



[Session HS4.3] | Mon, 26 Apr | EGU21-13262

Machine learning approaches to parameter calibration and uncertainty propagation for seasonal flood risk prediction

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Introduction & Motivation

- Extreme weather events are happening more frequently, leading to increased flood risk with severe socioeconomic impact.
- Mathematical and computation models can help to predict future events and enable decision makers to act accordingly.
- Uncertainties in predictions must be well understood for model credibility.
- There are multiple sources of uncertainty:
 - inherent to the mathematical model, (epistemic/aleatoric uncertainty)
 - related to the model parameters being calibrated to (erroneous) validation data (epistemic uncertainty),
 - attached to the model driver data (e.g. seasonal climate uncertainties [1][2][3]). (aleatoric/epistemic uncertainty)
- Due to their non-linear relationships, these sources of error cannot be simply summed [4].
- It is thus of interest to find an approach to strategically quantify the combined uncertainty in the model predictions.
- Our approach comprises uncertainty estimation during parameter calibration (a problem still unsolved for climate models with large parameter spaces [5]), into which the uncertainties of the model drivers are then incorporated.

[1] Lee, Donghoon, Philip Ward, and Paul Block. "Attribution of large-scale climate patterns to seasonal peak-flow and prospects for prediction globally." *Water Resources Research* 54.2 (2018): 916-938.

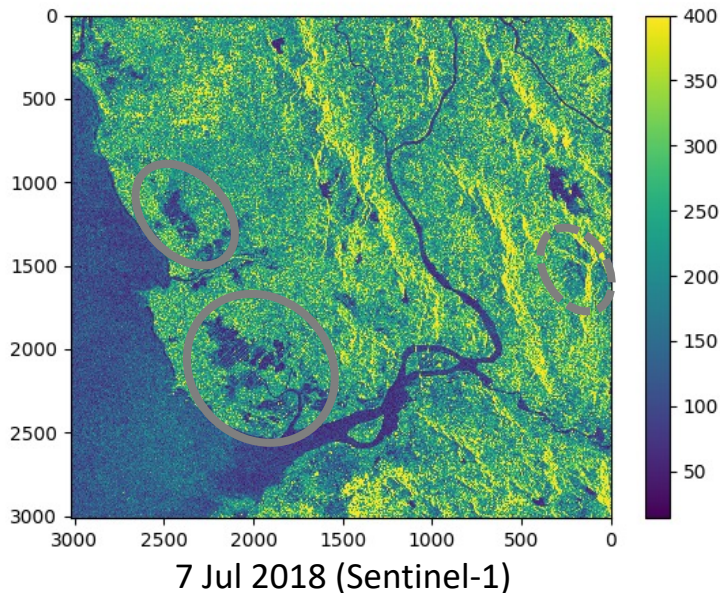
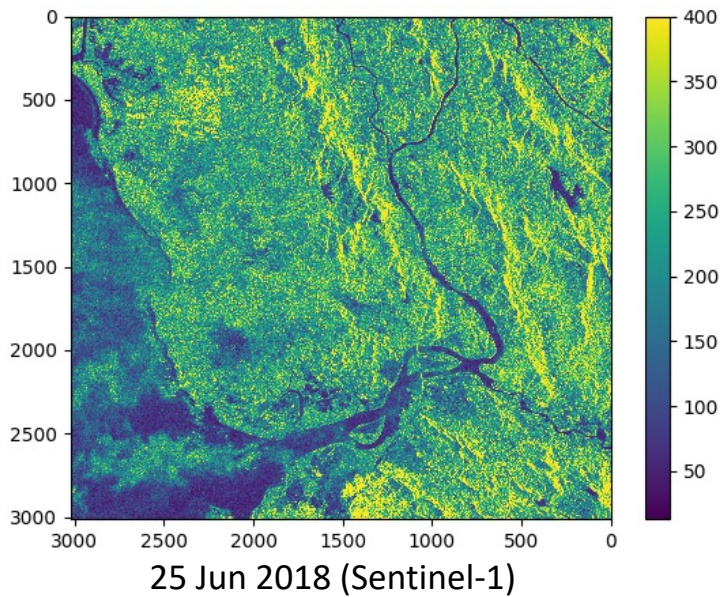
[2] Do, Hong Xuan, et al. "Global-scale prediction of flood timing using atmospheric reanalysis." *Water Resources Research* 56.1 (2020): e2019WR024945.

[3] Huang, Kangdi, et al. "Risk analysis of flood control reservoir operation considering multiple uncertainties." *Journal of Hydrology* 565 (2018): 672-684.

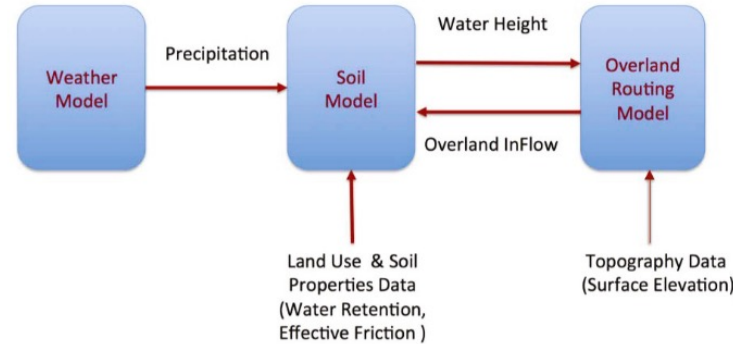
[4] Emerton, Rebecca, et al. "Developing a global operational seasonal hydro-meteorological forecasting system: GloFAS-Seasonal v1. 0." *Geoscientific Model Development* 11.8 (2018): 3327-3346.

[5] Salter, James M., et al. "Uncertainty quantification for computer models with spatial output using calibration-optimal bases." *Journal of the American Statistical Association* (2019).

