Nowcasting Flash Floods and Steps towards a Universal Radar Validation Framework

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About me

❑Master:
▪Water Resource Management
▪Sharif university (Iran): 2015-2017
❑Ph.D.:
❑Sharif university (Iran): 2017-2022
▪University of Strasbourg (France): 2019-2022
▪ Title: Integrating remote sensing information into a distributed hydrological model for improving water budget predictions

▪Probabilistic framework for water budget estimation in low runoff regions

▪Improvement of soil moisture and groundwater level estimations using a scale-consistent river parameterization for the coupled ParFlow-CLM

▪Multivariate satellite data assimilation for improving coupled ParFlow-CLM hydrological model

Motivation

- **Evaluation of QPE and QPN improvements in a nowcasting framework**
  - Data Assimilation (discharge and soil moisture)
  - Application of different hydrological models (conceptual and physically-based)
- **Focus on Improving:**
  - DA efficiency (Kalman Gain)
  - Model's (ParFlow) predictions

Research Gap

- **Traditional Kalman Filter:**
  - The covariance matrix (P) of the errors is obtained based on a linear relationship.
- **Data-Driven-Kalman Filter:**
  - Leverages Data-Driven to estimate the covariance matrix
  - Captures non-linear relationships between variables

$$\mathbf{K}_k^* = \mathbf{P}_k^{\mathrm{f}} \mathbf{H}_k^{\mathrm{T}} \left(\mathbf{H}_k \mathbf{P}_k^{\mathrm{f}} \mathbf{H}_k^{\mathrm{T}} + \mathbf{R}_k \right)^{-1}$$

Objective

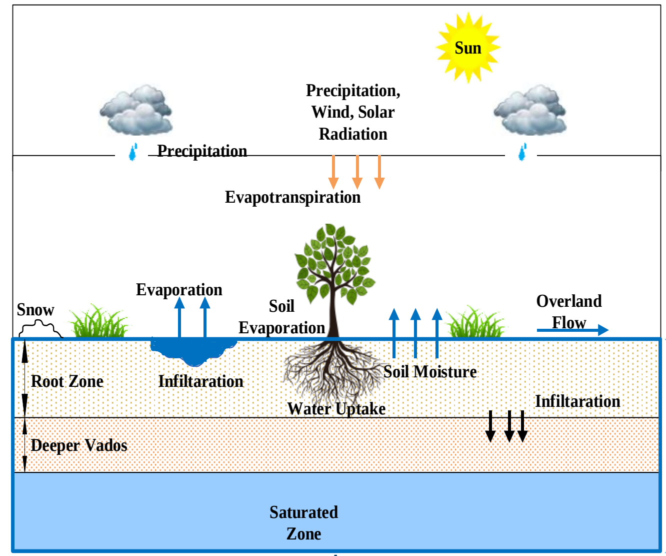
- ❑ **Improving model's predictions (flash flood or river discharge) in DA**

Data- Driven

Improved Model's predictions

Improved Kalman Gain

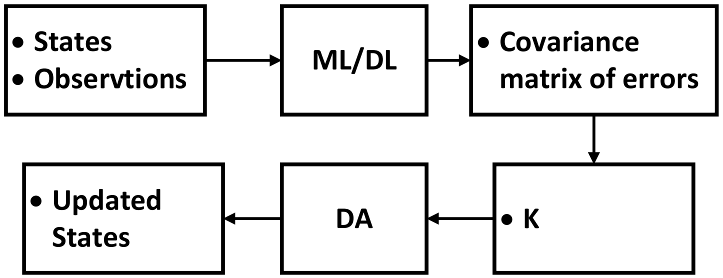
DA



Improved Model's predictions :Scaling approach

Methodology

❑1. Data learning: Data-Driven-DA



❑Data-Driven Methods:

- Covariance Neural Network (CovNet)
- Gaussian Process Regression (GPR)
- Convolutional Neural Networks (CNNs)
- Deep Belief Networks (DBNs)
- Auto-encoders

explicitly designed for estimating covariance matrices.

can provide uncertainty estimates along with the covariance matrix estimation.

