Updating a conceptual rainfall-runoff model based on radar observations and machine learning

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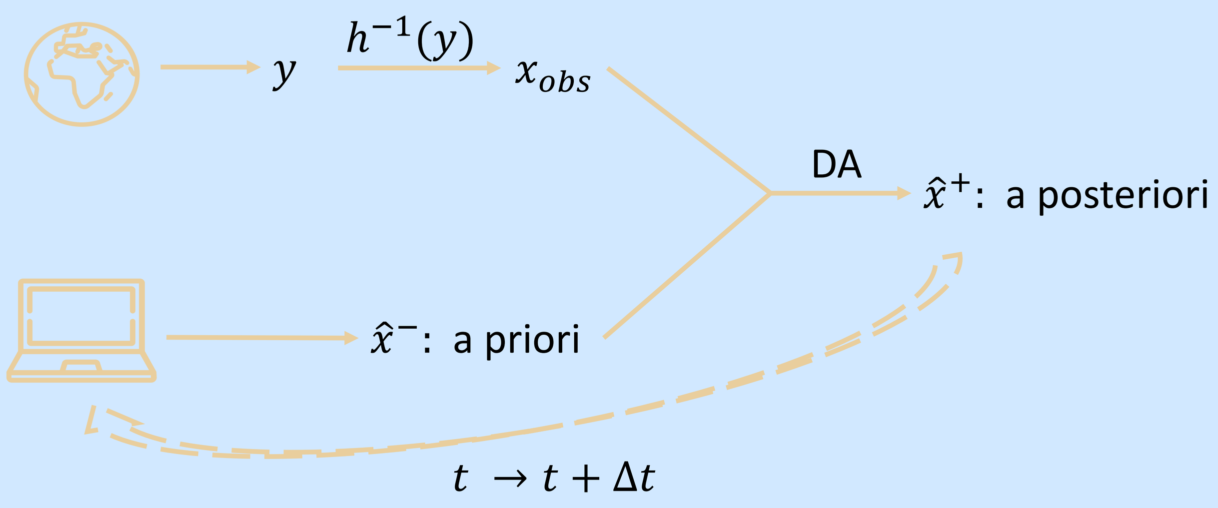
Introduction

Data assimilation (DA) for rainfall-runoff models:

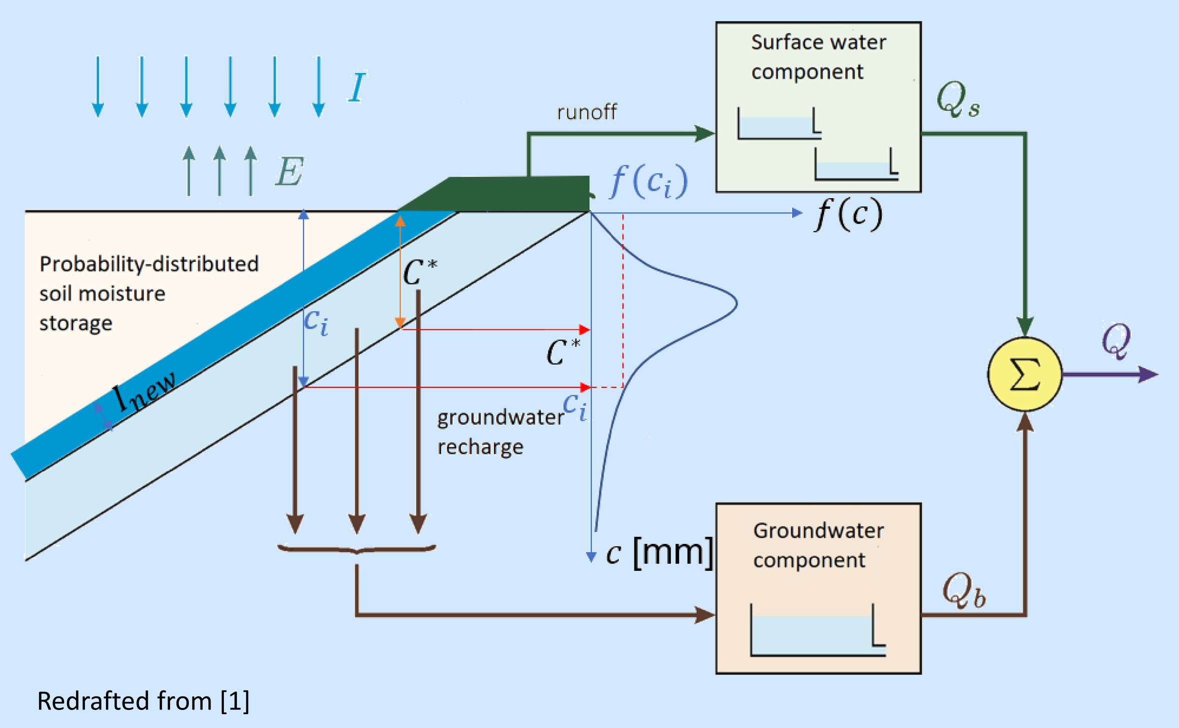
- **Physically based models**: observable state variable(s) $(x) \Rightarrow$ feasible DA (after bias correction)
- **Conceptual models**: non-observable state variables $\Rightarrow$ DA needs relationship (inverse observation operator h^{-1}) between observations (y) and state variable(s)

