Theory Guided Machine Learning to Improve Hydrology Models

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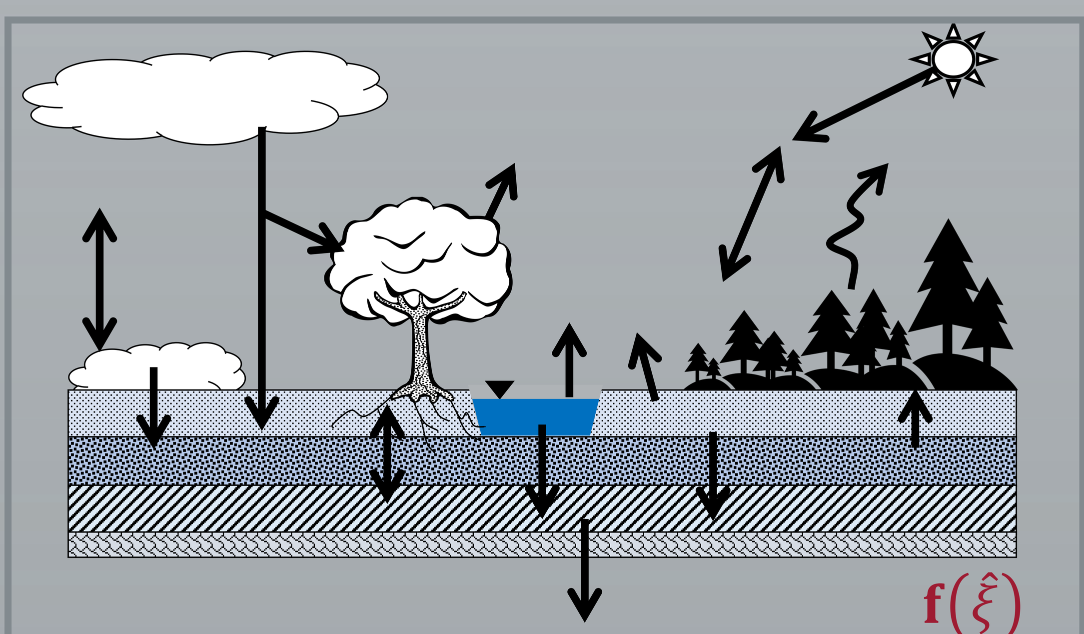
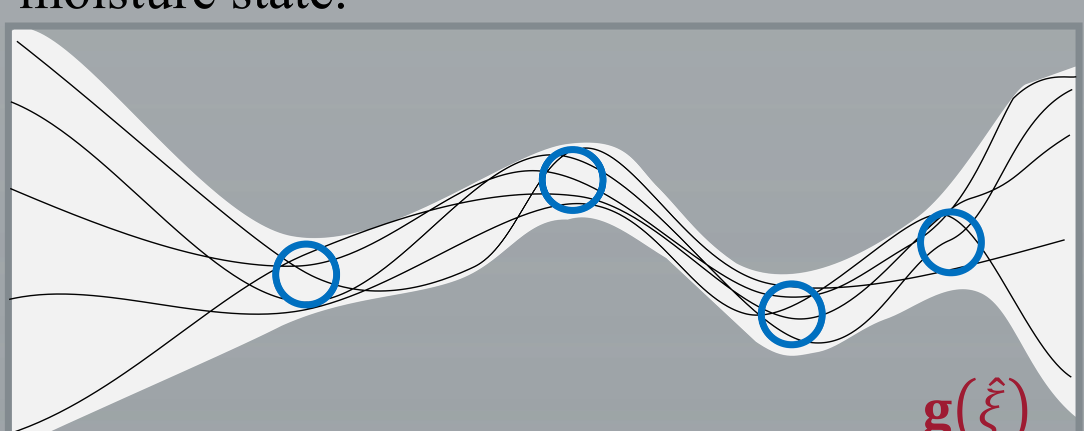
Background

There is a 'Grand Challenge' to combine process-based modeling with ML for simulating dynamical Earth systems. In a recent Nature paper, Reichstein et al. [2019] proposed that "the next step [in Earth Science] will be a **hybrid modelling approach, coupling physical process models with the versatility of data-driven machine learning**." This is called physics-informed ML, an emerging paradigm in the Earth Sciences [Karpatne et al. 2017].

We calibrated the physics-based **Noah-MP land surface model** (Noah) to soil moisture.

