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Could operational hydrological models be made compatible with satellite soil moisture observations?

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Abstract

Soil moisture is a significant state variable in flood forecasting. Nowadays more and more satellite soil moisture products are available, yet their usage in the operational hydrology is still limited. This is because the soil moisture state variables in most operational hydrological models (mostly conceptual models) are over-simplified – resulting in poor compatibility with the satellite soil moisture observations. A case study is provided to discuss this in more detail, with the adoption of the XAJ model and the Soil Moisture and Ocean Salinity (SMOS) level-3 soil moisture observation to illustrate the relevant issues. It is found that there are three distinct deficiencies existed in the XAJ model that could cause the mismatch issues with the SMOS soil moisture observation: i) it is based on runoff generation via the field capacity excess mechanism (interestingly, such a runoff mechanism is called the saturation excess in XAJ while in fact it is clearly a misnomer); ii) evaporation occurs at the potential rate in its upper soil layer until the water storage in the upper layer is exhausted, and then the evapotranspiration process from the lower layers will commence – leading to an abrupt soil water depletion in the upper soil layer; iii) it uses the multi-bucket concept at each soil layer - hence the model has varied soil layers. Therefore, it is a huge challenge to make an operational hydrological model compatible with the satellite soil moisture data. The paper argues that this is possible and some new ideas have been explored and discussed.

Keywords: Flood forecasting, Operational hydrological modelling, Satellite soil moisture observation, SMOS, Xinanjiang (XAJ), NLDAS-2

1. Introduction

Soil moisture is a significant state variable in real-time flood forecasting [*Ochsner et al.*, 2013]. Over the past decades, numerous hydrological models have been developed, representing more or less accurately the main hydrological processes involved at a catchment scale [*Aubert et al.*, 2003]. The challenge in forecasting floods in a reliable way stems mainly from the error accumulation of the models, particularly during unusual hydrological events and after a long period of dryness. Solutions have thus been introduced to enhance flood forecasting by matching the model with the current observations prior to its use in forecasting mode – termed as updating or data assimilation [*Christian*, 1997]. Since hydrological models are highly sensitive to the state change of the soil moisture [*Aubert et al.*, 2003], a better soil moisture observation over a catchment should improve the forecasting performance via correcting the trajectory of the model [*Ottlé and Vidal-Madjar*, 1994]. Nevertheless it is still a challenge to accurately monitor soil moisture that varies both spatially and temporally. Conventional in-situ networks are expensive and impractical in large areas, and they are still too sparse to represent the spatial soil moisture distribution [*Al-Shrafany et al.*, 2013; *Srivastava et al.*, 2013a; *Srivastava et al.*, 2013b; *Walker et al.*, 2004; *Wang and Qu*, 2009]. Model based estimates such as those from land surface models are another source of soil moisture data, but they are uncertain due to imperfect parameterisation, meteorological forcing data and time drift problems (e.g., accumulation of errors) [*Ridler et al.*, 2014; *Xia et al.*, 2012].

Alternatively, modern satellite remote sensing has shown potential for providing soil moisture measurements at a large scale [*Engman and Chauhan*, 1995]. However, with all orbiting sensors, only the surface layer soil moisture can be acquired. It has been shown in many studies that the soil penetration depth is around 0.1 – 0.2 times the sensor wavelength, where the longest wavelength is only about 21 cm (L-band, with a penetrating depth ~ 5 cm) [*Oh*, 2000; *Ulaby et* *al.*, 1996]. Conversely operational hydrological models (most often the conceptual hydrological models) consider a much deeper surface soil depth (up to 2 m), which also varies across a catchment. This unfixed and non-uniform structure of the soil representation is specially designed to achieve a better flow prediction result, which has been conducted in many widely used hydrological models (e.g., XAJ [*Zhao*, 1980], VIC [*Liang*, 1994], PDM [*Moore*, 2007], ARNO [*Todini*, 1996], etc.).

