Assessing spatial soil moisture patterns at a small agricultural catchment

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***Abstract*— A good understanding of soil moisture spatial patterns is useful for assessing the hydrological connectivity and runoff generation processes in a catchment. Thus, we have applied numerical modelling approaches to investigate the spatial patterns of soil moisture at the Nučice experimental catchment (0.531 km^2) in the Czech Republic. The catchment was established in 2011 to observe the rainfall-runoff processes, soil erosion and water balance in an agricultural landscape. The catchment consists of three fields covering over 95 % of the area. Eight field surveys were conducted to capture the soil moisture patterns at different scales. Even though the soil management and soil properties in the fields of Nučice seem to be nearly homogeneous, we have observed spatial variability in topsoil moisture. In numerical simulations, a 3D spatially-distributed model MIKE-SHE was used to simulate the water movement within the catchments. The MIKE-SHE simulation has been mainly calibrated with rainfall-runoff observations and point-scale soil moisture data. In the simulation, we have obtained the spatial patterns of soil moisture at each time step. The soil moisture spatial patterns from the simulation have been compared with the density of the vegetation cover (NDVI), and topsoil moisture patterns from field surveys. We found that the density of vegetation cover has a good correlation with the soil moisture spatial distribution. However, this correlation was not captured in the MIKE-SHE simulation. Future research will include Cosmic-ray neutron sensing and stable isotope analysis to improve the current understanding of the catchment.**

Keywords—soil moisture, hydrological processes; agricultural catchment; hydrological modelling

I. Introduction

Soil moisture is an essential parameter in hydrology, as it has a crucial influence over the infiltration process. Besides, the understanding of soil moisture dynamics is important in the field of agriculture for efficient crop and irrigation management. Therefore, it is necessary to have well-recorded spatially distributed soil moisture measurements in agricultural catchments to understand its dynamics.

There are many methods to monitor soil moisture. Conventional time-domain reflectometry (TDR) and time-domain transmissometry (TDT) in-situ point measurements can provide stationary soil moisture dynamics at various depths. However, the topsoil is usually highly influenced by agricultural activities. Also, the investigation of the soil moisture spatial pattern requires numerous sampling points. Besides, remote sensing can provide a wide range of soil moisture information at a shallow depth (2-5 cm), although this technique is limited by vegetation cover and surface roughness [1]. It becomes very problematic to monitor soil moisture at the high spatial and temporal resolution at the catchment scale [2, 3]. Also, observations of topsoil moisture content in catchments with intensive agricultural activity are more difficult as the sensors need to be removed prior to tillage operations [4, 5]. Besides, some studies indicate that physically-based hydrological models (e.g., Hydrus, HydroGeoSphere, MIKE SHE and ParFlow-CLM) are capable of simulating the dynamics of soil moisture at the catchment scale [6, 7]. Therefore, hydrological modelling can also be a useful tool to analysis soil moisture spatial patterns.

This study aims to investigate the spatial variability of soil moisture at the Nučice catchment. To accomplish this, we calibrated the MIKE-SHE model with stream discharge and point-scale soil moisture observations. Later, we obtained the soil moisture spatial patterns from the simulation. Meanwhile, we have conducted eight field surveys to measure the topsoil moisture spatial distribution across the catchment. We compared the observed and simulated soil moisture data with meteorological data to understand the correlation between the changes of topsoil moisture content and the variation of precipitation and air temperature. Further, we assessed how the soil moisture patterns from both the simulation and field surveys are correlated with vegetation cover (Normalized Difference Vegetation Index (NDVI)) at the catchment.

II. Study area

The study was conducted at the Nučice experimental catchment in the Czech Republic. The catchment (0.531 km^2) has the average elevation of 401 m a.s.l. (ranging from 382 to 417 m a.s.l.) and the average slope of 3.9 % (varying between 1 % and 12 %). A gauging station was installed in 2011 at the catchment's outlet (49°57'49.230"N, 14°52'13.242"E). Since then the metrological and hydrological characteristics of the catchment have been monitored. The climate condition at the catchment is humid continental: the average air temperature is 6 °C, with an annual mean precipitation of 630 mm and annual mean evapotranspiration of 500 mm. A homogenous land use pattern covers the whole catchment: more than 95 % is arable land, while the remaining parts are covered by the watercourse, riparian trees and shrubs, and paved roads. The soil is tilled to depth of approximately 12 cm and a plough pan is well-developed under the tilled topsoil. The topsoil has loamy texture with content of 9 % clay, 58 % silt, and 33 % sand. The bedrock is located at depths from 6 to 20 m based on geophysical monitoring. The catchment (Fig 1) is divided into 3 separate agricultural fields (1: the upper field, 2: the left field, and 3: the right field) with slightly different agricultural operations conducted during the soil moisture surveys [8, 9].