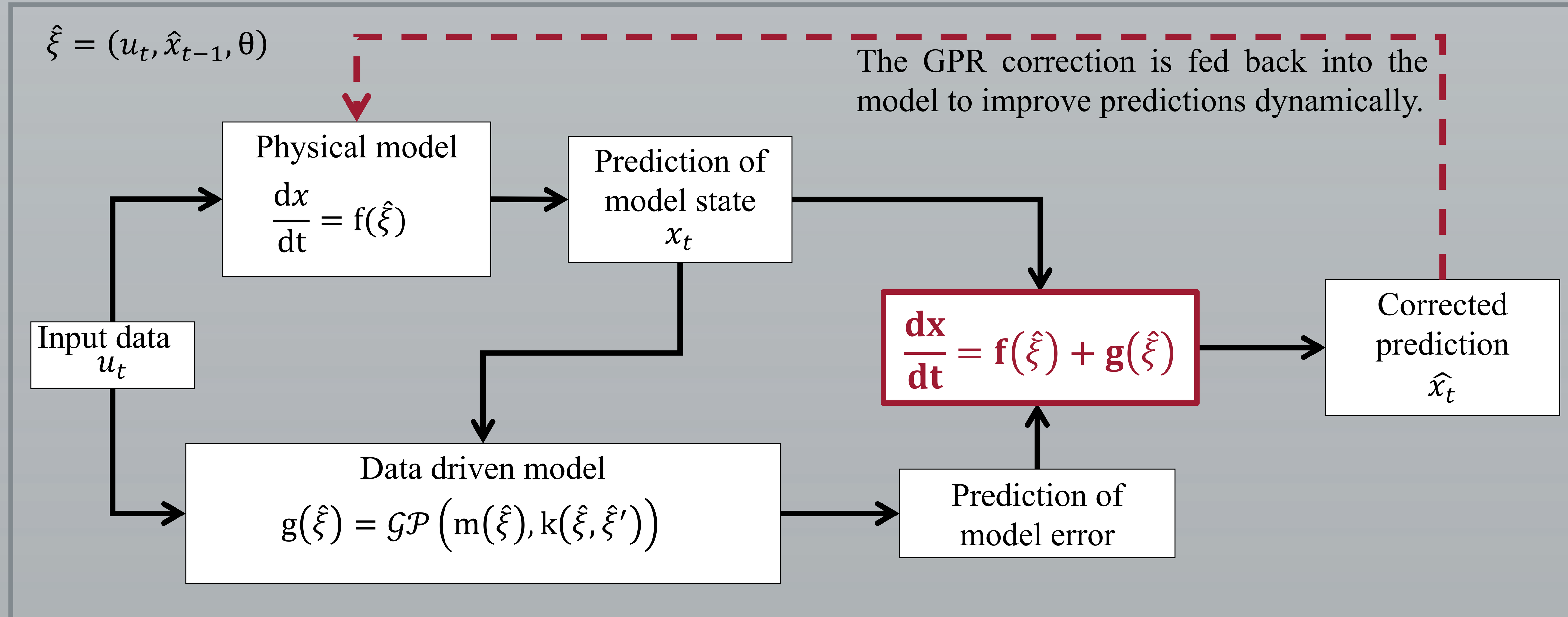


We used **Gaussian Process Regression** (GPR) to dynamically correct the soil moisture state.

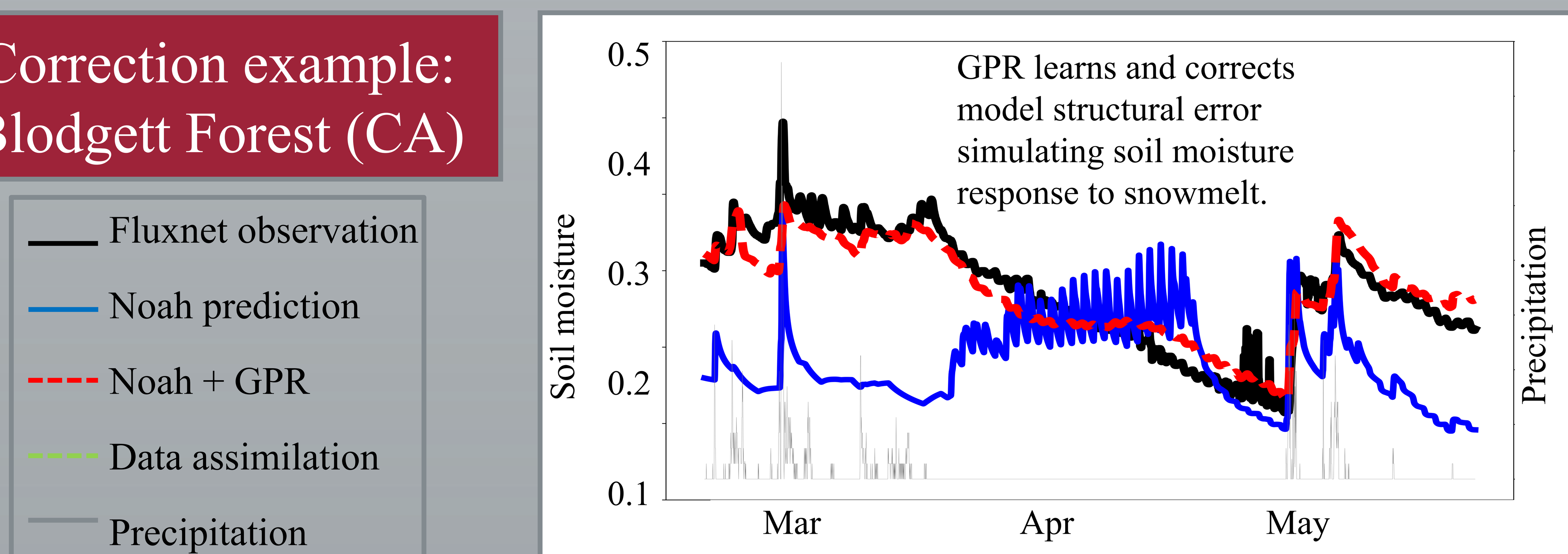


We tested our method with high quality, in-situ, **Fluxnet** data (soil moisture and forcing) from diverse hydrologic conditions.