Pluvial flood modelling in Palghar, India (July 2018)



IFM: Integrated Flood Model**

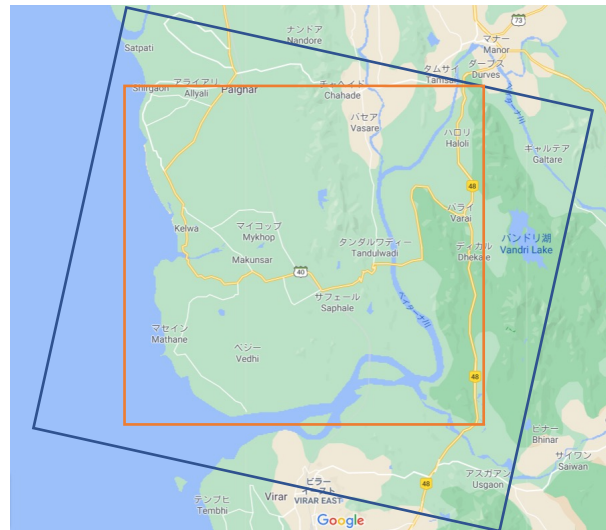


IBM Integrated Flood & Weather Modeling System [6]

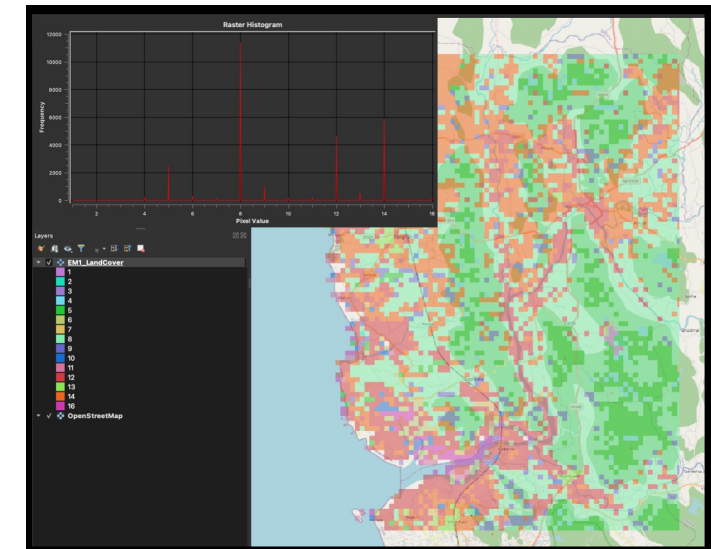
[6] Singhal, Swati, et al. "IFM: a scalable high resolution flood modeling framework." *European Conference on Parallel Processing*. Springer, Cham, 2014.

1) Define target region for flood modeling

Targeted area (□: Model; □: Sentinel-1)



2) Query land cover information and model driver data from IBM Weather Operations Center - Geospatial Analytics Engine <https://weatheroperationscenter.ibm.com>



****Check out related presentation focused on the here used modeling platform:**

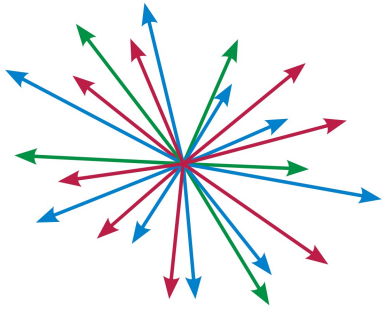
[Session HS3.1] | Fri, 30 Apr, 09:00–12:30 (CEST) | EGU21-14064

A geospatial and temporal analytics framework for flood risk mapping

Tatsuya Ishikawa, Takao Moriyama, Paolo Fraccaro, Anne Jones, Blair Edwards

Parameter calibration & UQ - Underlying Problem

Problem: Complex model with high dimensional parameter space



- 17 x 2 **land cover** parameter
- 13 x 3 **soil type** parameter

Needed: Efficient search algorithms

- Leveraging prior information to reduce dimension and narrow bounds
- Balanced exploitation-exploration

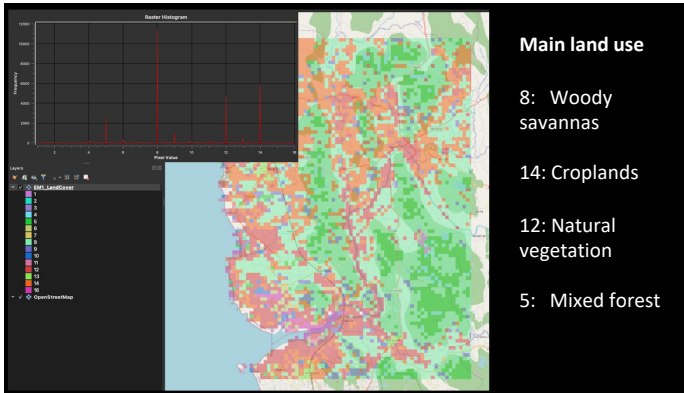
Finding: Parameter distributions and uncertainties

- Linking data and model uncertainties to prediction output uncertainties

	Surface roughness Water retention			Effective porosity Hydraulic conductivity Wetting front		
No data						
Needle leaf 1						
Broad leaf 1						
Needle leaf 2						
Broad leaf 2						
Mixed forest						
Closed shrublands						
Open shrublands						
Woody savannas						
Savannas						
Grassland						
Wetlands						
Croplands						
Urban and built up						
Natural vegetation						
Snow/Ice						
Barren						
	Land cover			Soil property		

Parameter calibration & UQ - Approach

Prior information on land cover



Preprocessing

Parameter distribution

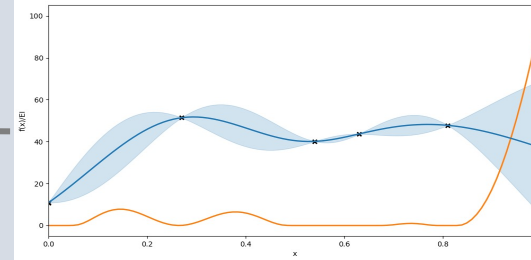
Parameter suggestion
e.g. Gaussian process