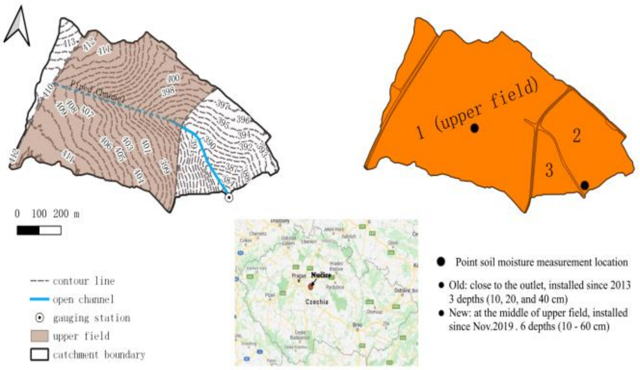

Fig 1.Location of the Nučice experimental catchment

III. HYDROLOGICAL MODELLING

MIKE-SHE is a fully-distributed, physically based, integrated hydrological modelling system [10–12]. MIKE-SHE covers the major processes in the hydrologic cycle, which includes evapotranspiration, infiltration, overland flow, unsaturated flow, groundwater flow, channel flow and their interactions [13]. Since the MIKE-SHE modelling system is user-friendly and well documented, many studies have applied MIKE-SHE to analyse hydrological processes (e.g. water balance, soil moisture) at the catchment scale [6, 14, 15].

TABLE 1. THE RESOLUTION OF THE NUČICE MODEL. (OL STANDS FOR THE OVERLAND FLOW, SZ REFERS TO THE SATURATED ZONE AND THE UZ TO THE UNSATURATED ZONE.)

Area	0.531 km^2
Grid size	10×10 m^2
Number of grid cells in each layer	5317
Number of layers in UZ	26
Number of layers in SZ	1
Depth of the SZ	5 m
Time steps in OL and UZ	1 hour
Time step in SZ	12 hours

The MIKE-SHE model at the Nučice catchment was simulated from 2013 to 2020 in hourly timestep with one-year warm-up period. The grid size in the horizontal plane is 10 m based on the DEM input. More detailed description of the resolution of the model in each module can be found in TABLE 1. The physical processes of the model are based on the following description: 1-D channel flow is assumed and based on Saint-venant equations. 2-D overland flow routing is based on the diffusive wave approximation of the Saint-venant equations, and 1D unsaturated flow is assumed and based on the Richard's equation. 2-D groundwater flow is assumed and simulated by one computational layer with the depth of 5 m in the saturated zone. The outer boundary condition of the saturated zone is defined as no-flow boundary and the lower boundary of the unsaturated zone is a pressure boundary which is determined by the water table elevation. To reduce the numerical errors, the bottom of the unsaturated zone is extended to the bottom of the saturated zone. An agricultural drainage system is defined by the underground drainage flow in the saturated zone occurring when the groundwater table exceeds the drain level. The level of drainage is set at the depth of 0.7-1 m.

The evapotranspiration mainly consists of soil evaporation and crop transpiration which depends on soil moisture in the unsaturated root zone. The plant indices are defined based on the leaf area index and root depth and are spatially distributed in the model based on the land-use: the crops in the three fields are set as winter wheat with similar growth circles. The bushes close to the stream are defined with the constant leaf area index and root depth. No vegetation is assigned to the paved roads.

The soil spatial distribution is based on the land-use and point-scale soil moisture observations. The tilled topsoil (the top 12 cm) is homogenously distributed across the three fields while the paved roads between the fields are set as compacted layers with low permeability. The subsoil (below the 12 cm depth) of the upper field are slightly different from the rest of the fields discovered due to the different behaviors of point-scale soil moisture found between the upper and lower fields (Fig 1).

The temporal resolution differs between modules: the maximum allowed time step specified for overland flow and unsaturated flow is 1 hour, and 12 hours for saturated flow (TABLE 1).

TABLE 2. THE SELECTED PARAMETERS FOR MODEL CALIBRATION.