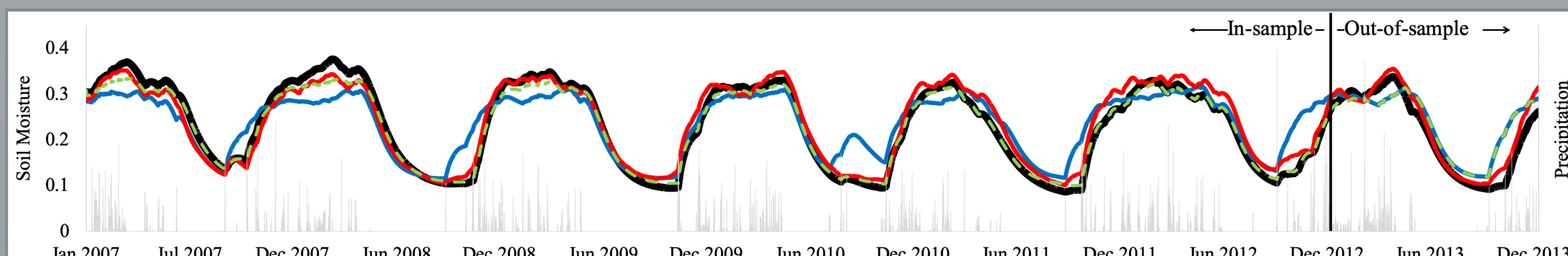
Method



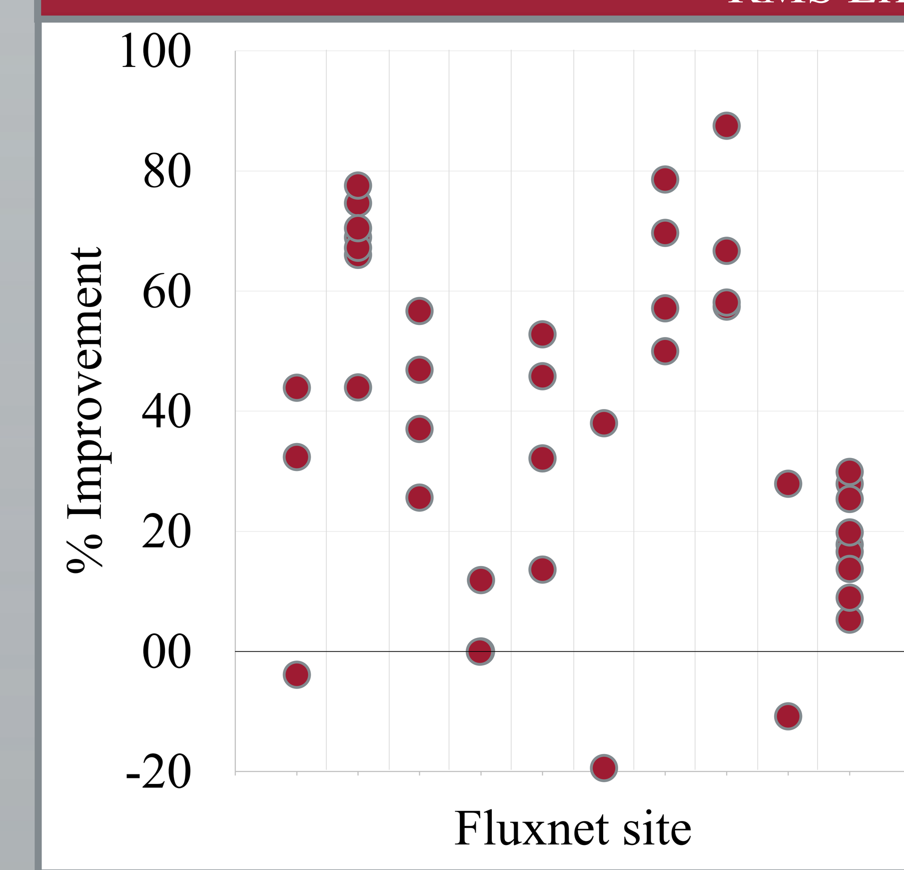
Correction example: Blodgett Forest (CA)



At this site Noah systematically underestimates the wet periods and overestimates the dry periods. The GPR corrects this systematic error in a similar way as data assimilation but has **learned the correction and continues to improve model performance out-of-sample**, shown below and to the right.



Result



RMS Error

	Noah	Noah + GPR	change
Max	0.123	0.098	88%
Mean	0.054	0.033	39%
Min	0.020	0.006	-19%

Cross validation results for 10 sites with data between 2-10 years. Sites with at least three years available for training show consistent improvement.