The impact of soil moisture data on the optimization of urban drainage models

L'impact des données sur l'humidité du sol sur l'optimisation des modèles de drainage urbain

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RÉSUMÉ

Les données relatives à l'humidité du sol sont essentielles pour décrire les processus hydrologiques des surfaces naturelles. Elles jouent un rôle mineur dans la modélisation des systèmes de drainage urbains imperméables, mais la présence croissante d'espaces verts dans les environnements urbains ouvre la possibilité de les utiliser également pour améliorer les modèles de drainage urbain. Dans le cadre de ce travail, l'impact des données sur l'humidité du sol dans le processus d'optimisation d'un modèle de bassin versant périurbain dans SWMM a été étudié. À l'aide d'une approche d'estimation généralisée de l'incertitude (GLUE), deux scénarios d'étalonnage ont été réalisés. Dans le premier scénario, seules les données de débit ont été utilisées pour optimiser le modèle, tandis que dans le second, les données de débit et d'humidité du sol ont été utilisées. Les deux scénarios ont ensuite été comparés pendant une période de validation. Les résultats ont révélé une légère amélioration de la précision des prévisions d'humidité du sol pour le deuxième scénario, mais aucune amélioration n'a été observée pour les prévisions de débit. Cependant, une réduction de l'incertitude des prévisions a été constatée pour le deuxième scénario pour tous les résultats. Des investigations plus détaillées sont nécessaires, mais les résultats préliminaires de cette étude ont montré que les données sur l'humidité du sol pouvaient réduire l'incertitude du modèle et améliorer les prévisions d'humidité du sol lorsqu'elles étaient utilisées dans l'optimisation des modèles de drainage urbain.

ABSTRACT

Soil moisture data are essential for describing hydrological processes of natural surfaces. They play a minor role in the modelling of impervious urban drainage systems, but the expanding presence of green areas in urban environments opens up the possibility of using them also for the improvement of urban drainage models. In this work, the impact of soil moisture data in the optimization process of a peri-urban catchment model in SWMM was investigated. Using a generalized likelihood uncertainty estimation (GLUE) approach, two calibration scenarios were carried out. In the first scenario only flow data were used to optimize the model, in the second flow and soil moisture data were used. The two scenarios were then compared during a validation period. Results revealed a slight improvement in the accuracy of the soil moisture predictions for the second scenario, but no improvement for flow rate predictions was observed. However, a reduction of the prediction uncertainty was found for the second scenario for all the outputs. More detailed investigations are necessary, but the preliminary results of this study showed the potential for soil moisture data to reduce model uncertainty and improve soil moisture predictions when using them in the optimization of urban drainage models.

KEYWORDS

GLUE, Model optimization, Soil moisture, SWMM, Urban drainage model

1 INTRODUCTION

The increasing use of green infrastructure as part of urban drainage systems has raised the necessity to properly include soil water processes in models of such systems. One way to take into account this contribution is to integrate soil-related information with conventional data, such as flow data, during the calibration process. Soil moisture data are a natural target to perform this role as they are suitable to characterize rainfall-runoff dynamics of green areas at a small scale (Nielsen et al., 2019) and they have been successfully used in the calibration of natural catchments hydrological models (Széles et al., 2020). Some authors have explored the possibility to use soil moisture data for modelling rainfall-runoff dynamic in medium and large catchments including urban areas, finding out that they can improve the runoff prediction performances (Fidal and Kjeldsen, 2020). In this work, soil moisture data will be used in the optimization phase of a SWMM peri-urban drainage model, to investigate potential benefits for model performance. A comparison between two optimization scenarios, one using only flow data, and a second one using also soil moisture, will be carried out.

2 METHOD

2.1 Study site and data collection

The investigated catchment is a peri-urban area located in Porsön, Luleå, Sweden, with an area of about 10.1 ha of which about 63% green areas. Rain, flow and soil moisture data for the model optimization and validation were collected at 1 minute interval between 15 June and 30 September 2025. Soil moisture data available between May and October 2025 were also used to determine soil hydraulics properties for the model. Flow data were collected using an ISCO 2150 flowmeter, installed in the 0.4 m diameter outflow pipe from the catchment, rain data using a Geonor T200 weighing gauge about 500 m from the flowmeter. The soil moisture data were collected using Meter Teros capacitance sensors installed at 15 cm depth in three swales (A, B and L) near the outflow drain. At the same depths and locations, Teros 21 water potential sensors were also installed. The swale outlets were located between 570 and 700 m from the weighting bucket.