Parameters	Units	Lower	Upper	Module
Manning	m s^{-1}	0.01	10	OL
Horizontal hydraulic conductivity	m s^{-1}	1e-7	1e-5	SZ
Vertical hydraulic conductivity	m s^{-1}	1e-7	1e-5	SZ
Drainage depth	m	-1	-0.7	SZ
Drainage time constant	s^{-1}	1e-9	1e-6	SZ
Hydraulic conductivity (topsoil)	m s^{-1}	1e-7	1e-5	UZ
Hydraulic conductivity (subsoil)	m s^{-1}	1e-8	1e-5	UZ
Alpha (topsoil)	cm^{-1}	0.01	0.035	UZ
Alpha (subsoil)	cm^{-1}	0.01	0.035	UZ

The calibration period is mainly in 2014 and 2020 was selected for validation period. During the model calibration, the soil parameters in the unsaturated zone always influence the soil moisture dynamic in the MIKE-SHE output [6]. Also, the drainage parameters play an important role in agricultural catchments [15]. Therefore, the saturated hydraulic conductivity in the unsaturated zone (UZ) and drainage parameters have been mainly selected for the calibration of the Nučice model (TABLE 2). All the sensitive parameters are calibrated using the MIKE calibration tool AUTOCAL. As calibration data we use the hourly runoff observation at the catchment outlet, and the hourly output from the soil moisture sensors at two different locations (Fig 1) and at each depth.

IV. SOIL MOISTURE FIELD MEASUREMENT

In this study, we used point-scale soil moisture measurement to evaluate the MIKE-SHE simulation. Besides, we conducted eight measurements with two Hydrosense II probes (Campbell Sci., UK) at the Nučice catchment during the winter and spring seasons (when the topsoil was not covered by crops and less influenced by agricultural activities). The Hydrosense II probe is a handheld TDT soil moisture sensor with 12 cm rods, which records the real-time soil moisture content with GPS location. The calibration functions were calculated for both Hydrosense II probes via gravimetric analysis of disturbed soil samples from the Nučice catchment.

The eight field surveys were conducted to cover the soil moisture distribution (TABLE 3). Two of the surveys covered the whole catchment while the rest were restricted to the upper filed or its hill-slope. The upper field covers a much larger portion of the catchment compared to the other two fields and contains only one homogenous farmland cultivated by one farmer using the same cultivation method.

The NDVI values were calculated from satellite images [16] during the field measurement campaigns with a spatial resolution of 3m.

TABLE 3. SUMMARY OF FIELD SURVEYS

Date	No. of points	scale	7 days antecedent rainfall (mm)	mean temperature (°C)
2019-10-01	1011	Field	8.8	15.28
2019-10-09	1274	Catchment	24.4	8.28
2019-11-06	159	Hillslope	5.5	5.77
2019-11-20	93	Hillslope	9.1	6.08
2020-01-16	1168	Field	1.1	2.17
2020-03-19	2043	Field	2.6	7.29
2020-03-27	936	Catchment	2	1.13
2020-05-12	186	Field	33.8	11.13

V. Results and Discussion

The model overall showed a good agreement with both the soil moisture dynamics at each depth (with Nash-Sutcliffe efficiency (NSE) above 0.7) and the stream discharge (with the NSE above 0.45) during the calibration (Fig 3).

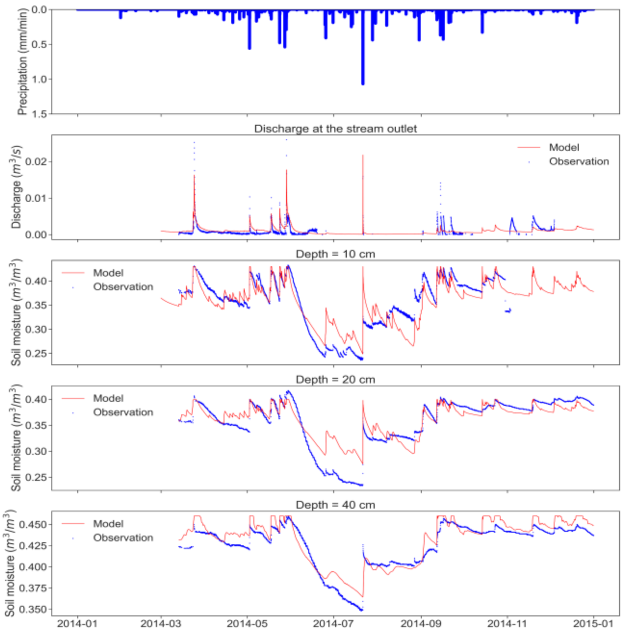

Fig 2. The time series of observation and simulation during the calibration period.

