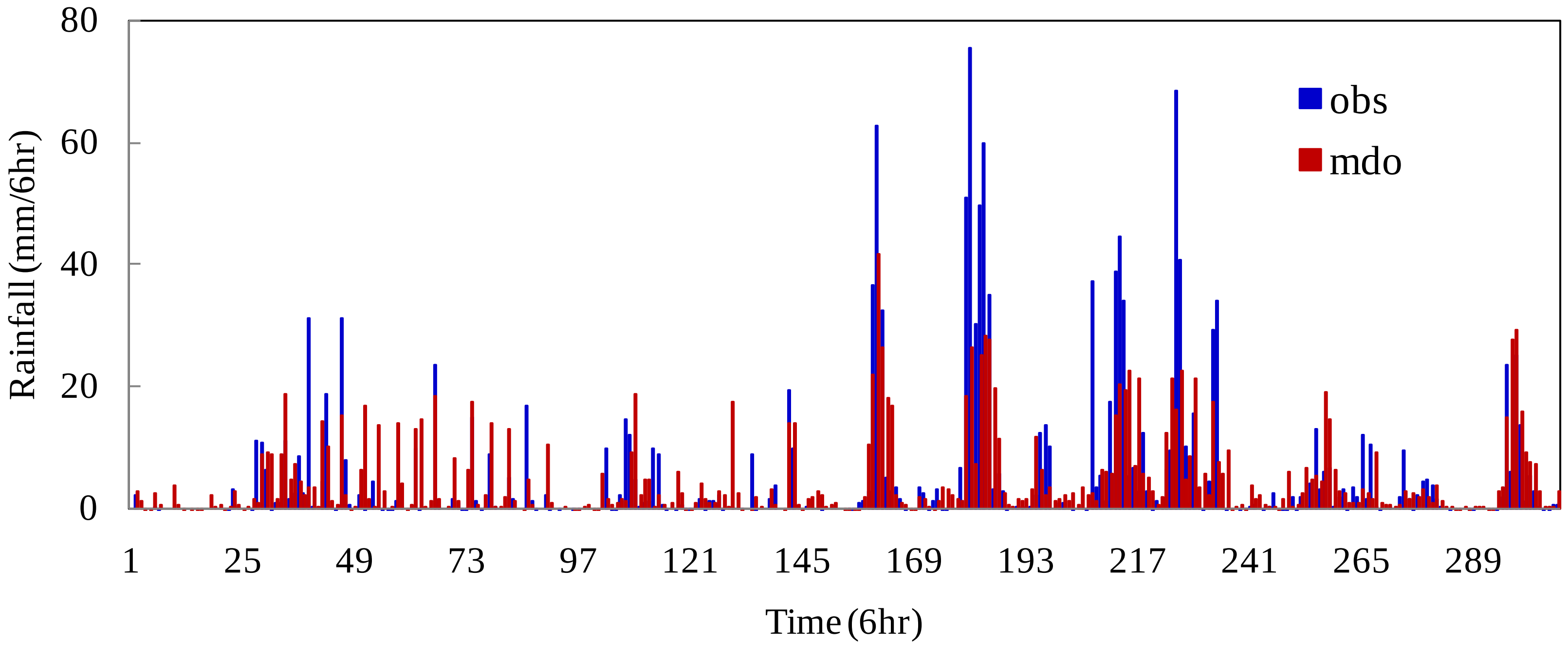


NWP Model

Global Spectral Model (GSM) is operational at Japan Meteorological Agency (JMA)

- Globally covered, 0.5^{O} spatial resolution, 60 vertical layers
- Initial time (4 times per day): 00UCT, 06UTC, 12UTC, 18UTC
- Forecast lead time:
  - 84 hours: 00UCT, 06UTC, 12UTC, 18UTC
  - 84-192 hours: 00UCT, 12UTC
- Precipitation is accumulated for 6-hr intervals: 00-06UTC, 06-12UCT, 12-18UTC, and 18-24UTC

Comparison of rainfall



Time series of observed and forecasted rainfall (Sep-Oct, 2008)

- The NWP overestimates/underestimates for light/intense rainfall respectively.

