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Flood Estimation and Prediction Using Particle Filters

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Data assimilation methods have received increased attention to accomplish uncertainty assessment and enhancement of forecasting capability in various areas. Despite their potential, applicable software frameworks for probabilistic approaches and data assimilation are still limited because most hydrologic modeling software are based on a deterministic approach. In this study, we developed a hydrologic modeling framework for data assimilation, namely MPI-OHyMoS. While adapting object-oriented features of the original OHyMoS, MPI-OHyMoS allows user to build a probabilistic hydrologic model with data assimilation. In this software framework, sequential data assimilation based on particle filtering is available for any hydrologic models considering various sources of uncertainty originating from input forcing, parameters, and observations. Ensemble simulations are parallelized by a message passing interface (MPI), which can take advantage of high-performance computing (HPC) systems. Structure and implementation processes of data assimilation via MPI-OHyMoS are illustrated using a simple lumped model. We apply this software framework for uncertainty assessment of a distributed hydrologic model in synthetic and real experiment cases. In the synthetic experiment, dual state-parameter updating results in a reasonable estimation of parameters to cover synthetic true within their posterior distributions. In the real experiment, dual updating with identifiable parameters results in a reasonable agreement to the observed hydrograph with reduced uncertainty of parameters.

Keywords: data assimilation, MPI-OHyMoS, hydrologic modeling framework, particle filtering, uncertainty assessment, dual state-parameter updating

1. Particle Filtering with MPI-OHyMoS

As MPI-OHyMoS is a stochastic and interactive version of OHyMoS, OHyMoS is constructed as a set of dynamic elements communicating with each other based on object-oriented programming. It provides an operation module, including the common functions required in hydrological simulations, such as initialization of parameters and state variables and setting the computational time steps and data exchange among element modules through input/output (I/O) ports. Through OHyMoS, users can easily develop their own hydrologic modules by connecting them to other modules and transferring data using predefined ports in the system library. In MPI-OHyMoS, hydrologic modeling is implemented in the stochastic way. **Fig. 1** shows how model ensembles are interactively assimilated in MPI-OHyMoS. Each ensemble member, representing a probable projection based on different parameters and state variables, is implemented independently. When a new observation arrives, the likelihood of ensemble members is estimated. In the resampling step, the whole information of each ensemble is renewed, depending on its weight. In this way, ensembles can move to the regions with high conditional probability in each time step. **Fig. 2** illustrates the processes of particle filtering via MPI-OHyMoS using a linear reservoir model.

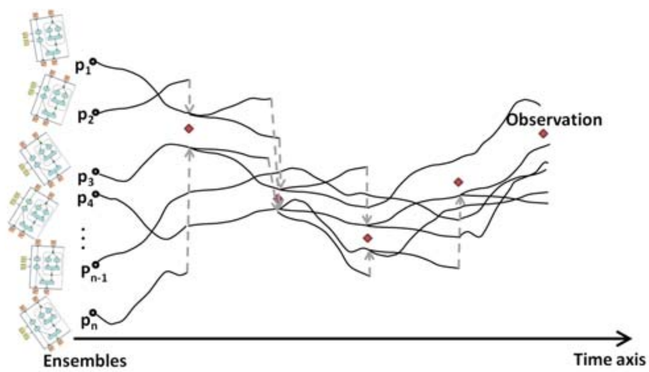

Fig. 1. Concept of particle filtering via MPI-OHyMoS.

2. Uncertainty Assessment Using a Distributed Hydrologic Model

Synthetic and real experiments are implemented for uncertainty assessment of a fully distributed hydrologic model to illustrate the applicability of the MPI-OHyMoS. The study area is the Maruyama River catchment in Japan with an area of about 909 km^2. We construct a probabilistic distributed hydro-logic model for the Maruyama River catchment based on three element modules: a hillslope runoff generation module, a river routing module, and a likelihood function. The hillslope and river routing modules were developed as elements of a deterministic distributed hydrological model using the kinematic wave theory. In this model, it is considered that the catchment consists of a number of rectangular slope elements which

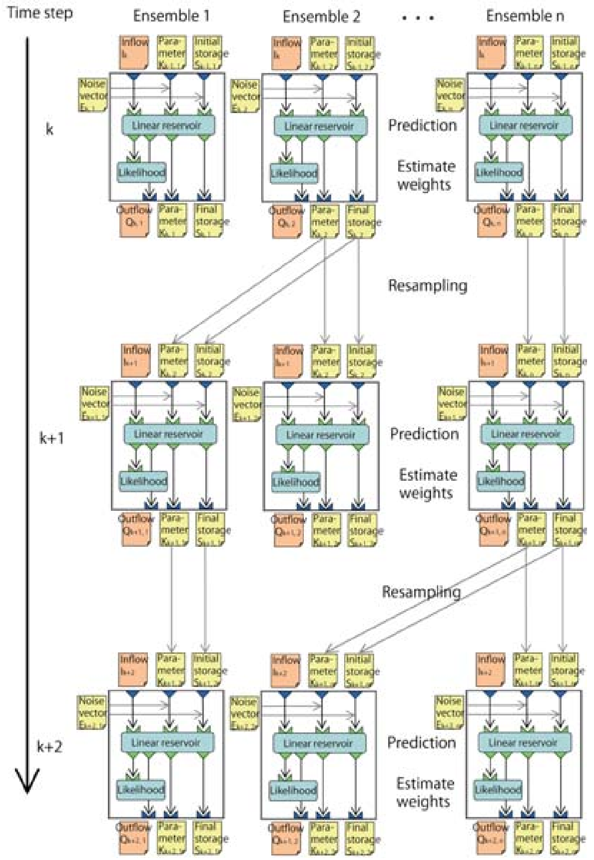

Fig. 2. Data assimilation processes of a linear reservoir model via MPI-OHyMoS.