However, according to the NSE, the model performance on soil moisture dynamics were considerably better than the performance on the stream discharge. We have observed that the runoff at the Nučice catchment often reacts rapidly to rainfall events. Also, a previous study [17] suggests that the simulated runoff fits better with the flow during the vegetated seasons (approximately from April to October) than the discharge during the winter seasons. The runoff calibration result shows that the model can capture the fast runoff events during the vegetated season while it fails to fit the fast runoff events in the autumn and winter seasons and the baseflow in general (Fig 2). The reason for this could be that the model has overestimated the evapotranspiration during the autumn and the uncertainty of runoff measurement during the winter due to the frozen of the sensors.

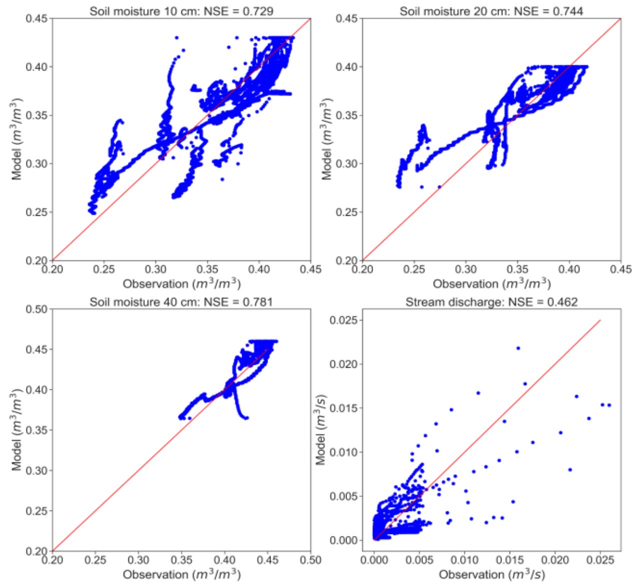

Fig 3. The comparison between the observed and simulated soil moisture and discharge during the calibration period.

During model validation, we compared the simulated runoff with the stream discharge at the outlet in 2020 (Fig 4). Further, because of the data gap and damage to the old soil moisture sensors, only the new soil moisture sensors at the upper field were used for the validation of the soil moisture dynamic (Fig 5).

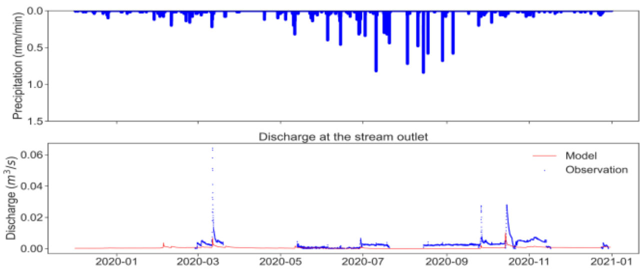

Fig 4. The rainfall (upper panel) and simulated runoff with observation during the validation period (lower panel).

Although the model performance is poorer during the validation period, the simulated soil moisture dynamic maintained relatively good performance during the validation period. Especially the top layer (10 cm depth) had the best fit result with an NSE of 0.56. For the soil moisture variation in the deeper layers (depth from 20 to 60 cm), the model overestimated the soil moisture during dry conditions while it underestimated the soil moisture value in the wet season. Hence, we need to increase the variation of the soil moisture in the subsoil to improve the model performance.

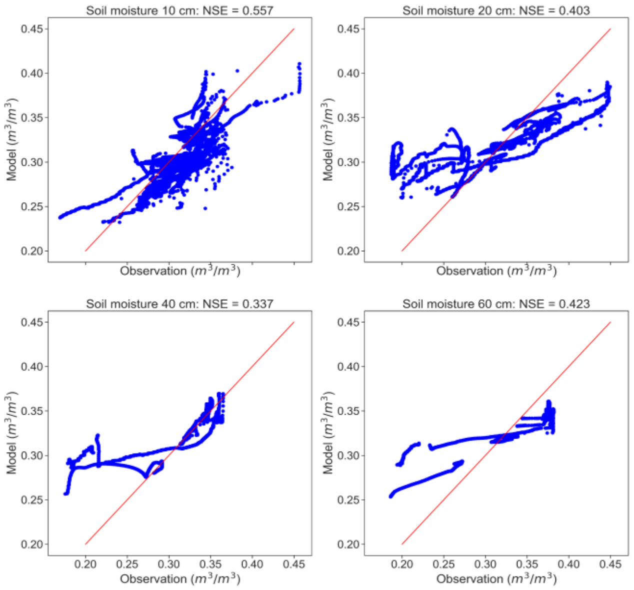

Fig 5. The comparison between the observed soil moisture dynamics from the sensors at the upper field and simulated soil moisture during the validation period.