Model Output Statistic

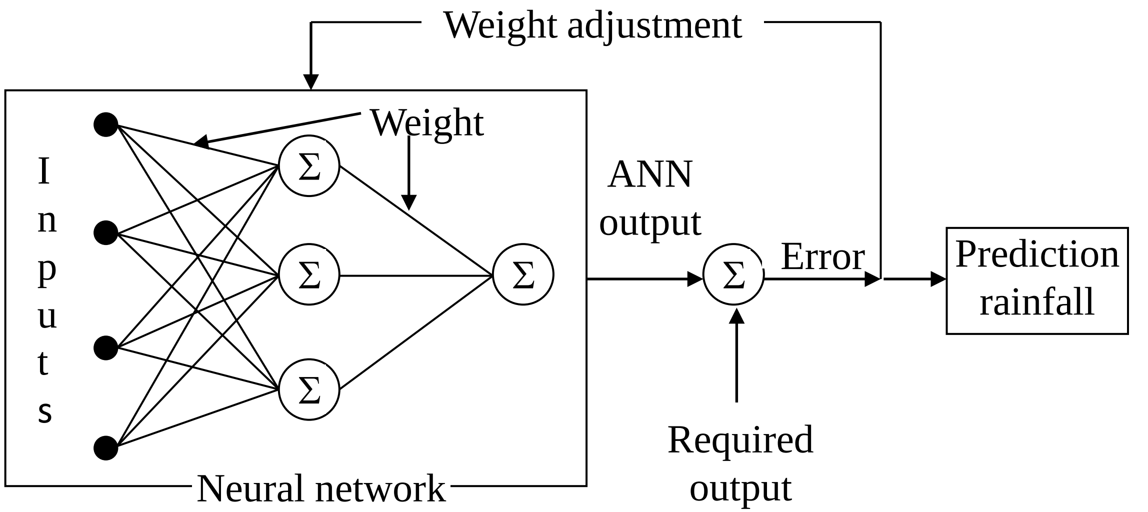
- Model output statistic (MOS)
  - Glahn *et als* (1972) proposed MOS approach in objective weather forecasting. The MOS consists of determining a statistical relationship between a predictant and predictors.
  - Predictant: events for which the MOS are intended to produce forecasts.
  - Predictor: output fields from NWP and other meteorological data used in making forecasts.
- Multiple linear regression (MLR) for MOS equation development

$$R_{mlr} = a_o + a_1 R_{dmo} + a_2 X_2 + \ldots + a_n X_n$$

R_{mlr} = Multiple linear regression QPF; R_{dmo} = direct model output QPF; $X_{2,n}$ = independent NWP parameters; a_o = regression constant; $a_{1,n}$ = regression coefficients; n = number of independent parameters.

Model Output Statistic

- Artificial neural network (ANN)



- Backpropagation ANN algorithm is used to predict rain rate.
- The approximation used for the weight change is given by the delta rule.