Clearly there is a mismatch between the shallow satellite soil depth and the deeper soil layer considered in many hydrological models, which has caused a commensurate issue for the full utilisation of remotely sensed soil moisture products in operational hydrology. Although many studies have been carried out on the evaluation of satellite soil moisture observations for hydrological modelling [*Al-Shrafany et al.*, 2013; *Lacava et al.*, 2012; *Srivastava et al.*, 2013a; *Srivastava et al.*, 2013b; *Srivastava et al.*, 2014], with some correlations explored between the satellite soil moisture datasets and the hydrological models' soil moisture state variables, their results have limited success and could be improved further. One possible way is by analysing the fundamental differences between the hydrological model simulated soil moisture and the satellite measured soil moisture, so that the hydrological model itself might need to be modified accordingly (e.g., to improve the agility of some model parameters or have a fixed soil layer option) to better match the satellite measured soil moisture. Furthermore it is known that most operational hydrological models are designed to accurately predict flow, and their soil moisture state variables do not act in the same way as in the real world. As a result many conceptual hydrological models are not compatible with satellite soil moisture observations. A topical research question is whether we can improve the simulation of soil moisture from the current hydrological models, while maintaining or even improving the flow simulation performance.

In this context we first compare the major satellite soil moisture measurement techniques, then discuss some physical issues that could cause low effectiveness of the satellite soil moisture data in hydrological modelling, illustrate the shortcomings through a case study and make practical recommendations that should lead to improved compatibility of the satellite soil moisture products in hydrological modelling.

2. Spectral measurements for soil moisture estimation

Numerous studies have shown that near surface soil moisture (~ 5 cm) can be measured by many techniques including optical, thermal infrared and microwave [*Petropoulos et al.*, 2015; *Walker*, 1999]. The major differences among them are the region of electromagnetic spectrum employed, the power of the corresponding electromagnetic energy, the signal received by the sensors, and the relationship between the retrieved signal and the soil moisture [*Walker*, 1999; *Wang and Qu*, 2009]. Table 1 lists the advantages and limitations of each technique for surface soil moisture measurement and their characteristics. Only a brief description of them is summarised here and interested readers are encouraged to read further details from the references provided.

- *Optical*: it measures the reflected radiation of the Sun from the Earth's surface, known as the reflectance [*Sadeghi et al.*, 1984]. Its correlation with the soil moisture has long been recognised [*Ångström*, 1925]. Although there are a large number of optical sensors currently serving in orbit, relatively fewer studies have been carried out regarding their application in soil moisture assessment [*Muller and Decamps*, 2001]. This is partially because the optical sensors can only detect the reflectance or emittance at the top few millimetres of the Earth surface. Compared with the longer microwave wavelength, the optical signal is highly affected by cloud contamination and vegetation cover. Furthermore the received soil reflectance is not solely affected by the soil moisture, but also influenced by mineral composition, organic matter, soil texture and observation conditions, which makes this technique less popular for soil moisture estimation [*Moran et al.*, 2004; *Musick and Pelletier*, 1988]. Therefore the optical technique is normally applicable only under restricted conditions for soil moisture determination (e.g., with specific soil types, bare soil, and climate dominated by clear sky) [*Muller and Decamps*, 2001; *Wang et al.*, 2007].

- *Thermal infrared*: it measures the Earth radiative temperature, which is then converted to soil moisture either singularly or by combination with the vegetation index information obtained from the optical wavebands (e.g., Normalised Difference Vegetation Index (NDVI) from the MODIS satellite). Since soil water content governs the thermal properties (i.e., the soil thermal conductivity and the soil heat capacity) of the soil, it should be expected that regions with wetter soil are usually cooler during the day and warmer at night [*Griend and Engman*, 1985]. Driven by this concept a considerable number of studies have shown good accuracy of soil moisture measurements by this technique, such as through the simple thermal inertia approach [*Schmugge*, 1978] and the 'Universal Triangle' method [*Carlson et al.*, 1994; *Gillies et al.*, 1997]. While these approaches are powerful and have thorough physical meanings, they are still restricted by various factors, similar to those in the optical wavebands. Therefore their accuracy varies across time and meteorological conditions (e.g., wind speed, air temperature and humidity) [*Czajkowski et al.*, 2000; *Smith and Choudhury*, 1991]
- *Microwave*: its primary theory is based on the large contrast between the dielectric properties of water (~80) and dry soil (<5). Therefore when the soil becomes moist, the dielectric constant of the soil-water mixture rises, and this emission fluctuation is recorded by microwave sensors [*Dobson et al.*, 1985; *Njoku and Kong*, 1977]. For passive sensors, the retrieved emission from