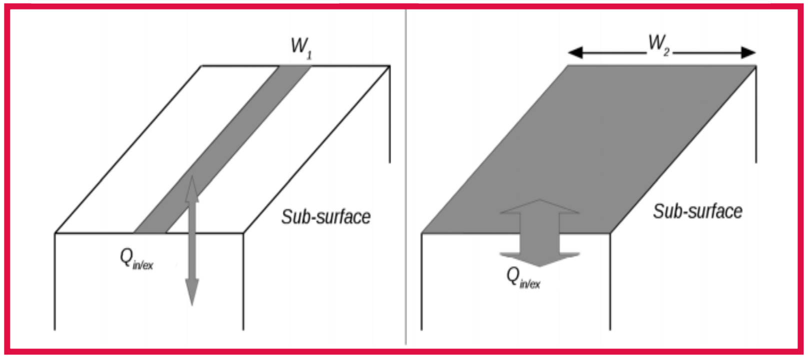
can be used to estimate the covariance matrix by modeling the conditional distribution of the latent variables given the observed data.

Methodology

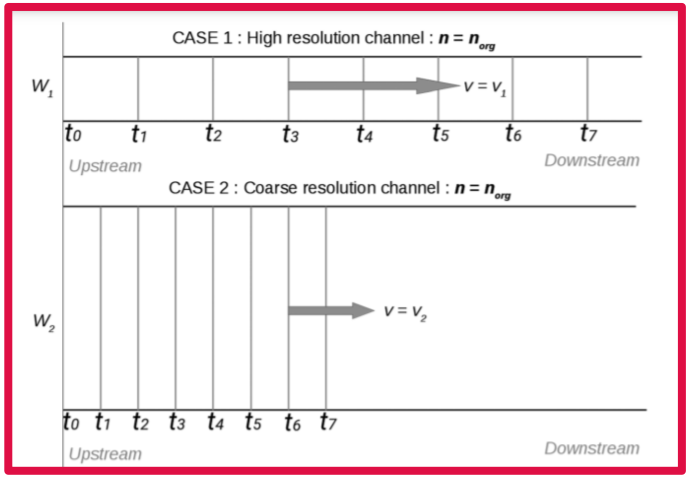
❑ 2. Modeling rivers in ParFlow

- ❑ParFlow is a grid-scale model.
- ❑Large scale simulations: ParFlow should be used at coarse resolution.
- ❑Coarse resolution can be also imposed by data availability.

Coarse resolution: Accuracy of the simulated exchange rate surface-subsurface



Coarse resolution: Accuracy of the simulated flow in the river



(Schalge et al., 2019; Soltani et al., 2022)

Methodology: Scaling approach

Saturated hydraulic conductivity: (Ksat)

$$\int_{A_2} K_{sat\_scaled}\, dA_2 = \int_{A_1} K_{sat\_org}\, dA_1$$

$A_2 = W_2 \times W_2$ is the area of the river in model and $A_1 = W_2 \times W_1$

$$\int_0^{W_2}\int_0^{W_2} K_{sat\_scaled}(x,y)\,dxdy = \int_0^{W_2}\int_0^{W_1} K_{sat\_org}(x,y)\,dxdy$$

$$K_{satscale} = K_{satorg} \cdot \frac{W_1}{W_2}$$

Improving the accuracy of the simulated exchange rate surface-subsurface

Manning's coefficient: (n)

$$\psi_1 = \left(\frac{Q.n_{org}}{w_1.\sqrt{s_f}}\right)^{3/5}$$

$$v_1 = \frac{1}{n_{org}}.\sqrt{s_f}.\psi_1^{2/3}$$

$$\frac{1}{n_{scale}}.\sqrt{s_f}.\left(\frac{Q.n_{scale}}{w_1.\sqrt{s_f}}\right)^{2/5} = \frac{1}{n_{org}}.\sqrt{s_f}.\left(\frac{Q.n_{org}}{w_1.\sqrt{s_f}}\right)^{2/5}$$

$$n_{scale} = n_{org}.\left(\frac{W_1}{W_2}\right)^{2/3} = \lambda.n_{org}$$

Improving the accuracy of the simulated flow in the river

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Implementation Steps

- ❑Developing Data-Driven methods
- ❑Testing the methods by artificial data
- ❑Selecting case study and time period
  - E.g. Wachtberg, Ammer and Bode watersheds
- ❑Running the ParFlow model
  - Scaling approach
- ❑Implementing the methodology Data-Driven-DA
- ❑Evaluating results

References

❑Schalge, B., Haefliger, V., Kollet, S., Simmer, C.J.H.p., 2019. Improvement of surface runoff in the hydrological model ParFlow by a scale-consistent river parameterization.

Hydrol. Processes 33 (14), 2006–2019.

❑Soltani, S.S., Fahs, M., Al Bitar, A. and Ataie-Ashtiani, B., 2022. Improvement of soil moisture and groundwater level estimations using a scale-consistent river parameterization for the coupled ParFlow-CLM hydrological model: A case study of the Upper Rhine Basin. Journal of Hydrology, 610, p.127991.

Thank you for your attention!