In contrast to the soil moisture dynamics, the simulated runoff had poor performance during the validation period (Fig 4). Overall, the model underestimated the fast runoff events and the baseflow. Especially after July, the observed baseflow is much higher than the simulated runoff. The reason could be the model was trained during the relatively dry period with low baseflow conditions. Thus, the parameters need to be redefined under wet conditions for the future simulations.

TABLE 4. THE WATER BALANCE OF THE WHOLE SIMULATION PERIOD. (P REFERS TO PRECIPITAION, E TO EVAPORATION AND T TO TRANSPIRATION, AND Q STANDS FOR RUNOFF, Δ IS THE CHANGE OF THE SUBSURFACE STORAGE.)

Year	P (mm)	E (mm)	T (mm)	Q (mm)	Δ
2013	571	220	170	102	74
2014	573	298	232	61	-18
2015	455	179	279	44	-49
2016	529	221	273	44	-9
2017	295	151	245	25	-126
2018	388	167	239	9	-27
2019	546	198	277	13	56
2020	666	308	227	30	100

Also, the model was running continuously from 2013 to 2020, the gap of rainfall observation in 2017 significantly affected the storage in the subsurface (TABLE 4) which could further deteriorate the model performance during the validation period. Noticeably, the simulated discharge in 2020 is lower than 2014 while the precipitation in 2020 is about 100 mm higher than 2014. Therefore, future studies need to take this into account and use modified precipitation data in 2017, which should be filled with the neighboring weather stations or the average values from the other years. Besides, future simulations could also be conducted in two separate periods: 2013-2016, and 2018-2020 to avoid the data gap.

TABLE 5. THE RUNOFF COMPONENTS IN EACH YEAR. DRAIN REFERS TO THE SUBSURFACE DRAINAGE, OL IS THE OVERLAND FLOW.

Year	Drain (mm)	OL (mm)	Baseflow (mm)
2013	63	27	12
2014	44	5	12
2015	31	3	9
2016	32	2	10
2017	18	1	6
2018	5	0	4
2019	8	0	5
2020	21	2	7

In TABLE 5, the simulated runoff is mainly attributed to the subsurface drainage in the model while the overland flow contributed the least to the runoff. Besides, the subsurface storage changes (TABLE 4) influences the amount of baseflow which contributes to the stream discharge. In the model, the fast runoff reaction is mainly attributed to the subsurface drainage, whereas the baseflow contributes to the discharge in low flow conditions. Clearly, the groundwater level in the simulation plays an important role in controlling the amount of discharge because both the subsurface drainage and the baseflow are directly affected by the changes of the groundwater level. Thus, it is necessary to further investigate the subsurface condition at the catchment and then include the groundwater observations into the calibration process.

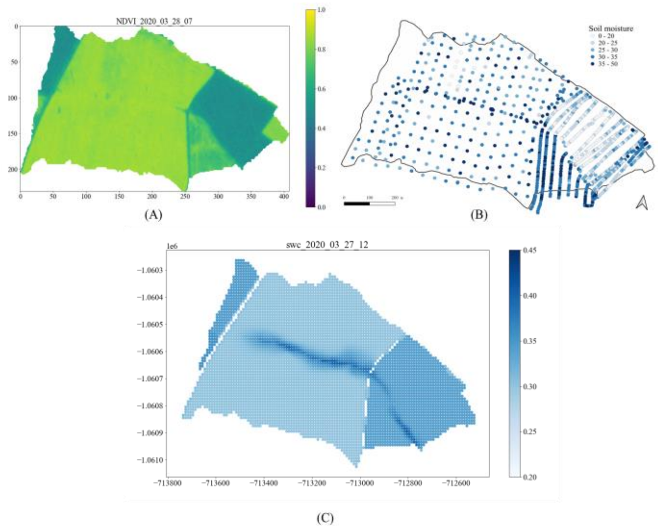

Fig 6. The comparison between the NDVI, the soil moisture survey and the topsoil moisture output from the MIKE-SHE model: (A) is the NDVI values obtained from the satellite image taken on the date close to the field survey; (B) is the soil moisture distribution at the catchment from the field survey on 2020-03-27; (C) is the soil moisture at the top 2 cm layer from the MIKE-SHE model on the same as the field survey.