the Earth surface is proportional to the product of surface temperature and surface emissivity, which is commonly referred to as the microwave brightness temperature [*Kerr et al.*, 2001]. For active sensors, a microwave pulse is first sent and then received. The power of the two signals is then compared to determine the backscattering coefficient of the surface, which has been proven to be sensitive to soil moisture [*Entekhabi et al.*, 2010]. For both sensor types, the measurement efficacy is related to wavelength, where longer wavelengths (> 10cm) penetrate deeper into the soil and have more ability to pass through cloud and some vegetation cover (such as the Soil Moisture and Ocean Salinity (SMOS) satellite with the L-band wavelength (21 cm), which is able to probe about 5 cm into the ground) [*Njoku and Kong*, 1977]. Comparatively, microwave bands have more advantages in soil moisture estimation than other spectral bands. With the modern microwave satellites such as the Advanced Microwave Scanning Radiometer on Earth Observing System (AMSR-E; from 6.9 to 89.0 GHz; [*Njoku et al.*, 2003]) which operated on the AQUA satellite between 2002 and 2011, the SMOS (1.4 GHz) launched in 2009 [*Kerr et al.*, 2001] and the Soil Moisture Active/Passive mission (SMAP; 1.20-1.41 GHz; [*Entekhabi et al.*, 2010]) which was just launched in early 2015, it is anticipated that more advanced soil moisture measurements would be available. Although many attempts have been made to link the microwave soil moisture products with in-situ networks [*Al Bitar et al.*, 2012; *Albergel et al.*, 2012; *Jackson et al.*, 2012], land surface models [*Ridler et al.*, 2014; *Ridler et al.*, 2012] and physical based hydrological models [*Laiolo et al.*, 2014; *Ridler et al.*, 2014], there is still a lack of sufficient research on their application in operational hydrological modelling.

Clearly there have been tremendous efforts and funds spent by many organisations to build up the global satellite soil moisture datasets for broad applications. However, utilisation of these products in hydrology is still in a state of infancy, especially in real-time flood forecasting. Therefore the following case study is employed to explore in more detail the potential problems that could cause this phenomenon.

3. Case study – data and methodology

In this section, an example is provided to discuss the existing mismatches, through a comparison between a widely used conceptual hydrological model - XAJ [*Zhao*, 1980] and a satellite soil moisture observation system (i.e., SMOS).

3.1 Study area and datasets

The Vermilion River at Pontiac, (1500 km^2) is a medium sized catchment, which is located in central Illinois, USA (40.878°N, 88.636°W). It has a hot summer continental climate [*Peel et al.*, 2007], and is covered primarily by cropland [*Bartholomé and Belward*, 2005; *Hansen*, 1998] on Mollisols [*Webb et al.*, 2000]. Average annual rainfall is 867 mm. The layout of the Pontiac catchment is shown in Fig. 1 along with the location of its flow gauge, NLDAS-2 grids (a total of 20 grids) and distribution of the river networks.

The NLDAS-2 [*Mitchell et al.*, 2004] precipitation (P) [*Daly et al.*, 1994] and potential evapotranspiration (PET) at 0.125^{o} spatial resolution and daily temporal resolution (converted from hourly resolution) are selected as the data input to the XAJ model. Both PET and P datasets have been transformed into one catchment-scale dataset using the weighted average method to operate the lumped XAJ model. Readers are referred to [*Xia et al.*, 2012; *Zhuo et al.*, 2015b] for a full description of the NLDAS-2 data products. The USGS daily flow data from January 2010 to April 2011 have been selected as the XAJ calibration dataset and the period of May 2011 to

December 2011 is employed for validation. The SMOS level-3 soil moisture dataset used in this study is from the SMOS Barcelona Expert Centre (SMOS-BEC) [*BEC-SMOS*, 2013], covering the period between January 2010 and December 2013. The retrieved soil moisture dataset has been converted into a catchment-scale dataset by the weighted average method.

