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# Field-scale soil moisture predictions using in situ sensor measurements in an inverse modelling framework: SWIM²

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With the rise of affordable, autonomous sensors and IoT (Internet-of-Things) technology, it is possible to monitor soil moisture in a field online and in real time. This offers opportunities for real-time model calibration for irrigation scheduling. A framework is presented where realtime sensor data are coupled with a soil water balance model to predict soil moisture content and irrigation requirements at field scale. SWIM², Sensor Wielded Inverse Modelling of a Soil Water Irrigation Model, is a framework based on the DREAM inverse modelling approach to estimate 12 model parameters (soil and crop growth parameters) and their uncertainty distribution. These parameter distributions result in soil moisture predictions with a prediction uncertainty estimate, which enables a farmer to anticipate droughts and estimate irrigation requirements.

The SWIM² framework was validated based on three growing seasons (2021-2023) in about 30 fields of vegetable growers in Flanders. Kullback–Leibler divergence (KLD) was used as a metric to quantify information gain of the model parameters starting from non-informative priors. Performance was validated in two steps, i.e. the calibration period and prediction period, which is in correspondence with the real-world implementation of the framework. The RMSE, correlation (R, NSE) and Kling-Gupta efficiency (KGE) of soil moisture were analyzed in function of time, i.e. the amount of available sensor data for calibration.

Soil moisture can be predicted accurately after 10 to 20 days of sensor data is available for calibration. The RMSE during the calibration period is generally around 0.02 $m^3/m^3$, while the RMSE during the prediction period decreases from 0.04 to 0.02 $m^3/m^3$ when more calibration data is available. Information gain (KLD) of some parameters (e.g. field capacity and curve number) largely depends on the presence of dynamic events (e.g. precipitation events) during the calibration period. After 40 days of sensor data, the KGE and Pearson correlation of the calibration period become stable with median values of 0.8 and 0.9, respectively. For the validation period, the KGE and Pearson correlation are increasing in time, with median values from 0.3 to 0.7 (KGE) and from 0.7 to 0.95 (R). These good results show that, with this framework, we can simulate and predict soil moisture accurately. These predictions can in turn be used to estimate irrigation requirements.

Precipitation radar data was primarily considered as an input without uncertainty. As an

extension, precipitation forcing error can be treated in DREAM by applying rainfall multipliers as additional parameters that are estimated in the inverse modelling framework. The multiplicative error of the radar data was quantified by comparison of radar data to rain gauge measurements. The prior uncertainty of the logarithmic multipliers was described by a Laplace distribution and was implemented in DREAM. The extended framework with rainfall multipliers shows better convergence and acceptance rate compared to the main framework. The calibration period shows better performance with higher correlations and lower RMSE values, but a decrease in performance was found for the validation period. These results suggest that the implementation of rainfall multipliers leads to overfitting, resulting in lower predictive power.