2.2 Model setting

A SWMM model composed of 156 subcatchments was used in this study. The modified Green-Ampt method was selected to model the infiltration process in the pervious areas. In the three swales where soil moisture sensors were installed, the SWMM groundwater module was used for long-term modelling of soil moisture. An aquifer was assigned to each one of the swales. Actual evapotranspiration (AET) was estimated as the product between an adimensional crop factor K_c taken equal to 0.75 (Obriejetan and Krexner 2024), and the potential evapotranspiration estimated using the Oudin model, chosen for its suitability in norther climates (Johannessen et al. 2017). The parameters selected for optimization (and the corresponding range) are reported in Table 1. Some parameters were assumed identical for all subcatchments, while saturated hydraulic conductivity (K_{sat}), soil moisture deficit (SMD) and conductivity slope (HCO) were assigned individually to subcatchments A, B and L. The matric potential for the Green-Ampt model was calculated from K_{sat} according to the SWMM manual (Rossman and Huber, 2016).

Table 1 Parameters selected for optimization

Parameter	Range	Parameter	Range
K_{sat} (mm*h^{-1})	(0.3 – 117.8)	**SMD_A** (m^3/m^3)	(0.1 – 0.26)
SMD (m^3/m^3)	(0.1 – 0.3)	**HCO_A**	(27-61)
Manning impervious (s*m$^{-1/3}$)	(0.01 – 0.015)	**K_{satB}** (mm*h^{-1})	(0.3 – 117.8)
Manning pervious (s/m$^{-1/3}$)	(0.1 – 0.5)	**SMD_B** (m^3/m^3)	(0.1 – 0.28)
Depression impervious (mm)	(0 -2.5)	**HCO_B**	(27-61)
Depression pervious (mm)	(0 – 20)	**K_{satL}** (mm*h^{-1})	(0.3 – 117.8)
Manning pipe (s/m$^{-1/3}$)	(0.01 – 0.017)	**SMDL** (m^3/m^3)	(0.1 – 0.31)
K_{satA} (mm*h^{-1})	(0.3 – 117.8)	**HCO_B**	(27-61)

For the aquifer module in SWMM, porosity was set as the maximum soil moisture detected in the time series. Field capacity was calculated as the 25th percentile of the soil moisture data having a water potential between -10 and -33 kpa (De Oliveira et al., 2015). The K_{sat} in the unsaturated zone of the aquifer was assumed equal to the K_{sat} in the Green Ampt model and a wilting point of 0.15 was used for all the swales. Lower groundwater loss rate was assumed 0.004 mm h^{-1}, based on a representative value of hydraulic conductivity for shallow aquitards (Zhuang et al., 2024). The upper limit of the initial soil moisture deficit range was defined by the difference between the porosity and wilting point.

2.3 Model optimization and scenario evaluation

For the model optimization a generalized likelihood uncertainty estimation (GLUE) (Beven and Binley, 1992) approach was used. 20 000 simulations with uniformly distributed parameter sets were run during the optimization phase, from 15 June to 31 of July 2025, generating flow and soil moisture outputs at a 5 minute interval. Behavioural parameter sets (i.e. sets resulting in good enough model performance) were selected based on a threshold criteria using Nash Sutcliff Efficiency (NSE_F) for flow rate and mean absolute percentage error ($MAPE_{SM}$) for soil moisture data defined as (Jackson et al. 2019):

$$MAPE_{SM} = 100 * \sum_{i}^{N} \left| \frac{SM_{i,obs} - SM_{i,sim}}{SM_{i,obs}} \right|$$

Where N is the number of available observation and $SM_{,obs}$ and $SM_{i,sim}$ are the observed and simulated soil moisture.

Two optimization scenarios were investigated, one using only flow data and another including also soil moisture data. In the first scenario, only parameter sets with NSE_F>0.75 were accepted. In the second, a combined criterion with NSE_F>0.75 and $MAPE_{SM}$ <15 was used for selecting the behavioural parameter sets.

The behavioral parameter sets for the two scenarios were then used to run simulations during a validation period between 1 August and 30 September 2025. For each scenario, the envelope of flow rate and soil moisture outputs were analyzed in terms of NSE_F for the flow rate and $MAPE_{SM}$ for the soil moisture. Median value and 90% interval quantile of the efficiency metrics were calculated for the validation period for each scenario. Prediction intervals were generated as the central 90% interval of the simulated values. These prediction intervals were then evaluated in terms of their spread measured with the average interval length (AIL) in the sections where observed data were available:

$$AIL = \frac{\sum_{i}^{N} p95_i - p05_i}{N}$$

Where $p95_i$ and $p05_i$ are the upper and lower limit of the quantile prediction interval.