3.2 XAJ hydrological model

The XAJ model, developed in the 1970s, is a well-tested conceptual rainfall-runoff model [*Zhao*, 1992; *Zhao et al.*, 1995]. It is the first hydrological model that introduced the multi-bucket concept with improved flow modelling result, and its concept has been adopted in many other hydrological models such as the PDM, ARNO and VIC models [*Beven*, 2011]. Therefore the XAJ model is selected in this study as a typical conceptual hydrological model.

XAJ's main concept is the generation of runoff on repletion of its storage capacity, which means that runoff is not generated until the soil water content of its aeration zone reaches field capacity. It has been widely applied to numerous catchments around the world [*Khan*, 1993; *Rahman et al.*, 2015; *Reed et al.*, 2004; *Wang*, 1991; *Zhao*, 1992]. The adopted flowchart of the XAJ model is illustrated in Fig. 2. It includes an evapotranspiration unit, a runoff production unit and a runoff routing unit. The runoff component is also known as a water balance model which simulates lumped values of runoff into surface, interflow and groundwater components according to the free water storage. The simulated effective rainfall (runoff) is then routed as river flow through a routing module to the catchment outlet. The Muskingum routing method is applied in this study. The XAJ model only requires areal mean P and PET data as model inputs and the measured flow for model calibration and validation [*Peng et al.*, 2002]. In this study the XAJ model's 17 parameters are calibrated using measured flow [*Zhao*, 1980; *Zhao*, 1992].

There are three soil layers (upper, lower and deep) that represent the three evapotranspiration components in the XAJ model; and their corresponding soil moisture states are represented by the Soil Moisture Deficit (SMD, m). SMD is a significant soil moisture indicator in hydrology, which demonstrates the amount of water to be added to a soil profile to bring it to the field capacity [*Calder et al.*, 1983; *Rushton et al.*, 2006]. In this study only the upper soil layer's SMD (referred to as SMD hereafter) is used to compare with the SMOS surface soil moisture retrievals. The SMD can be calculated using the following equation (Srivastava et al., 2013b):

$$SMD = FC - SMC \tag{1}$$

where *FC* is the field capacity, which is considered as the upper limit in hydrological modelling for soil water storage; *SMC* is the soil moisture content. In the XAJ model, FC is not uniform over the whole catchment, which is represented by a soil water storage curve. This means that FC varies across the catchment. This is also true with the SMD and the SMC which are also nonuniform. Therefore Eq. 1 is true at any catchment point. If an integration is applied to all the three variables over the whole catchment, Eq. 1 is also true in the integrated form with its effective values.

3.3 SMOS surface soil moisture measurement

Among all the microwave sensors, SMOS is the first mission dedicated to monitoring direct surface soil moisture and sea surface salinity on a global scale [*Kerr et al.*, 2010]. It has been providing soil moisture data for almost six years since its launch in 2009. SMOS detects the brightness temperature at the frequency of 1.4 GHz (L-band, 21 cm), which is a function of the emissivity and hence the near surface soil moisture (approximately 5 cm). The spatial resolution is 35-50 km [*Kerr et al.*, 2001; *Kerr et al.*, 2010] with soil moisture retrieval unit in m^3/m^3. SMOS gives a global coverage at the equator crossing times of 6 am at the local solar time (LST) (ascending) and 6 pm (LST, descending), with an accuracy of approximately 0.04 m^3/m^3 [*ESA-cci*, 2013; *Kerr et al.*, 2012]. In this study the daily SMOS-BEC [*BEC-SMOS*, 2013] soil moisture product with the EASE grid (Equal Area Scalable Earth grid) is employed, because the EASE grid is widely used. In addition only the descending dataset is considered, because it has been found that the performance of descending retrievals is much better than ascending values in this catchment [*Zhuo and Han*, 2015; *Zhuo et al.*, 2015a]. Readers are referred to [*Kerr et al.*, 2012] for a full description of the retrieving method.