$$\Delta w = -\in \frac{\partial E^2}{\partial w}$$

where, $\in$ is the learning rate, w is the weight, E is the error

Predictor selection

❖ Preliminary selection

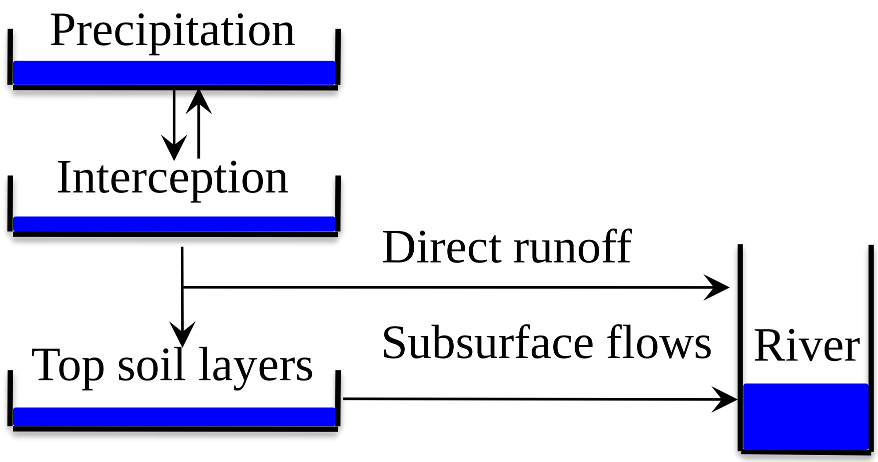
- GSM product provides forecast of 104 parameters at different pressure levels, from 10hPa to the earth surface.
- Preliminary selection of predictors based on convention that orographic rainfall is predominant in the study area.

Parameters	Unit	Pressure layer (hPa)
Accumulative precipitation	(mm/6-hr)	Surface
Meridional wind velocity	(m/s)	700, 850
Zonal wind velocity	(m/s)	700, 850
Pressure vertical velocity	(Pa/s)	700, 850
Total	parameter	7

❖ Final selection

- Stepwise regression (or forward selection) technique was usually used to select a good set of predictors (Wilk, 2006).

Tank Model

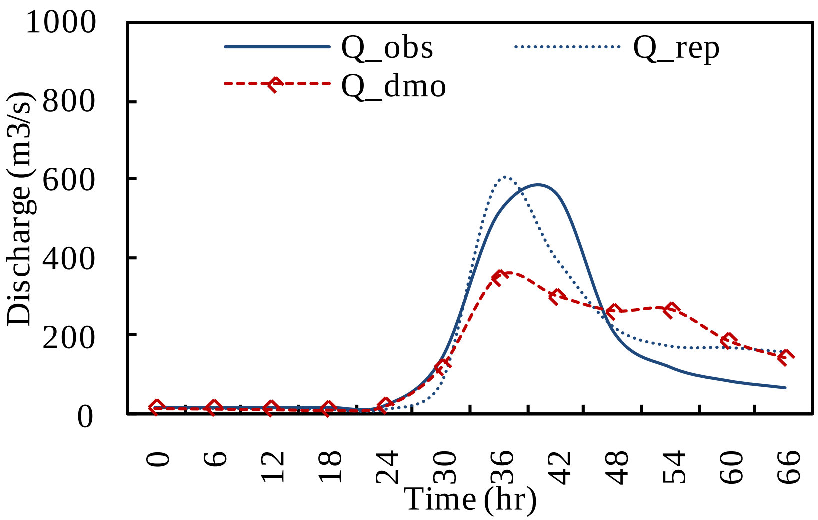


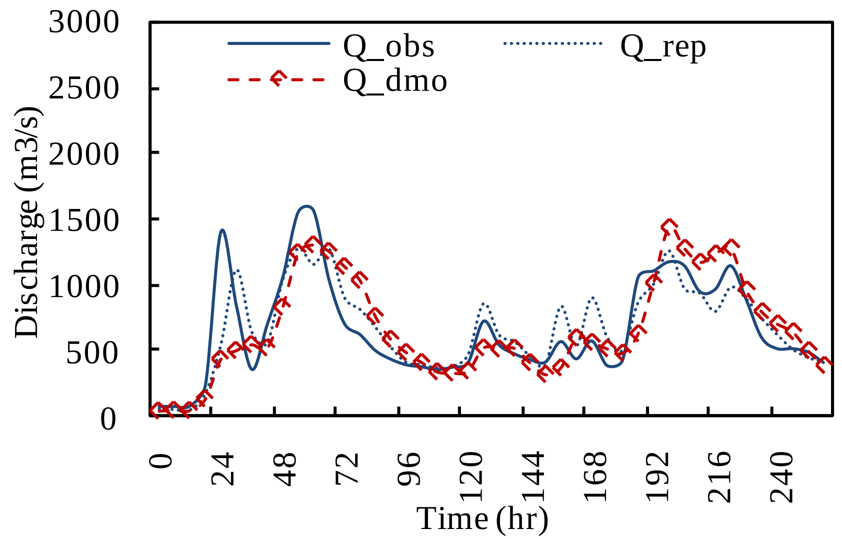
Tank model is a physically based, semi-distributed rainfall runoff model that simulates flow in the river, Kato and Mano (2003). The Tank model was selected based on following considerations:

- ❖ Wide range of application for various spatial and temporal scales.
- ❖ Model parameters are minimized and nearly free from calibration requirement.
- ❖ Calibration required parameter, the dimensionless modification coefficient (*c*) on the saturated hydraulic conductivity, optimal value of *c* is about 10.

Results and discussion

❖ Flood forecast based on actual output from NWP – 24hr lead time





Obs. v.s forecasted river flow for: single flood event Oct 10th – 13th (left), continuous flood events Nov 17th – 27th (right), 2008

- Model statistics

Single storm event

Discharge	NSI	Error (%)		
		Runoff	Volume	Peak
Q_{Rep}	0.83	44.83	3.95	5.62
Q_{MDO}	0.63	49.92	4.94	38.06

Continuous storms event

Discharge	NSI	Error (%)		
		Runoff	Volume	Peak
Q_{Rep}	0.92	21.78	1.89	15.48
Q_{MDO}	0.89	25.40	1.72	33.26

Results and discussion

❖ MOS to improve QPF

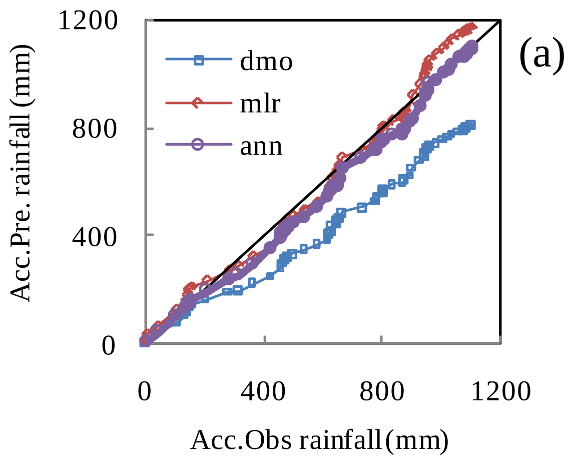
▪ Separate equations for single storm events and continuous storm events were formulated based on training data of the wet season, 2008.

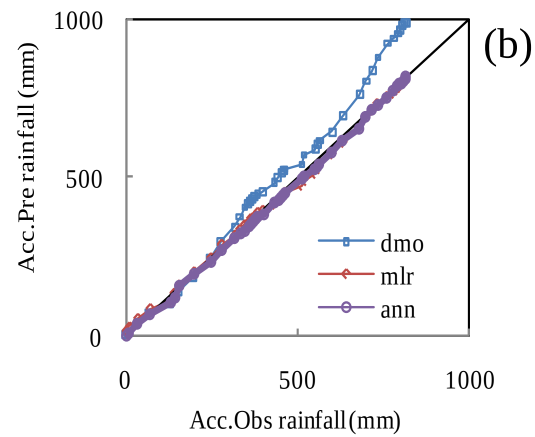
$$R_{mlr} = a_o + a_1 R_{dmo} + a_2 P_{V700} + a_3 P_{V850}$$

▪ Regression constants and regression coefficients used in MOS equations

Type of storm event	a_o	a_1	a_2	a_3
Single (a)	-3.37	1.31	0.00	-7.95
Continuous (b)	9.84	0.58	-13.42	10.97

▪ ANN training network includes three input nodes, single hidden layer, and one output node.