Research objectives:

- Use machine learning (ML) methods to establish **inverse observation operator** for the PDM
- Improve flow forecasts by assimilating the retrieved state variable



Probability Distributed Model (PDM)

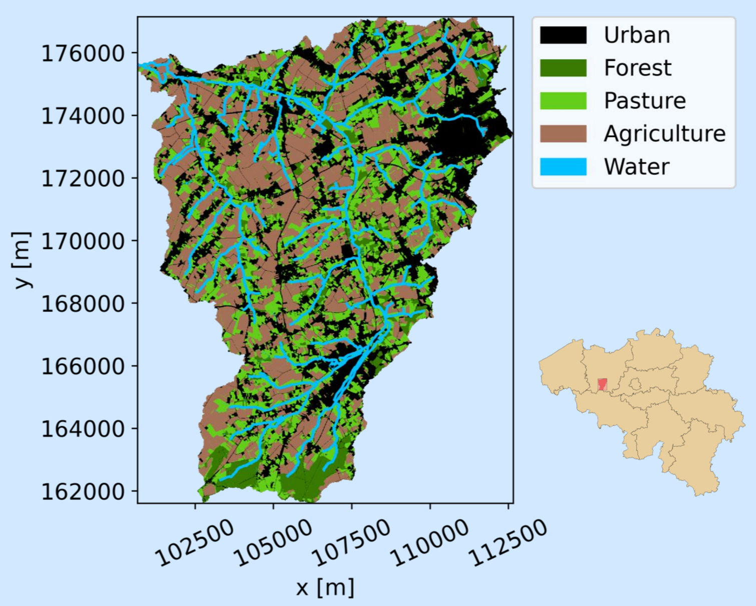


The PDM is a conceptual, lumped rainfall-runoff model [1].

- **Inputs**: precipitation (I) and potential evaporation (E)
- Routing by three reservoirs:
  1. **Probability-distributed soil moisture storage**: storages of capacity c_i are distributed in the catchment with probability density $f(c_i)$. All storages with $c_i < C^*$ (the critical capacity), produce direct runoff
  2. **Surface water component**: 2 linear reservoirs
  3. **Groundwater component**: 1 non-linear reservoir
- Output: flow at catchment outlet Q

NSE for Zwalm catchment 10/2012 – 11/2022: 0.760
14 parameters calibrated with Nelder-Mead method for 01/2012 - 12/2019

Satellite data for Zwalm Catchment



Sentinel-1 SAR backscatter ~ soil moisture ~ C^* → 10 x 10 m γ^0 : VV and VH

Sentinel-3/PROBA-V: LAI ~ vegetation effect on backscatter → 300 x 300 m LAI

Every timestep: spatial average per land use category

LAI and γ^0 timeseries per land use[1] category: 06/2015 – 11/2023

[1]Water and urban regions are masked

Machine learning inverse observation operators

Features: Observational timeseries
Targets: PDM generated C^*
Goal: Learning h^{-1} to produce a C^*_{obs} reflecting observed conditions

Focus on 1 timestep in, 1 timestep out

$$C^*_{obs,t} = h^{-1}(\gamma^0_t, \mathrm{LAI}_t, \mathrm{DOY}_{sin/cos})$$

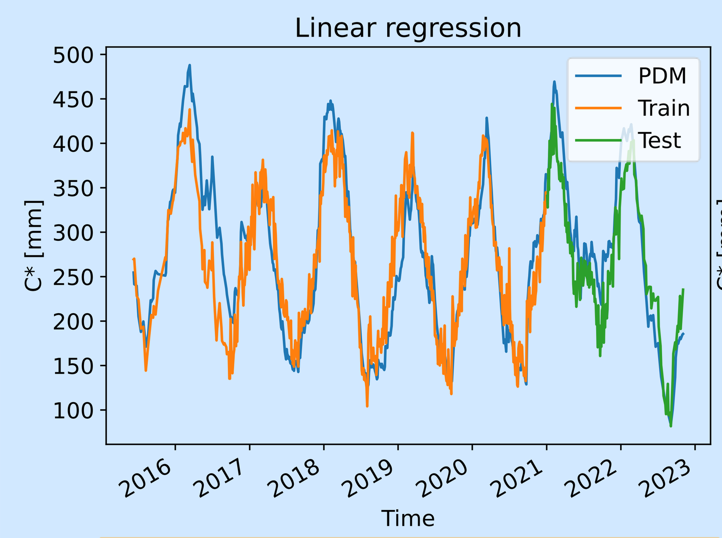
ML algorithms for h^{-1}:

- Linear: **linear regression** (LR), ridge/lasso regression, ϵ –SVR
- Non-linear: **gaussian processes** (GP) , FF-MLP, LSTM

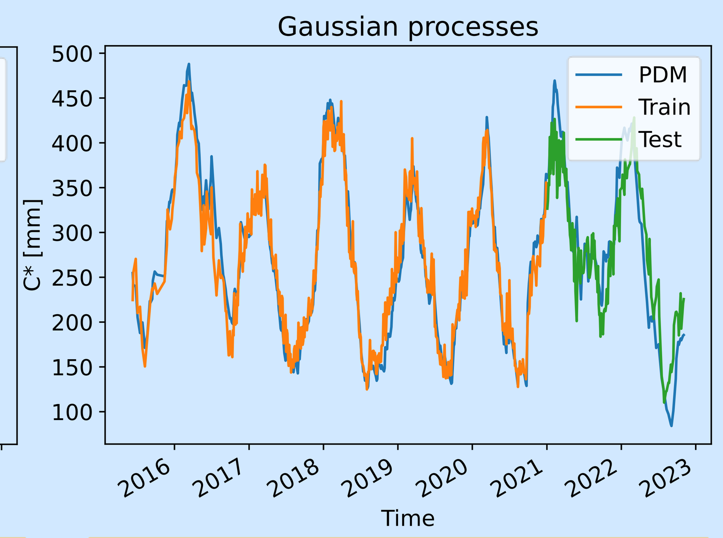
General trends for ML algorithms:

Linear models	Non-linear models
(+) Good generalisation	(-) Prone to overfitting
Few (hyper)parameters	More (hyper)parameters

! Only ≈ 600 training samples !



$R^2_{train} = 0.822$, $R^2_{test} = 0.808$



$R^2_{train} = 0.942$, $R^2_{test} = 0.812$

Data assimilation: Newtonian nudging

Update the C^* state variable within time window of a Sentinel-1 observation:

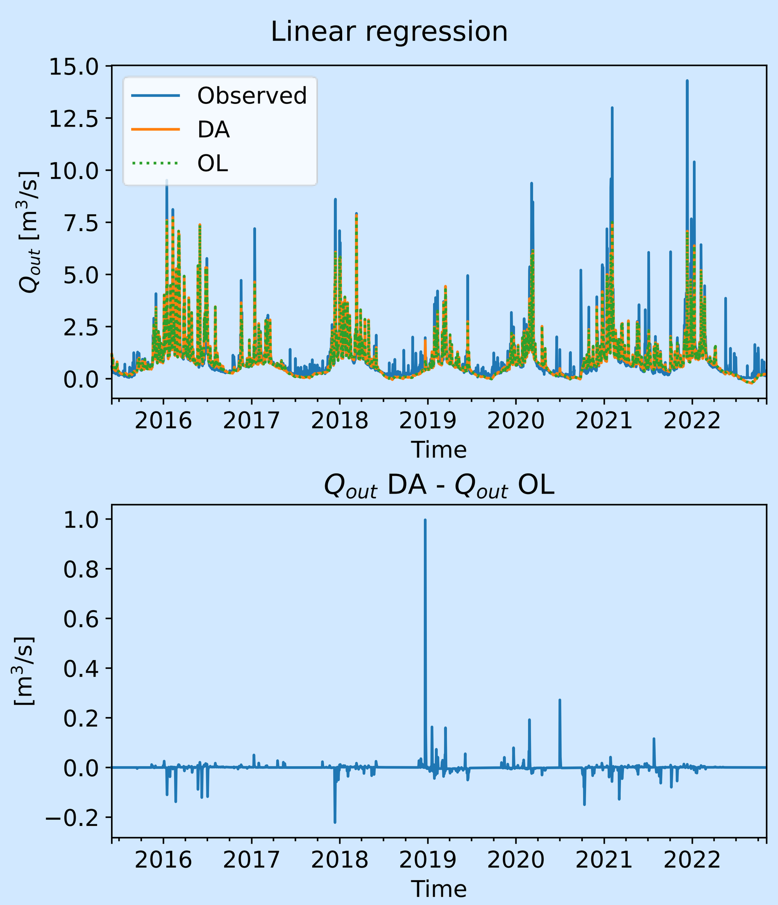
$$\hat{C}^{*+} = \hat{C}^{*-} + K \cdot W_t \cdot \gamma(C^*_{obs} - \hat{C}^{*-})$$