4. Case study - results and discussion

The Nash-Sutcliffe Efficiency (*NSE*) [*Nash and Sutcliffe*, 1970] is used as an objective function for XAJ calibration and validation because it is the most widely applied formula for examining the performance of the hydrological models [*Krause et al.*, 2005]. It is calculated as:

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Q_i - \hat{Q}_i\right)^2}{\sum_{i=1}^{n}\left(Q_i - \bar{O}\right)^2} \qquad (2)$$

where Q_i is the observed flow, $\hat{Q}$ is the simulated flow, and $\bar{O}$ is the mean value of the observed flow. n is the number of data pairs.

4.1 XAJ flow simulation

The XAJ parameters calibrated in this study are described in Table 2 with the ranges used and the optimal values. The time series plots of rainfall and flow during the calibration and validation periods are presented in Fig. 3. It is indicated by the hydrographs that the XAJ model matches the observed flow relatively well while there is a slight deviation at some points during the calibration period, revealing that the model is incapable of perfectly simulating the non-linear behaviour of the hydrological processes. This is particularly evident during the recession curves and the low flow periods. For the validation period there is an overestimation of the overall flow, which could be the result of the approaches used for model parameter identification or the defect of the model structure itself. Nevertheless, during most of the monitoring periods the XAJ model produces a relatively good performance and both *NSE* values are sufficiently high ($NSE \geq 0.8$) for an acceptable hydrological model. In another word, the generated SMD should be a reliable indicator of the catchment soil moisture (albeit in an inverse relationship), given the fact that the XAJ model is able to simulate the hydrological processes in the catchment, even though the model is calibrated using the river flow. Therefore from the point view of hydrological modelling, the generated SMD could be regarded as a benchmark to evaluate a soil moisture product before employing it for practical usage (e.g., through data assimilation, observed soil moisture could be used to update the model's soil moisture state variable during real-time flood forecasting [*Al-Shrafany et al.*, 2013; *Srivastava et al.*, 2013a; *Srivastava et al.*, 2014]). Details on the XAJ flow simulation in this catchment can be found in *Zhuo et al.* [2015a].

4.2 XAJ soil moisture simulation

The time series of the SMOS soil moisture measurement and the XAJ SMD are illustrated in Fig. 4. It is clear that there are some interesting phenomena that need to be explored. As seen from Fig. 4, the XAJ SMD ranges from as low as 0 m (i.e., at field capacity) to the maximum value at 0.047 m (i.e., total dryness). However, for the SMOS soil moisture the data points are more freely dispersed and there is no evident limiting boundary at either end. In addition there are a considerable number of days where the soil is completely dry at the maximum value of the SMD, which is infrequent in a cropland catchment. Moreover the XAJ simulated soil moisture dries up more quickly than the SMOS retrievals (i.e., the XAJ soil moisture stops at 0.047 m SMD, while the SMOS observed soil moisture is still in the progress of drying). Once the XAJ soil water gets to field capacity (i.e., 0 m SMD), it will not hold any more water. This is because in the XAJ model, the excess rainfall (above field capacity) becomes runoff and is therefore excluded from the soil water component immediately.