3 RESULTS

The first scenario (based only on NSE_F) resulted in 6 475 accepted sets of parameters out of 20 000, while adding the criteria on soil moisture resulted in only 394. Results from the validation period runs are shown in Figure 1. The introduction of a threshold for soil moisture data did not have a great impact on the overall predictions for the flowrate, causing only a slight reduction of the median NSE_F. In contrast, predictions of soil moisture were overall positively affected when adding a soil moisture criterion during the optimization process. The median value of $MAPE_{SM}$ was slightly reduced for all the swales, with more than 20% reduction for Swale B, which had the worst prediction performances. In particular, the lowest performance (highest MAPE) was improved considerably when adding soil moisture data in the model.

As reported in Table 2 the average interval length (AIL) for both flow and soil moisture showed a reduction when optimization was carried out including soil moisture, meaning a reduction of overall prediction uncertainty with the latter criteria.

Low percentage of observed data covered by the quantile prediction interval (Cov. (%)) were observed for the flow and soil moisture of swale B and a decrease was observed for all the outputs except swale B when introducing soil moisture data, as showed in Table 2. The low Cov. (%) values for the flow rate highlighted that some adjustments to the model setup are still needed. However, the reduction of Cov. (%) is consistent to some extent with the tightening of the interval itself considering that the prediction performances of the soil moisture improve, but the exact cause of this reduction was not determined in this work.

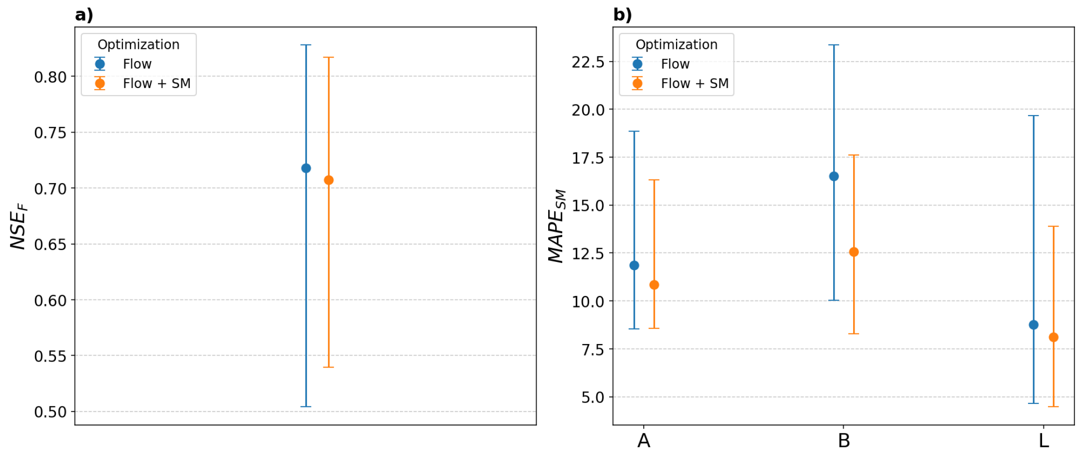

Figure 1 Median and 90% quantile range of a) NSE_F (flow) and b) $MAPE_{SM}$ (soil moisture) from the validation period

Table 2 Average interval length (AIL) and % of observed value within the 90% quantile prediction interval Cov. (%)

SCENARIO	AIL_F (l/s)	AIL_{SMA} (m^3/m^3)	AIL_{SMB} (m^3/m^3)	AIL_{SML} (m^3/m^3)	Cov. (%) flow	Cov. (%) SM_A	Cov. (%) SM_B	Cov. (%) SM_L
Flow	1.55	0.090	0.051	0.099	23.4	77.5	7.6	77.4
Flow + Soil moisture	1.39	0.068	0.039	0.077	19.3	70.9	10.2	73.4

4 CONCLUSIONS

The comparison of two calibration scenarios, one using only flow data and another one using also soil moisture data, highlighted that the latter approach reduced model prediction uncertainty for both flow and soil moisture output. However, in this second scenario only soil moisture predictions were more accurate, while for the flow rate the NSE was slightly reduced.

While this shows the potential for improving overall urban drainage models performance, more investigations are necessary to understand in detail which calibration configurations can lead to benefit both in terms of model accuracy and uncertainty reduction.

Furthermore, refinement of the model setup is needed to enhance the coverage of observed data by the prediction interval.

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