REAL-TIME FLOOD FORECASTING USING ECMWF ENSEMBLE PRECIPITATION FORECAST IN THE UPPER NAN RIVER BASIN, THAILAND

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Introduction (1)

- frequently experienced with high rainfall intensity due to tropical storms (Typhoon).
- For example, in recent years; Dianmu 2016, Talas 2017, Bebinca 2018, Sinlaku 2020 and Koguma 2021.
- The catchment has a steep slope in topography.
- the basin is vulnerable to flood disasters.

Introduction (2)

- <u>To mitigate</u> the extensive damage and disruption to societies caused by floods, forecasting is an effective means to provide timely hazard information.
- However, the **forecast has limitations** in accuracy (forecast uncertainty) with **increasing forecast lead time**.
- Instead of deterministic forecasting, probabilistic forecasting with Ensemble Prediction System (EPS) has advanced in the last decade.

Objectives

- We aim to develop the <u>real-time forecasting scheme</u> using ensemble precipitation forecasting (EPF) with a distributed hydrological model (DHM).
- How well can we **forecast the flood hydrograph** using **medium-range EPF**?

Prediction model

Improved 1K-DHM (Meema and Tachikawa, 2020) Was applied for this study.



- Using the physical-based Distributed Hydrological Model (DHM) for real-time flood forecasting has an advantage in the spatial distribution of the forecast output.
- The severe storm events in 2016, 2017 and 2018 were collected for model calibration and validation.
- The SCE-UA algorithm has been adopted for calibration by searching for the parameters which minimize RMSE.

T. Meema, Y. Tachikawa. Structural improvement of a kinematic wave-based distributed hydrologic model to estimate long-term river discharge in a tropical climate basin. Hydrol. Res. Lett., 14 (2020), pp. 104-110, 10.3178/hrl.14.104

Real-time forecast scheme

- For real-time forecast, the model was updated the state variables regarding the current observation during the initial analysis period (until t0) before performing the forecast (forecast period) using observed rainfall.
- The model state variables at t0 (initial forecast time) were used as model initial condition of the forecast period.
- The ensemble flood forecasting was performed using EPF as forcing data.



Ensemble Kalman Filter (EnKF)

Flood forecast scheme at time *t0* to lead time *t*+1

- Incorporate Ensemble Precipitation Forecast (EPF) information with Ensemble Kalman Filter (EnKF) technique.
- EnKF is adopted to determine model states at time t0 (initial conditions) using observed precipitation.
- The <u>forecast period</u> was performed without assimilation from time t0 until the proposed lead time using EPF.



Sensitivity analysis of DA approaches

- Sensitivity analysis of DA was performed to select the DA parameters for the study basin.
- The tropical storm events in 2016 (Dianmu), 2017 (Talas) and 2018 (Bebinca) were selected for sensitivity analysis.
- For sensitivity analysis of DA approaches, obs. Rainfall was applied considering as a perfect rainfall forecast in the forecast period.

Experimental setup of EnKF

| Member (<i>n</i>) | Observation Noise (ε _{obs}) | System Noise(ε _{state}) | Spatial Correlation (λ, km) |
|---------------------|--|--------------------------------------|--------------------------------|
| 16 | 0.05 | 0.05 | NA 1 |
| | | 0.2 | 5 25 |

Noise Model

- System Noise
- $\boldsymbol{\omega_i} \sim N(\boldsymbol{0}, (\boldsymbol{\varepsilon_{state}} \times \boldsymbol{Q_{state}})^2)$
- Observation Noise

$$v_i \sim N(0, (\varepsilon_{obs} \times Q_{obs})^2)$$

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Spatial correlation
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distance between grids *i* and *obs. grid* $\begin{array}{c}
\boldsymbol{l_{ij}}\\
\boldsymbol{\lambda}\\
\text{correlation distance}\end{array}$

The parameters of $\varepsilon_{obs} = 0.05$, $\varepsilon_{state} = 0.3$ and $\lambda = 5$ km resulted in minimum error (RMSE) in forecast result during the Sensitivity analysis period.

Analysis DA approach

1 hour ahead of forecasting discharge at N.1



Incorporating EnKF with the DHM resulted in a better streamflow prediction than offline simulation.

Real-world application: A case study of the tropical storm "Sinlaku" in 2020

Ensemble Precipitation Forecast (EPF)

ECMWF (European Centre for Medium-Range Weather Forecasts)

- **51** members
- Approximately **0.5** degree resolution
- Forecast of 15 days
- 6 hours of temporal resolution





Forecasting results (at N.13A)



Some forecast members present the possibility of flood since a long-lead-time (>12 days).

The <u>mean of forecast members</u> could capture the flood hydrograph approximately 3 days in advance.

Forecast performance



- The forecast error tends to decrease when the forecast lead time decreases.
- Because of the increase in the accuracy of precipitation forecasts.

Forecast time before peak [hr]

Conclusions (1)

- Using the DHM, there is an **advantage in the spatial distribution of forecast outputs** (at any river section can be forecasted).
- By using the scheme for this study, <u>the mean of forecast members</u> could capture the flood hydrograph approximately 2-3 days in advance.
- This could provide timely hazard information as an advantage in a long-lead-time forecast.

Conclusions (2)

- Coupling EnKF and EPF for real-time forecast, there is a disadvantage in simulation cost.
- This requires the high performance of computation resources.
- The scheme requires an accurate precipitation forecast.
- The scheme needs to verify with further events.

Thank you for your kind attention..