State Estimation using a physically based Hydrologic Model and the Particle Filter

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I. INTRODUCTION

The modern burst of development in hydrologic modelling dates from the last decades, when concepts of statistics and systems analysis were applied to hydrology.
The relationship between precipitation and discharge is one of the fundamental research topics in hydrology. The development of information technology allowed hydrologists to increase the complexity of the modelling, following the descriptive and predictive modelling approaches.
Descriptive models represent all processes of the hydrologic cycle. All these processes are interdependent, making the construction of descriptive models very complex. For this reason, a number of assumptions must be made, which has lead to the development of a large number of descriptive hydrologic models during the last decades. Descriptive models are called Soil-Vegetation Atmosphere Transfer Schemes (SVATS) or Land Surface Models (LSM).
The volumetric soil moisture and temperature profiles define the state of the land surface model. State estimation is used in order to adapt the results of model simulations, using external observations. The state estimation using land observations is also known as Land Data Assimilation. Data assimilation is used in many different disciplines such as earth sciences, space sciences, computer graphics, and industrial applications.

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Nonlinearities in the model of the system, state dimension and computational demand when the assimilation algorithm is applied, must be taken into account for the selection of an assimilation method. Evensen [1] presents the Ensemble Kalman Filter (EnKF) as a Monte Carlo approach to the nonlinear filtering problem. Recently, the Particle Filter (PF), which is a sequential Monte Carlo method for state estimation, has been widely applied in mobile robot localization with promising results.
The goal of this study is to evaluate the performance of the PF as a land data assimilation method. Further research will include a comparative study between the EnKF and the PF.

II. THE STUDY AREA

The study area is the Alzette watershed, which is located in Luxembourg. The area of the catchment is 356 km^2. Measurements of volumetric soil moisture content and discharge of water to the river are recorded every one hour. Atmospheric forcings such as precipitation, air humidity, wind speed and air temperature are obtained from a meteorological station.

III. THE HYDROLOGIC MODEL

The Hydrologic model chosen for this study is the Community Land Model (CLM) [2], CLM is a global LSM. Surface heterogeneity is represented through different land cover types: glacier, vegetation, urban and wetlands. The vertical structure is represented by one vegetation layer, 10 soil layers and up to 5 snow layers. Figure 1 shows the vertical and horizontal CLM structure.

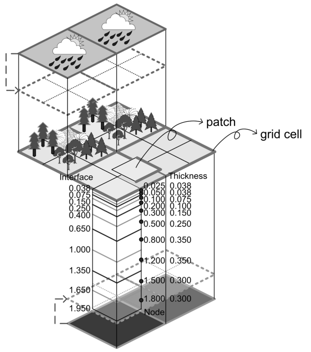

Figure 1. CLM: vertical and horizontal structure.

IV. The State Estimation technique

Particle filter is a technique for implementing recursive Bayesian filter using sequential Monte Carlo methods [3]. The main idea is to represent the posterior density function by a set of random samples with associated weights $\{x_k^i, w_k^i\}_{i=1}^{N_p}$. This method allows for a complete representation of the posterior distribution of the states. The weights associated to each particle are defined by:

$$w_k^i \alpha w_{k-1}^i \frac{p(z_k|x_k^i)p(x_k^i|x_{k-1}^i)}{q(x_k^i|x_{k-1}^i, z_k)} \qquad (1)$$

Where x is the state, w the weight, i the particle index, k the discrete time index, z the measurement and $p(.), q(.)$ are probability functions.
Implementation of particle filters is based on importance sampling, hence, the design of a proposal distribution $q(x_k^i|x_{k-1}^i, z_k)$ is very important. The most common strategy is to sample from the probabilistic model of the states evolution $p(x_k|x_{k-1})$. In this study, the Sequential Importance Resampling (SIR) particle filter is used, the SIR method is based on the Sequential Importance Sampling (SIS) approach and the resampling algorithm is used in order to avoid the degeneracy problem. The SIR algorithm is presented in figure 2. Artificial soil moisture data is assimilated and the number of particles is 64.

- Particle generation $x_k^i \sim p(x_k|x_{k-1})$
- Weight computation $w_k^{*i} = p(z|x_k^i)$
- Weight normalization $w_k^i = \frac{w_k^{*i}}{\sum_{i=1}^{N_p} w_k^{*i}}$
- Estimate computation $E(x_k^i) = \sum_{i=1}^{N_p} x_k^i w_k^i$
- Resample step $\{x_k^i, \frac{1}{N_p}\}_{i=1}^{N_p} \sim \{x_k^{*i}, w_k^{*i}\}_{*i=1}^{N_p}$

Figure 2. SIR algorithm

V. Preliminary Results

Figure 3 presents the performance of the PF when volumetric soil moisture state is estimated using the soil moisture measurement corresponding to julian day 46. The benefit of

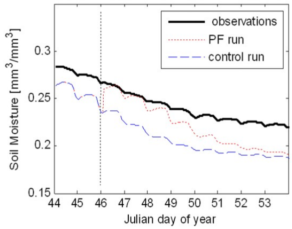

Figure 3. Surface soil moisture

updating soil moisture at one day seems to persist for a number of days.

VI. Conclusions

The SIR particle filter implementation as a land data assimilation method has been presented. Further validation of the method will involve a comparative study of the PF and the EnKF and to assess the impact of soil moisture assimilation on discharge generation.

References

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[2] Oleson K.and Dai Y., Bonan G., and Dickinson, "Technical description of the community land model clm," Tech. Rep., NCAR Technical note, 2004.
[3] M. Sanjeev Arulampalam, Simon Maskell, and Neil Gordon, "A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking," *IEEE Transactions on Signal Processing*, vol. 50, pp. 174–188, 2002.