To further explore the reasons for the aforementioned phenomena, it is necessary to investigate the soil water mechanism of the XAJ model. The distribution of the tension water capacity in the XAJ model is illustrated in Fig. 5. It is evident that in the real field situation there are four typical states of the soil moisture: saturation, field capacity, wilting point and total dryness (Table 3). In reality, after a heavy rainfall event, the top layer soil should saturate fairly quickly, and then it can take approximately 2-3 days for the excess water to be drained away to reach field capacity [*Rubin*, 1966; *Veihmeyer and Hendrickson*, 1931]. However, in the XAJ model any excess soil water above field capacity after a rainfall event (i.e., the shaded area marked with R) will be moved immediately to a free water tank (i.e., marked with F), which will then be separated into individual runoff components (i.e., immediate surface runoff and gradually released interflow runoff and runoff as percolation into groundwater). Clearly there is a gap between the field capacity curve (the upper soil moisture limit in the XAJ model) and the saturation curve (as in the SMOS soil moisture observation). This runoff mechanism has been widely adopted in many well-known hydrological models (such as the PDM model [*Moore*, 2007] and the HBV model [*Lindström et al.*, 1997]), because it is very effective in flow simulation. Another incongruity is that evaporation in the XAJ model occurs at the potential rate at its upper soil layer and until the water storage in the upper layer is exhausted, the evapotranspiration process from the lower layers will not commence - leading to an abrupt soil water depletion as shown in Fig. 4. Clearly, this is not realistic, as in the real field situation soil water in the deeper layers has already started to replenish through the capillary rise action. Capillary action is dependent on the diameter of the water conduit, and it is known that the smaller the conduit diameter the higher the rise would be and vice versa. However the water movement rate of capillary action is proportionate to the cross-section area of the conduit (i.e., water moves faster in a larger conduit due to higher hydraulic conductivity, and slower in a smaller conduit due to lower hydraulic conductivity). If the soil is wet and its pores are mostly filled with water, the conduit for the water movement is relatively large (i.e., almost the same size as the pores of the soil). Therefore capillary rise is able to move a large quantity of water at a faster rate from a lower soil level to a higher soil level (albeit with a limited lower height). As the soil dries up, only smaller parts of the pores are filled with water and the conduit used to convey water is narrower (i.e., equivalent to a smaller diameter). As a result, capillary action is only able to move a small quantity of water at a reduced rate from a lower level to a higher level, but with a much larger height (i.e., from the deeper soil). In summary, capillary action is more significant when the upper soil layer is wet (not when it is dry), and then its movement rate is less so as the soil dries up. Therefore the lower soil moisture limit set in the original XAJ model is wrong and could be somewhere above the wilting point (the real lower limit depends on individual catchment conditions) as shown in Fig. 5.

The reason why XAJ can simulate river flow commendably is that it is only interested in river discharge at the outlet. Hence the immediate removal of the excess water from the soil component to a temporary free water storage will not have significant impact on the flow output. However, the XAJ model is not able to generate realistic soil moisture information for the catchment, especially in the upper soil layer. This flaw in the model soil moisture representation greatly reduces its compatibility with the satellite soil moisture data. In addition, the XAJ soil layers are not fixed. Unlike a bucket model with a fixed size, XAJ conceptualises that a catchment should be made of a large number of buckets with different sizes in each soil layer. The tension water capacity curve presented in Fig. 5 in another aspect indicates the bucket size distribution in a soil layer (i.e., bucket sizes can vary from zero (for impervious areas) to the value of the maximum tension water capacity of that catchment, *WMM*). It has been proven that this type of hydrological model could perform more accurately in river flow modelling than fixed-depth models in practice [*Beven*, 2011; *Zhao et al.*, 1995]. However, this leads to incompatibility with the satellite soil moisture depth (e.g., ~ 2 m against 5 cm). Presumably, these are the reasons why more attention to satellite soil moisture data usage has been given in climate and meteorological modelling, which employ comprehensive model structures and explicitly physical processes [*Drusch*, 2007; *Reichle and Koster*, 2005; *Reichle et al.*, 2007]. Although there are some physics-based hydrological models that are designed in a similar way, their large data requirements and number of parameters, rather complicated model structures and comparatively poor flow modelling outcomes have hindered their practical application in real-time flood forecasting [*Mendoza et al.*, 2015; *Overgaard et al.*, 2006; *Reed et al.*, 2004].

5. Discussion and conclusions

In this paper we argue that the unsuitable mechanisms in a typical conceptual hydrological model can hinder its full utilisation of satellite soil moisture products. As in the case study presented here, there are three clear incongruities between the XAJ soil moisture state variable and the SMOS soil moisture observation. Since availability of global satellite soil moisture products is increasing, the aforementioned hydrological model deficiencies can weaken the effectiveness of these soil moisture datasets in real-time flood forecasting. Therefore critical amendments to existing hydrological models are required to minimise the mismatch between the satellite soil moisture and the hydrological model generated soil water information, and to better link the shallow satellite soil layer with the deeper and variable soil layers in the hydrological model.