The spatial patterns of the simulated soil moisture at the topsoil has been further investigated. We compared the simulated soil moisture with the NDVI and one soil moisture survey on 2020-03-27 (Fig 6). The spatial pattern of the simulated soil moisture on 2020-03-27 showed that the spatial variations in the model are mainly dominated by the topography, land use and soil types. On the other hand, the soil moisture from the field survey (2020-03-27) showed similar spatial patterns as the NDVI map from the satellite image which was taken one day after the field survey (Fig 6). Notably the soil moisture is higher when the field is covered by vegetation with relative higher NDVI values on the right field. Whereas the topsoil is dryer when there is no vegetation cover with relative lower NDVI values on the left field. The reason could be that the vegetation cover can reduce the evaporation in the topsoil layer caused by wind and solar radiation. Moreover, the roots of the vegetation may "lift" the water from the subsoil to the rootzone which increases the moisture content in the topsoil.

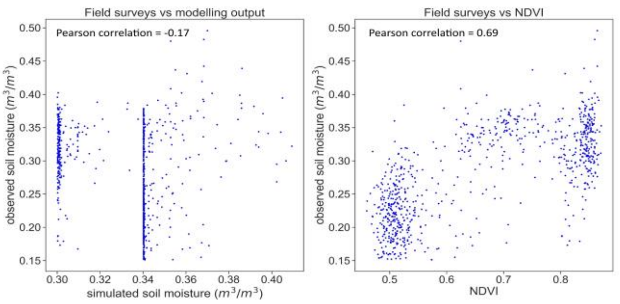

Fig 7. The comparison of the field measurements (2020-03-27) with the modelling output (left) and the NDVI (right).

To further demonstrate the relationship between the field surveys, the modelling output, and the vegetation density, we plotted the field survey results with the modelling output and the NDVI values, respectively (Fig 7*).* Subsequently, the Pearson correlation coefficient was calculated for the field survey against both the modelling output and the NDVI values (Fig 7). We noticed that the soil moisture from the field survey had a good correlation with the density of vegetation cover (NDVI values) while the simulated results failed to align with the observed soil moisture. In the MIKE-SHE simulation, the vegetation and the root water up take only contribute the transpiration function which reduced the water in the subsurface. In other words, the reduction of the soil evaporation ascribable to the vegetation cover is not considered in the MIKE-SHE modelling processes. Consequently, the MIKE-SHE model is not able to capture the spatial variation of the moisture content in the topsoil due to the differences in the density of vegetation cover. Therefore, the future studies should focus on the comparison of the MIKE-SHE modelling output and the soil moisture spatial patterns from the field surveys with homogenous vegetation cover or no vegetation cover. Additionally, the topographic indexes (e.g. elevation, slope, and TWI) need to be included in the comparison.

VI. SUMMARY

In this study, we applied numerical modelling to assess the soil moisture dynamics at the Nučice catchment. The MIKE-SHE model is calibrated and validated with soil moisture dynamics at point sensors in two different fields and the discharge measurements. In general, the model had good agreement with the observed soil moisture dynamics, especially in the topsoil. However, the model had relatively poor performance on the runoff simulation, especially during the validation period. Therefore, we need to analyze the rainfall runoff regime in both wet and dry period to improve the model outcomes. In addition, the groundwater levels at the catchment should be investigated and included into the model calibration processes to enhance the reliability of the model. Moreover, eight field surveys were conducted to capture the soil moisture patterns at different scales. Based on the field surveys, we found the topsoil moisture content at the catchment is highly dynamic even with homogenous land-use patterns. In this paper, we compared the soil moisture spatial patterns from the modelling output with the field surveys and vegetation covers. We found a good correlation between the density of vegetation cover and the variation on the moisture content in the topsoil from the field survey. Nonetheless, there is less similarity found between the modelling output and field survey of the moisture content in the topsoil. We believe that the physical description of the MIKE-SHE model cannot capture the spatial variation of the topsoil moisture caused by the differences in the density of vegetation cover. Thus, we suggest comparing the simulated soil moisture spatial patterns with the topographic indexes (e.g., elevation, slope, and TWI) and the field surveys during the season with homogenous vegetation cover or no vegetation cover in future studies. Also, any future work should include other datasets (e.g., CRNS, stable isotope analysis) to further understand the soil moisture dynamics and runoff generation processes at the catchment.

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