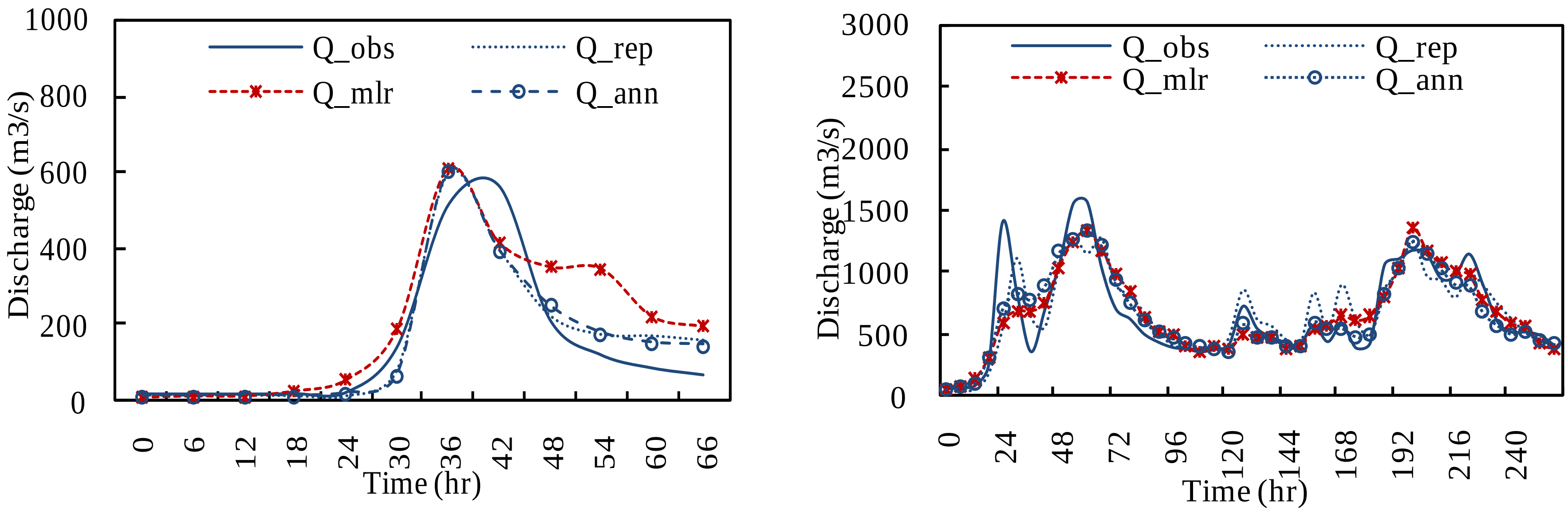




Hyetographs of accumulated rainfall prediction with 24-hr lead time
(a) single event, Oct 10th – 13th, 2008; and (b) continuous events, Nov 17th – 27th, 2008

Results and discussion

❖ Flood forecast based on MOS quantitative precipitation forecast – 24 hr lead time



Obs. v.s forecasted river flow for: single flood event Oct 10th – 13th (left), continuous flood events Nov 17th – 27th (right), 2008