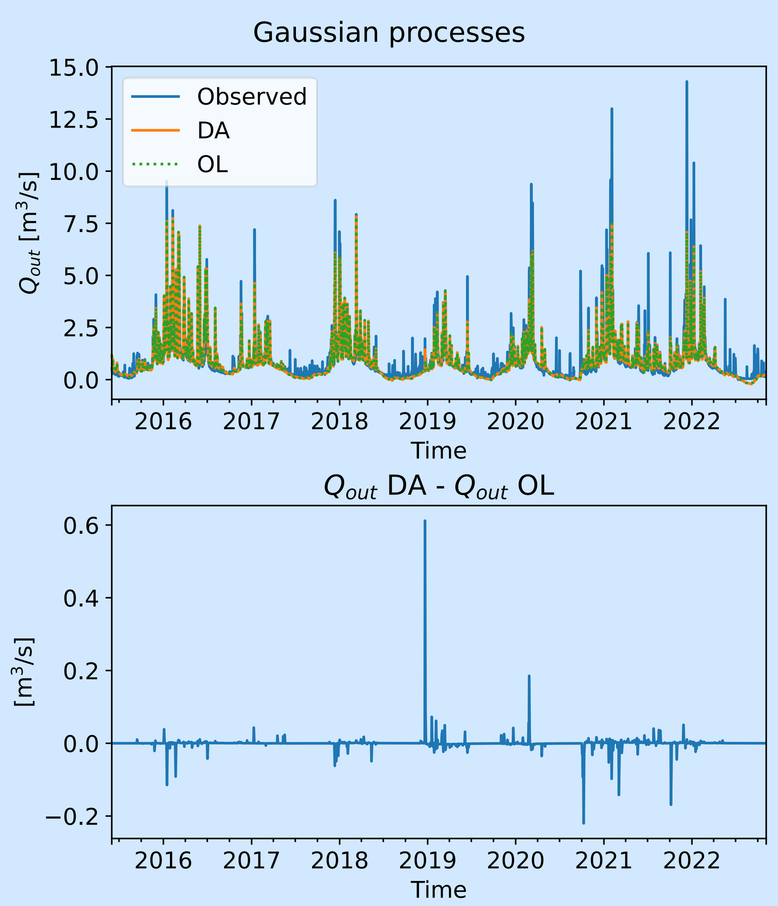
- $\hat{C}^{*+}$: a posteriori, updated critical capacity
- W_t: temporal weighing functions (assimilate τ hours before and after observation)
- $\hat{C}^{*-}$: a priori critical capacity from PDM
- γ: observational uncertainty
- C^*_{obs}: "observed" critical capacity from h^{-1}
- K: Nudging factor

Experiments with $\tau = 5$ h and $\gamma K = 0.5$

Period	PDM calibrated	ML h^{-1} trained	ΔNSE LR	ΔNSE GP
06/2015-12/2019	✓	✓	0.0013	0.0006
1/2020 – 12/2020	✗	✓	0.0026	0.0018
1/2021 – 11/2022	✗	✗	0.0004	-5e-5

General trend for choice of τ and γK:
Increased τ and/or $\gamma K \Rightarrow$
ΔNSE period 1 ↑, ΔNSE period 3 ↓





Conclusions and perspectives

- Newtonian Nudging DA of C^*_{obs} has minimal influence on model performance
- Non-linear inverse observation operators do not yield better performance in DA
- Fundamental question: Can a C^*_{obs} containing valuable observational information be retrieved if h^{-1} is trained on C^* from the PDM?

Possible methodological improvements:

- γ of Newtonian Nudging in function of model and observational uncertainty
- Application of a more advanced DA technique (e.g. ensemble Kalman Filter)

Broader research perspective:

- Replace PDM and DA by ML methods capable of dealing with irregularly sampled and partially observed timeseries such as the ODE-RNN [2] and ODE-LSTM [3] structures

Ref:
[1] Moore, R. J. (2007). The PDM rainfall-runoff model. Hydrology and Earth System Sciences, 11(1),483–499.https://doi.org/10.5194/hess-11-483-2007
[2] Rubanova, Yulia & Chen, Ricky & Duvenaud, David. (2019). Latent ODEs for Irregularly-Sampled Time Series. CoRR, abs/1907.03907. http://arxiv.org/abs/1907.03907
[3] Lechner, M., & Hasani, R. (2020). Learning Long-Term Dependencies in Irregularly-Sampled Time Series. https://arxiv.org/abs/2006.04418

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https://github.com/olivierbonte/master_thesis