Appraisal of NLDAS-2 multi-model simulated soil moistures for hydrological modelling

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Abstract

Soil moisture is a key variable in hydrological modelling, which could be estimated by land surface modelling. However the previous studies have focused on evaluating these soil moisture estimates by using point-based measurements, and there is a lack of attention for their appraisal over basin scales particularly for hydrological applications. In this study, we carry out for the first time, a detailed evaluation of five sources of soil moisture products (NLDAS-2 multi-model simulated soil moistures: Noah, VIC, Mosaic and SAC; and a ground observation), against a widely used hydrological model Xinanjiang (XAJ) as a benchmark at a U.S. basin. Generally speaking, all products have good agreements with the hydrological soil moisture simulation, with superior performance obtained from the SAC model and the VIC model. Furthermore, the results indicate that the in-situ measurements in deeper soil layer are still usable for hydrological applications. Nevertheless further improvement is still required on the definition of land surface

model layer thicknesses and the related data fusion with the remotely sensed soil moisture. The potential usage of the NLDAS-2 soil moisture datasets in real-time flood forecasting is discussed.

Keywords Hydrological modelling, Land surface modelling, Xinanjiang, Soil Moisture Deficit, NLDAS-2, evaluation

1. Introduction

Soil moisture has been identified as one of the Essential Climate Variables (ECV) in the Global Climate Observing System (GCOS) (esa 2010). The existence of soil moisture at the land surface and atmosphere interface has a strong influence on the water and energy balance at this particular interface (Kerr et al. 2001), because dry soil emits little or no water vapor to the atmosphere. It has been recognized as a key variable in a wide range of studies (Ganji 2010; Mendicino and Versace 2007; Nandintsetseg and Shinoda 2011; Norbiato et al. 2008; Seneviratne et al. 2010; She et al. 2014; Srivastava et al. 2013b), including meteorology, climate change, hydrology, agriculture and drought monitoring Moreover initial soil moisture conditions are among the most important hydrological properties affecting flood triggering (Mishra et al. 2004). Therefore, it is vital to accurately monitor and estimate spatial and temporal variations of soil moisture.

Ground measurements, remote sensing and land surface models are the main sources that could provide soil moisture information. Point-scale measurement techniques are currently limited to discrete measurements at particular locations, making them less representative for spatial distribution because soil moisture is highly variable both spatially and temporally (Engman and Gurney 1991; Tombul 2007; Walker et al. 2004) and are therefore inadequate for basin level studies (Srivastava et al. 2013a; Srivastava et al. 2013c). Soil moisture retrieved from remote sensing techniques provide a feasible capability to monitor soil moisture over a range of spatial and temporal scales (Jackson and Schmugge 1989; Kerr et al. 2001) and in particular have engendered much enthusiasm and interest with their promise of global data coverage and long-term soil moisture monitoring (Ochsner et al. 2013). However soil moisture retrieved by satellites can be interfered by poor weather conditions (e.g. rainfall and clouds) and dense vegetation coverage; moreover they produce data with coarse spatial resolution and shallow sensing depth, which significantly restrict them for many applications (Wagner et al. 2007).

Soil moisture simulated by Land surface models (LSMs) often serves as alternatives (Robock et al. 2000). The role of soil moisture by LSMs in regional weather prediction, as well as in global climate change investigation has been widely recognized and demonstrated in many studies (Chen et al. 2010; Koster et al. 2011; Patil et al. 2011; Sahoo et al. 2008; Xia et al. 2014). However most previous studies have focused on either improving or evaluating the LSM's performance (Cai et al. 2014; Koren et al. 2014; Rosero et al. 2009; Yang et al. 2011), and its soil moisture evaluation using point-based measurements. As a result, there is a lack of attention for their appraisal over basin scales particularly for hydrological applications.