One may argue that the XAJ model already works well in operational flood forecasting with its existing inputs, and therefore there is no need to use the satellite data. However, there are many cases in which it does not work well enough. For example, if there is missing data concurrent with an imminent storm, soil moisture observations such as those from the satellites will be very useful for quickly initialising the model's soil moisture state (i.e., to reduce the need for warming up/ spinning up the model), so that the model is ready for flood forecasting. Another case is when there is an accumulated error with the model's evapotranspiration and precipitation estimation which can cause time-drift of the model's soil moisture state. Soil moisture observations in this case can help to adjust this time-drift by data assimilation techniques, and in this way the over- and under-estimation of the flow peaks could be minimised. A successful hydrological model should be able to make full use of the available data, and satellite soil moisture observations do provide extra information to compliment the conventional hydrological measurements. It is important to recognise the weaknesses in existing models, and encourage the community to explore the ways to improve those models' compatibility with the new measurements.

One possible solution is that the soil moisture fluctuation in the hydrological model should be extended to full saturation. However, this contradicts the original concept of many hydrological models (e.g., XAJ, PDM, HBV) where field capacity is set as the upper limit of soil moisture content. The current hydrological model works fairly well in practice, and it is uncertain if this alteration will reduce the effectiveness of the model in simulating river flows. On the other hand such a change may improve the model further. Therefore in the improved method, the soil moisture state variable is allowed to rise to the saturation point, but because it is above field capacity, the soil particles are not capable of holding the excess water for a very long time. The improved model should allow the excess water to be gradually released from the soil to runoff - hence a water release curve should be introduced. According to Fig. 2, the water release curve is made of two components: *RI* and *RG* (i.e., interflow runoff and runoff into groundwater, respectively). A straightforward solution is to use the combination of the existing XAJ's *RI* and *RG* release curves in the improved modelling scheme, to calculate the water gradually released from the soil column. Although the concept is clear, further study about this curve is needed. Regarding the XAJ lower soil moisture limit, the original boundary at total dryness should be modified. It is known that in the XAJ model, when the second and third layers' evapotranspiration amounts are calculated, reduction ratios are applied (e.g., for the second layer calculation, a ratio of the actual water storage to the capacity storage is applied). Similar ratios could also be applied to the updated upper soil layer of the XAJ model. Alternatively a minimum water storage in the upper soil layer could be set and calibrated based on individual catchment conditions. We hope these proposed ideas could solve the soil moisture range problem in the current XAJ model.

A potential issue related to the spatial difference between the satellite footprint and the catchment area may also need consideration. Unlike the other issues discussed, this is beyond the hydrological model domain. Ideally it is hoped that the satellite footprint is the same size as the catchment area; however, it is not always possible to achieve this with existing sensors. If the satellite footprint is smaller than the catchment, then it is not an issue because the aggregation of the satellite pixels within the catchment can be matched to the catchment area. On the other hand, if the satellite footprint is larger than the catchment area, this could be a problem because if the soil moisture is unevenly distributed, the catchment soil moisture could be very different to the average soil moisture as measured by the large satellite footprint (for example, if the catchment is located in the drier part of the footprint, its soil moisture would be overestimated, whereas the opposite would happen for the wetter part of the footprint). *Schlosser* [1996], *Vachaud et al.* [1985], and *Wagner* [2008] have explained that in such a condition, the catchment spatial soil moisture patterns persist in time. However, a better way to handle this is through spatial downscaling using data fusion techniques (e.g., to combine coarse microwave data with fine surface temperature data), which should be explored in the future.

Finally it is worth noting that this study is not about a direct comparison between the model's soil moisture state variable and the satellite soil moisture, because they are different albeit linked. Therefore correlation is used instead. Although attempts have been made by many researchers to assimilate satellite soil moisture data into hydrological models, they are generally not very successful. We believe weaknesses of the existing conceptual hydrological model could be one of the reasons. The purpose of this study therefore is to raise the awareness of the shortcomings of soil moisture representation in current conceptual hydrological models because such models have been developed long before soil moisture remote sensing observations have become widely available. Hence prior to assimilating satellite soil moisture data in hydrological modelling, current hydrological models need to be improved by overcoming the aforementioned issues to make them more compatible with each other. It is hoped that future exploration and collaboration should be carried out by the hydro-metrological community so that multi-disciplinary experience and knowledge could be accumulated to improve the hydrological processes represented in current hydrological models.

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