Forward modeling

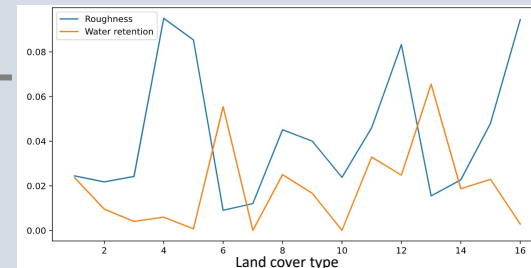
Climate model drivers

Uncertainty Quantification

Acquisition function



Sobol indices from surrogate model



Iterative calibration process

Update

Model prediction

Objective function

Ground truth, e.g. Sentinel-1

From previous observations

Validation metrics module

For now: validation at single timestamp

Calibration algorithms:

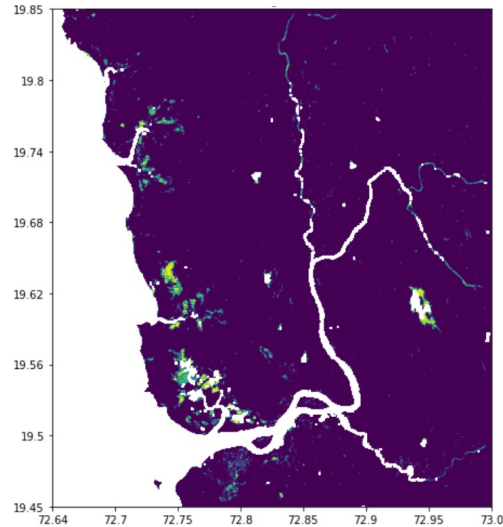
- Bayesian optimization (e.g. BOA [7], OPTUNA [8])
- Hamiltonian Monte Carlo (e.g. NUTS HMC [9])
- Variational Interference (e.g. ADVI [9])

[7] Pelikan, Martin, David E. Goldberg, and Erick Cantú-Paz. "BOA: The Bayesian optimization algorithm." *Proceedings of the genetic and evolutionary computation conference GECCO-99*. Vol. 1. 1999.
[8] Akiba, Takuya, et al. "Optuna: A next-generation hyperparameter optimization framework." *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*. 2019.
[9] Salvatier, John, Thomas V. Wiecki, and Christopher Fonnesbeck. "Probabilistic programming in Python using PyMC3." *PeerJ Computer Science* 2 (2016): e55.

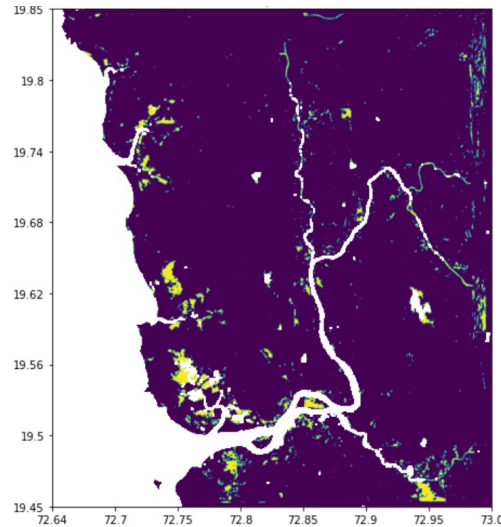
Parameter calibration & UQ - Validation metrics

Ground truth:

Ground truth from satellite image
(Otsu method [10], 10m res, 07/07/2018)



AI derived flood map**
(AI model, 10m res, 07/07/2018)



****For more details visit:**

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A geospatial and temporal analytics framework for flood risk mapping

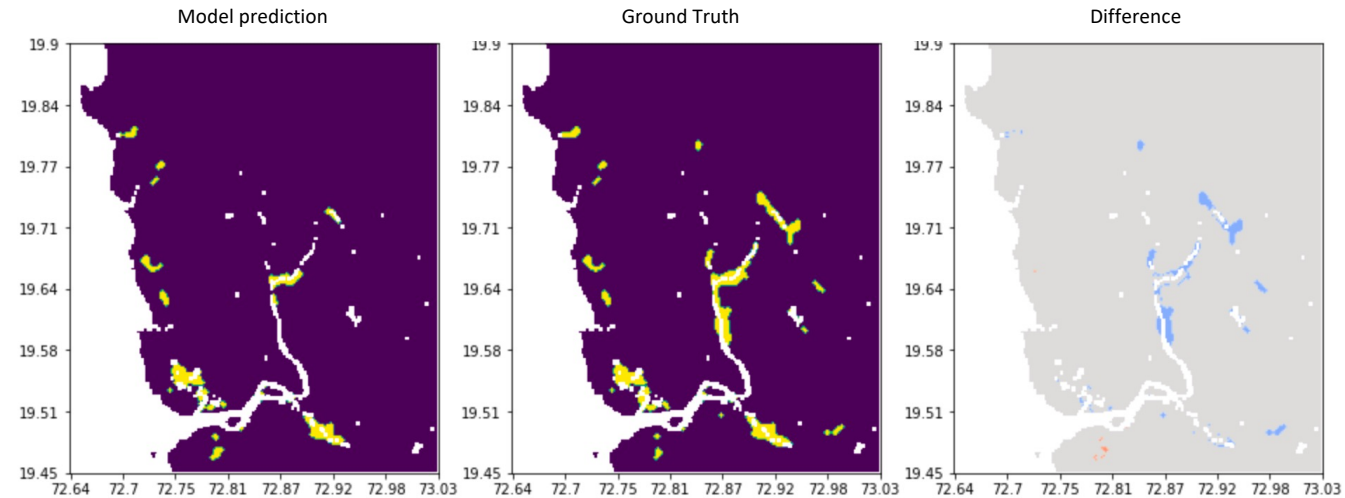
Tatsuya Ishikawa, Takao Moriyama, Paolo Fraccaro, Anne Jones, Blair Edwards

[10] Otsu, Nobuyuki. "A threshold selection method from gray-level histograms."
IEEE transactions on systems, man, and cybernetics 9.1 (1979): 62-66.