- Model statistics

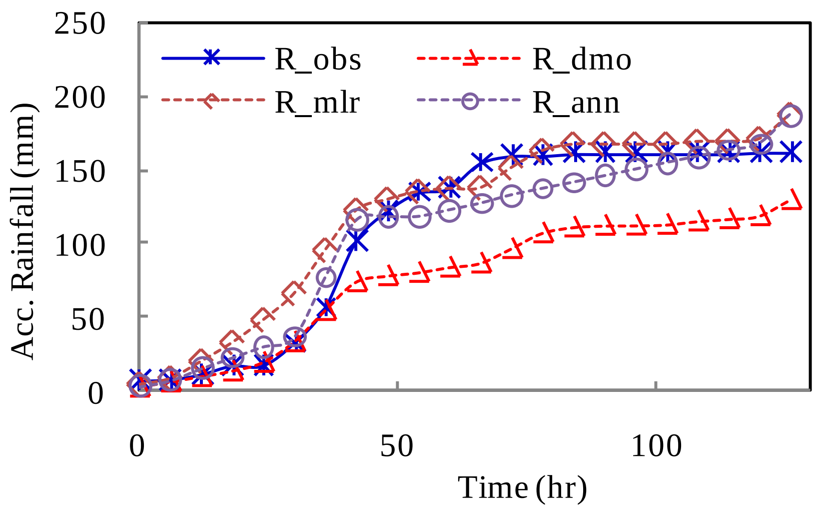
Single storm event

Discharge	NSI	Error (%)		
		Runoff	Volume	Peak
Q_rep	0.83	44.83	3.95	5.62
Q_mlr	0.76	88.44	39.94	8.41
Q_ann	0.83	35.78	6.20	5.24

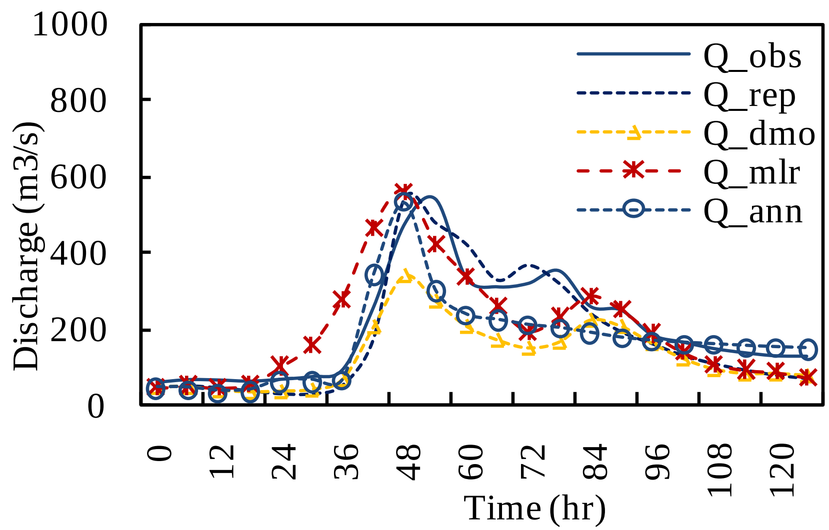
Continuous storms event

Discharge	NSI	Error (%)		
		Runoff	Volume	Peak
Q_rep	0.92	21.78	1.89	15.48
Q_mlr	0.93	21.44	0.26	27.35
Q_ann	0.94	17.10	0.66	20.72

Model validation



Hyetographs of accumulated rainfall prediction for the validated event on Dec 25th – 29th, 2008



Obs. v.s forecasted river flow for the single flood event on Dec 25th – 29th, 2008

- Model statistics

Discharge	NSI	Error (%)		
		Runoff	Volume	Peak
Q_dmo	0.51	37.22	37.23	37.44
Q_mlr	0.85	39.71	0.49	4.41
Q_ann	0.81	24.71	17.11	1.65

Conclusion

A short-term flood forecast model was proposed, the model has demonstrated very high potential for further development, and extension of forecast lead time. The key findings are summarized as following:

- Using direct model output QPF for flood forecast was found good agreement with observed discharge during continuous storm events, while remarkable uncertainties were found for single storm event (NSI = 0.63, runoff error = 50%, peak error = 38%).

- Flood forecast using MOS rainfall prediction significantly outperformed those using from MDO. For single storm event, NSI, runoff and peak errors were 0.83, 36%, and 5.2% respectively.

- The results showed that rainfall prediction using ANN was better than those obtained using MLR. Accordingly, forecasted river flows using ANN rainfall prediction depicted better agreement to the measured discharge.

Thank you very much for your attention