Table 1. Summary of model performance for real experiment.

	Deterministic		Particle filtering	
	NSE	RMSE (m^3s^{-1})	NSE	RMSE (m^3s^{-1})
Event 1	0.96	23	0.98	16
Event 2	-0.40	93	0.81	33
Event 3	0.94	217	0.98	117

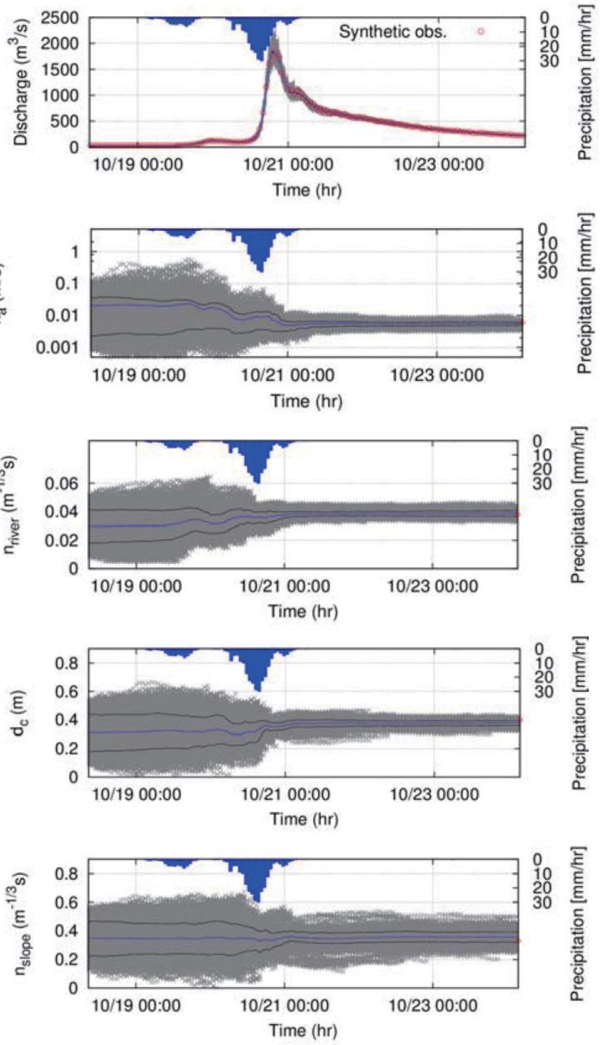

Fig. 3. Parallel simulations of the distributed hydrologic model with PF in the synthetic experiment's preliminary stage (Event 3). Red dots represent synthetic observation. Grey lines represent stream flow ensembles. Grey dots represent parameter ensembles. Blue lines represent means of ensembles. Black lines represent 60% confidence intervals.

drain to the deepest gradient of its surrounding.

A synthetic experiment is implemented using a distributed hydrologic model to demonstrate the applicability of MPI-OHyMoS for missing data problems in complex cases and assess the identifiability of parameters. **Fig. 3** shows results of the preliminary stage of synthetic experiment. Simulated stream flow, which is one-step-ahead prediction, shows good conformity with synthetic observation in terms of ensemble mean and distributions. Uncertainty of parameters lasts before the flood event as in the initial distributions and reduces sharply around the flood peak. Dual state-parameter updating via PF results in a reasonable estimation of parameters to cover synthetic true within their posterior distributions. However, identifiability of parameters is different and the roughness coefficient of slope shows diffusive distribution.

Following the synthetic experiment, a real experiment is conducted for different three events. Model performance is summarized in **Table 1** using two indices: Nash-Sutcliffe efficiency (NSE) and root mean square error (RMSE). Statistics show the improvement of the model performance via PF in all events compared to deterministic modeling cases. Parameter distributions estimated by PF at Event 1 result in good performance in Event 3, whose peak flood is about six times higher than Event 1. In Event 3, deterministic modeling presents improved performance, demonstrating transferability of the parameters for an unexperienced high flood. However, application into a smaller flood (Event 2) shows limited performance.

Due to uncertainties coming from hydrologic models and observations, optimal parameters may change according to the magnitude of flood events and initial conditions. The results of deterministic modeling show that parameters estimated at large events (Event 1) may not be appropriate for small events (Event 2) or vice versa. This situation is found frequently in numerous hydrologic modeling cases. However, probabilistic approach and dual stateparameter updating could compensate the uncertainty of model structures.