Binary metrics to validate flood extent

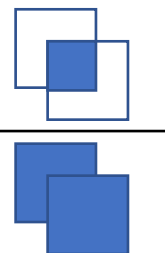
Threshold in water depths defines flooded and non-flooded area in both ground truth and model predictions which are subsequently compared

Uncalibrated model run with 250 m resolution and synthetic ground truth:



Intersection over Union: **IoU = 0.57**,

where $\text{IoU} = \frac{\text{Intersection}}{\text{Union}}$

A diagram showing two overlapping blue squares. The intersection of the two squares is highlighted in a darker blue. The union of the two squares is the area covered by both squares.

Acquisition function & Sobol indices

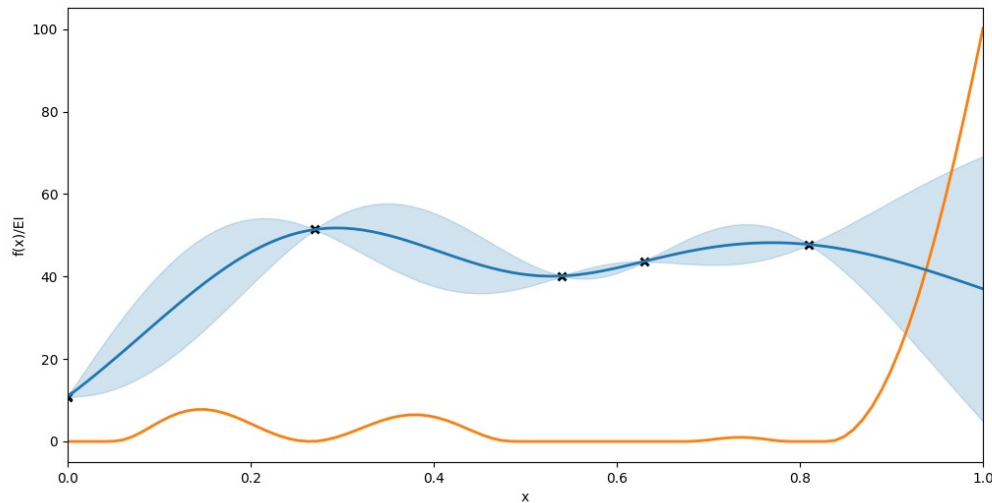
Acquisition Function

- Guides intelligent samples in the sequential optimization
- Inherently balancing exploration/exploitation

Calculated from the GP surrogate model, for example Expected Improvement (EI) [11]:

$$\alpha_{EI} = \mathbb{E} [\max(f(\mathbf{x}_*) - f(\mathbf{x}^+), 0)]$$

Where $f(\mathbf{x}^+)$ best observed loss and under parameters ($\mathbf{x}^+$)



[11] Berk, Julian, et al. "Exploration enhanced expected improvement for bayesian optimization." *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, 2018.

Sobol Indices

Provide an ordering of parameter importance based on first order Sobol Indices, learnt by sampling the surrogate model, and calculated through parameter contribution to variance [12]:

$$S_i = \frac{U_i - \mathbb{E}^2[y]}{\mathbb{V}[y]}$$

$$U_i = \int_{-\infty}^{\infty} \mathbb{E}^2(y | \theta_m^i = \hat{\theta}_m^i) \rho(\hat{\theta}_m^i) d\hat{\theta}_m^i$$

Algorithm: Sensitivity Analysis Steps

Result: $S_i, \theta_m(\text{reduced})$

Input: $\mathcal{GP}$ surrogate of $\mathcal{L}$ function after n steps;

Generate: Saltelli samples equivalent to N_S samples

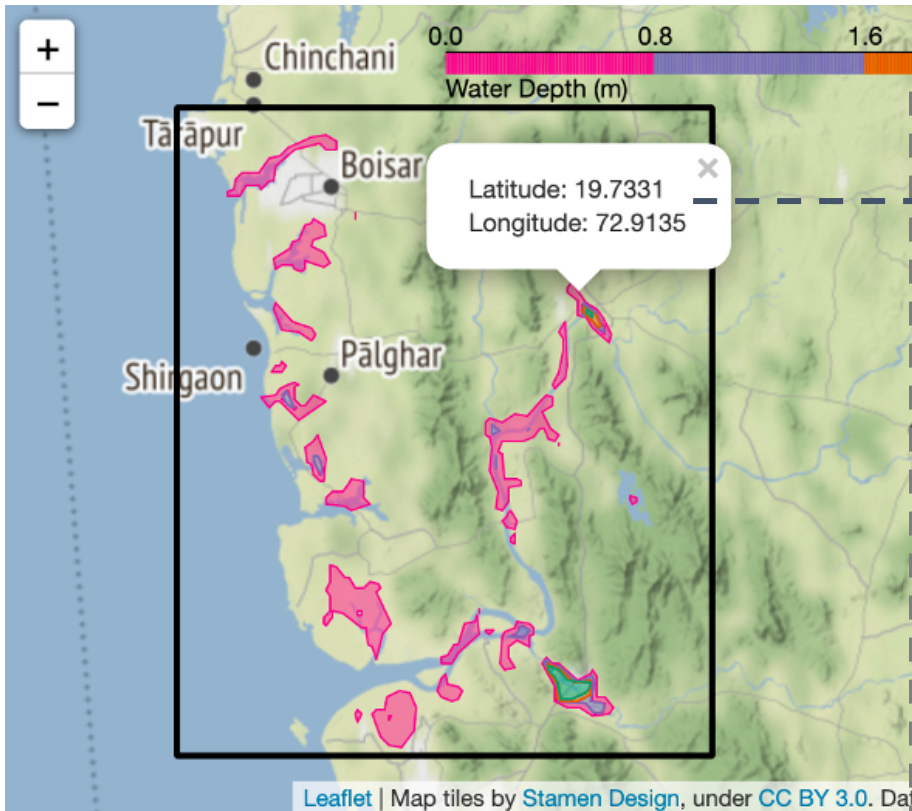
Sample: $\mathcal{GP}$ at locations N_S ;

Compute: S_i [Equation 3.23 and Equation 3.24];

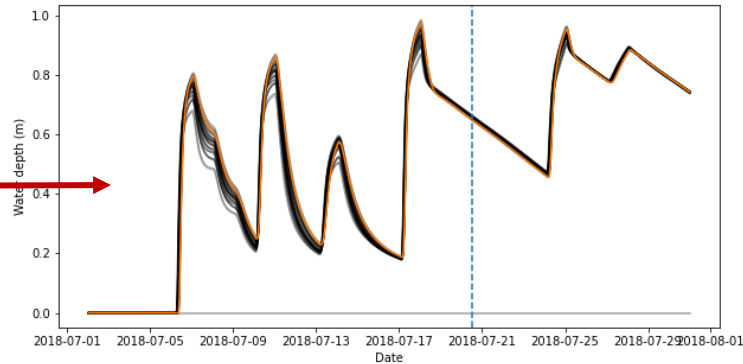
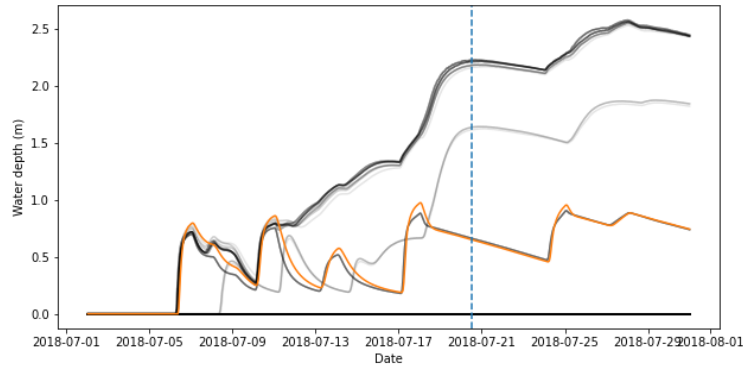
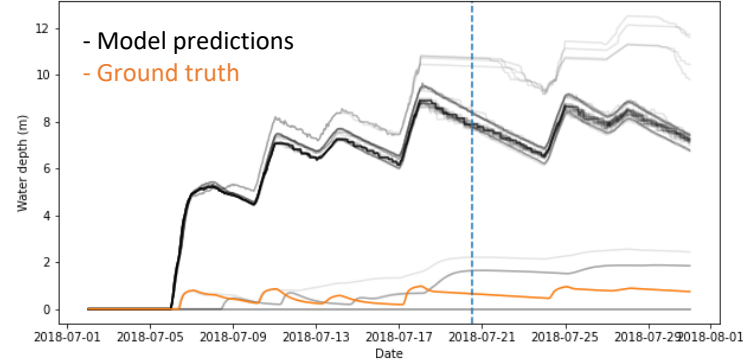
Return: S_i and $\theta_m(\text{ranked}) \rightarrow \theta_m(\text{reduced})$;

[12] Saltelli, Andrea. "Making best use of model evaluations to compute sensitivity indices." *Computer physics communications*, 2002

Example experiment - 250m resolution, synthetic ground truth



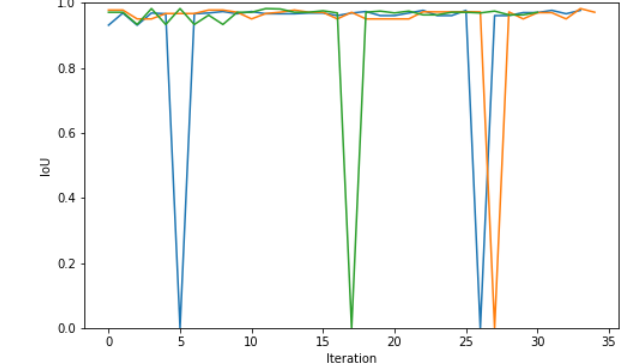
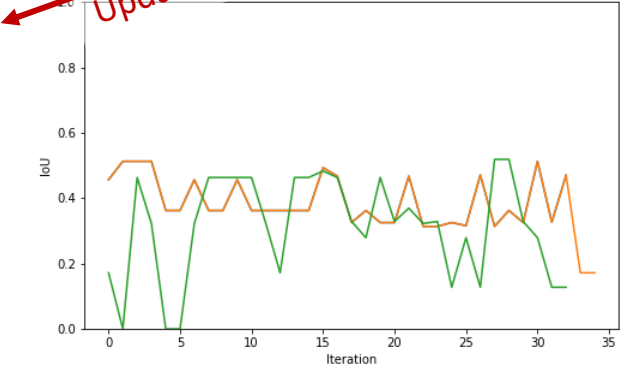
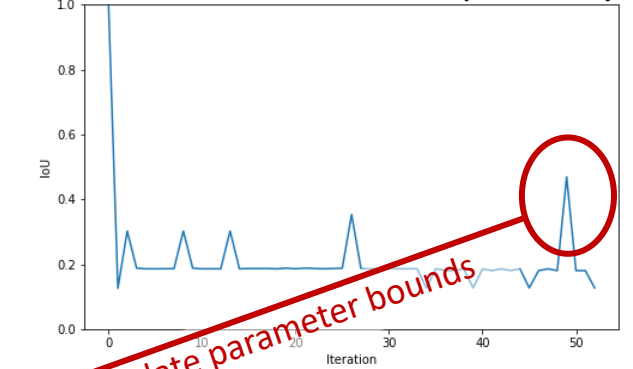
Water depth over time (one point)



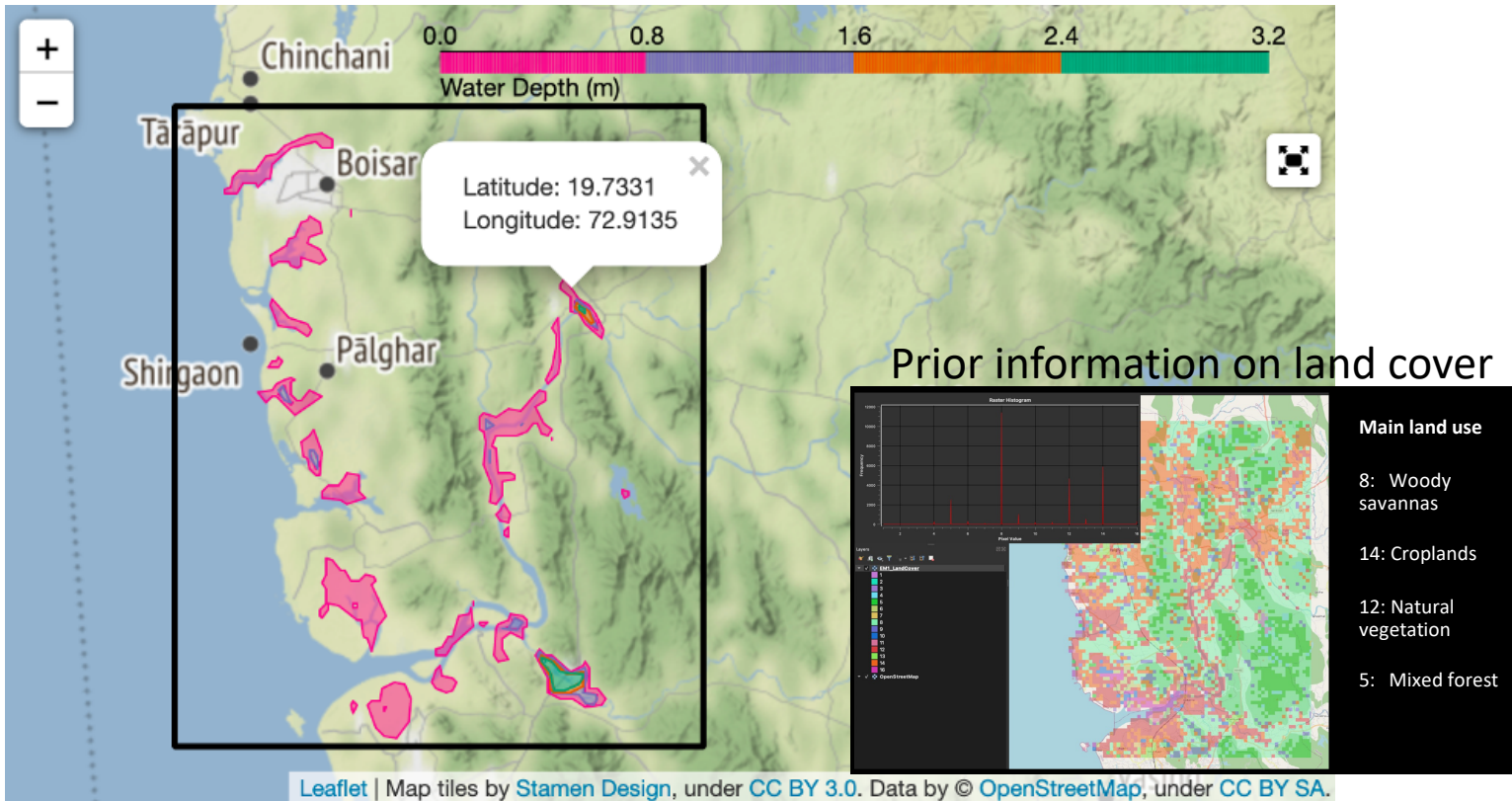
Prior information
on land cover

Reduce dimension
of parameter space

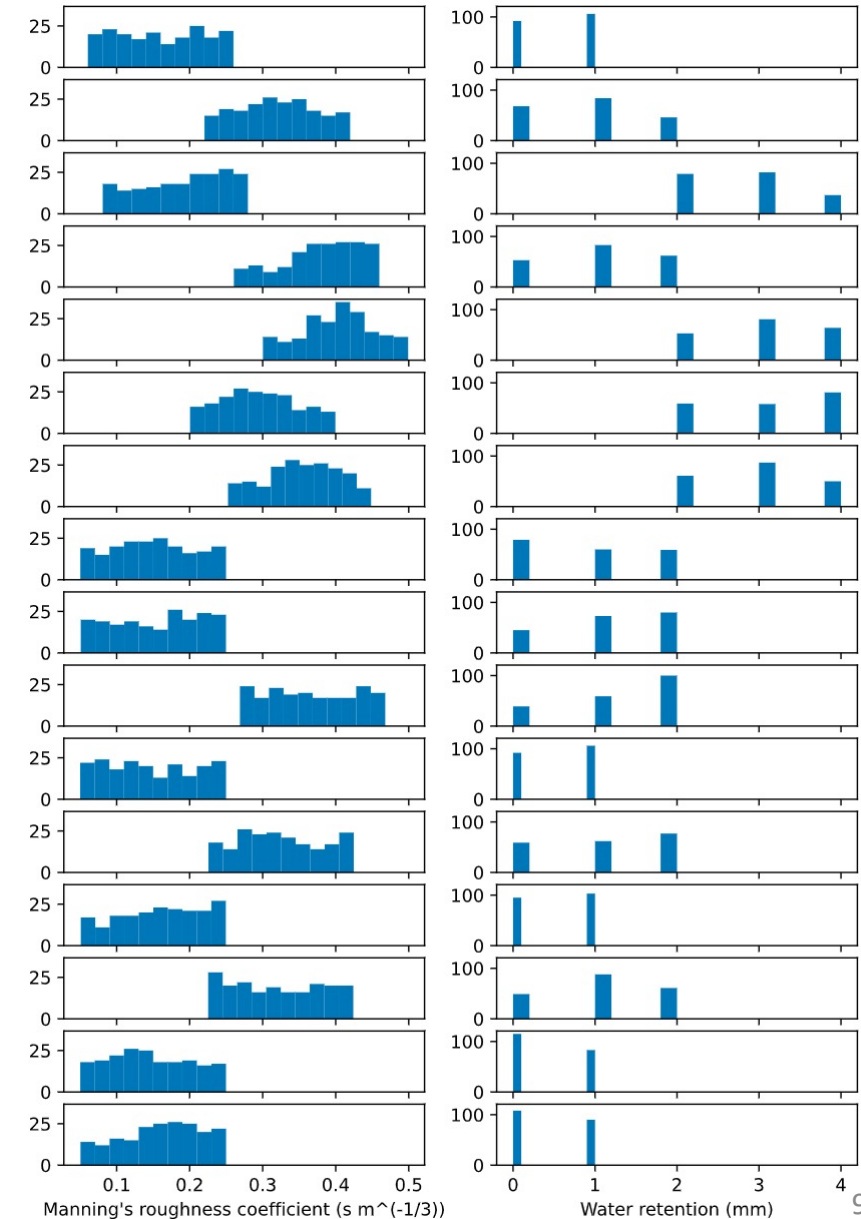
Metric over iterations (overall)



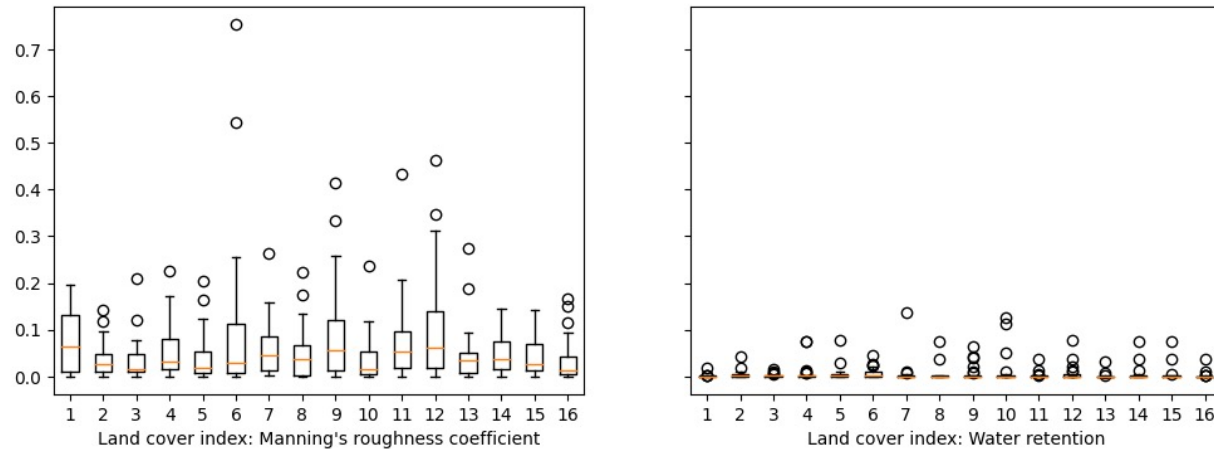
Example experiment - 250m resolution, synthetic ground truth



Parameter distribution (around 200 iterations)

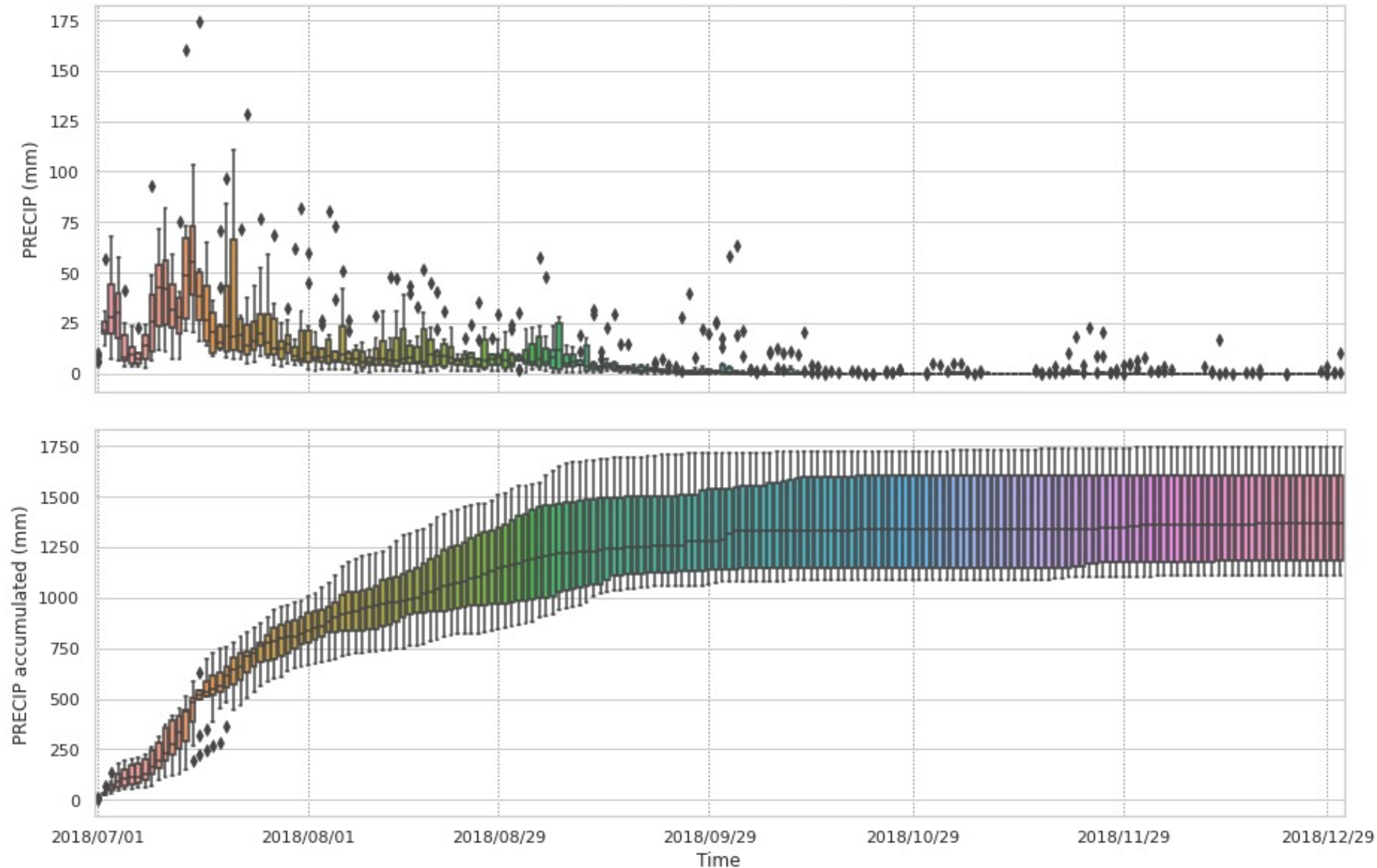


First order Sobol indices

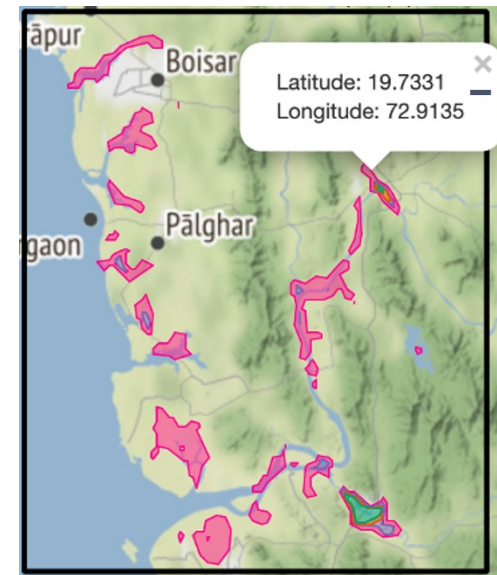


Parameter calibration & UQ - Seasonal forecasts

Ensemble of seasonal precipitation forecasts from **ECMWF Seas5 [13]**, processed through **TWC** (The Weather Company)



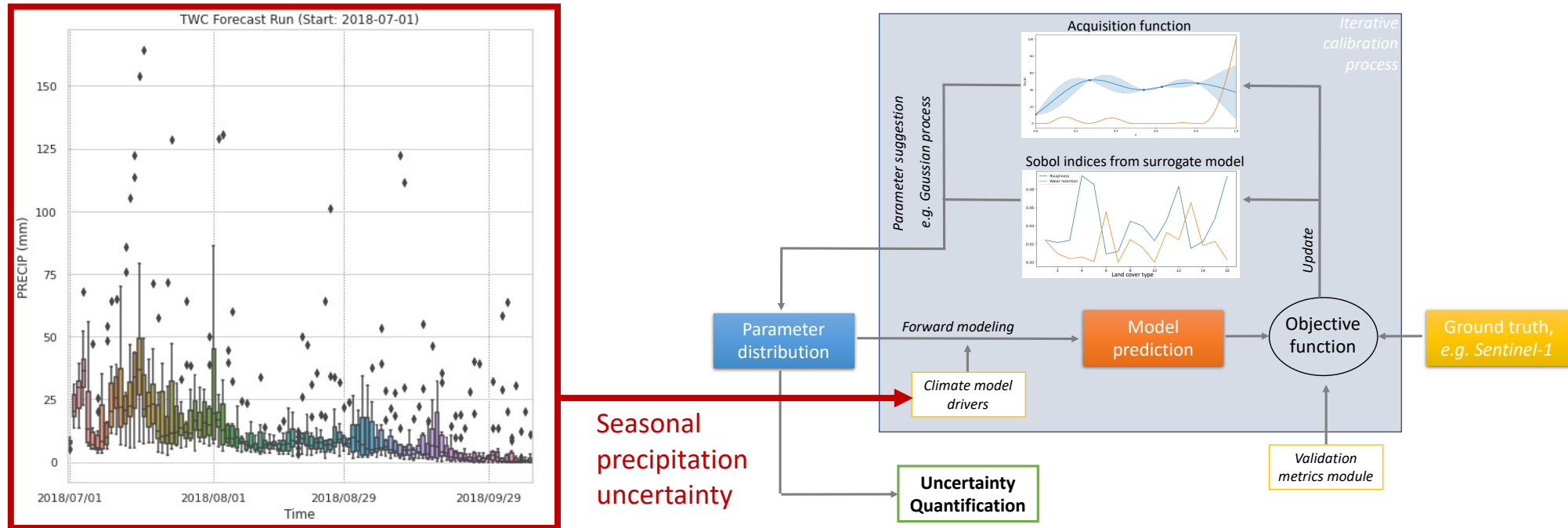
Variations in seasonal forecasts of precipitation from 10 ensemble members for a single coordinate:



As precipitation is the major model driver, these variations have a (long-term) impact on the uncertainties in the model predictions.

Parameter calibration & UQ - Next steps

- *Integrate variations of seasonal forecasts in the model calibration process.*



- *Account for uncertainties regarding spatial and temporal resolution of the driver data.*
- *Metrics: Besides flood extent, include the flood depth in the validation metrics.*