The real-time multi-model generated soil moisture from the North American Land Data Assimilation System phase 2 (NLDAS-2) simulations (Xia et al. 2012a; Xia et al. 2012b), have high temporal and spatial resolution, however they have not been evaluated for hydrological applications, especially at a basin scale. In this study, we carry out for the first time, detailed comparisons and assessments of five sources of soil moisture products (soil moisture simulated from the four NLDAS-2 LSMs, Noah, VIC, Mosaic and SAC, as well as in-situ soil moisture observations), against a widely used hydrological model Xinanjiang (XAJ) as a target. In hydrology, Soil Moisture Deficit (SMD) or depletion is an important soil moisture indicator, which demonstrates the amount of water (in mm) to be added to a soil profile to bring it to field capacity (Andersson and Harding 1991). It has been shown that the three-layer XAJ model is very useful in modelling SMD from the meteorological data (Ren-Jun 1992; Zhao et al. 1995). The results of this work are very relevant to the hydrological community, because the NLDAS-2 soil moisture datasets have a huge potential to be applied for hydrological purposes, especially for real-time flood forecasting.

2. Basin and data

2.1 Study area and datasets

The French Broad basin (2448 km^2) is selected as the study area, which is located in the western North Carolina of the U.S. (35.609^{o}N, 82.579^{o}W), influenced primarily by the humid subtropical climate (Peel et al. 2007). The major land use of this basin is mixed forest (Bartholomé and Belward 2005) on red clay soils (Webb et al. 2000). The average altitude of the basin is 819 m AMSL. The basin generally does not have significant human impacts (Duan et al. 2006), and the layout of the basin is shown in Fig. 1 along with the location of its flow gauge and soil station.

The NLDAS-2 (Mitchell et al. 2004) precipitation and potential evapotranspiration at 0.125^o spatial resolution and daily temporal resolution (converted from hourly resolution) are used to drive the XAJ model. The potential evapotranspiration is derived from the NARR (North American Regional Reanalysis). The precipitation data are derived from the temporal disaggregation of the gauged daily precipitation data from NCEP/CPC (National Centers for Environmental Prediction/Climate Prediction Center) with an orographic adjustment based on the monthly climatological precipitation of the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Daly et al. 1994). The four LSMs soil moisture outputs forced by the same NLDAS-2 meteorological forcings are downloaded from the NLDAS-2 website (Cai et al.

2014) during the period from Jan 2010 to Dec 2012; and have been converted from hourly to daily basis. Moreover as shown in Fig. 1, there are a total of 27 NLDAS-2 grids that cover the entire basin. Since XAJ is a lumped hydrological model, each of the NLDAS-2 products (i.e. precipitation, potential evapotranspiration and the soil moistures) has to be converted into one basin-scale dataset firstly by using the Thiessen Polygon method. The USGS daily flow data for the same monitoring period from January 2010 to December 2012 are used for XAJ model's calibration and validation. In-situ soil moisture datasets at the Asheville 13 S station is collected from the U.S. Climate Reference Network (USCRN) website for the same time period (Bell et al. 2013; Diamond et al. 2013). The station measures conventional meteorological variables such as air temperature, wind speed, solar radiation, relative humidity and precipitation. The in-situ observations were measured with triplicate coaxial impedance dielectric sensors calibrated with gravimetric observations. The volumetric soil moisture observations are given at the depths 5, 10, 20, 50, 100 cm on hourly basis, which have been converted to a daily interval for the comparison. The flowchart together with the description on the process used in this study is presented in Fig. 2.

2.2 NLDAS-2 LSMs soil moisture simulations

The overall modelling strategy of NLDAS-2 is to generate surface meteorological and hydrological products using observed gauge precipitation and bias-corrected reanalysis forcing to drive the four NLDAS-2 LSMs in an offline mode (Xia et al. 2014).. More details regarding the setup, parameters and forcing data can be found in Mitchell et al. (2004), Xia et al. (2012a) and Xia et al. (2012b). The spatial resolution of the simulated soil moisture is 0.125° and its temporal resolution is one hour. Moreover the datasets cover from 1 January 1979 to present (Xia et al. 2014).

Four LSMs were selected in NLDAS-2 (Noah, Mosaic, VIC and SAC). These four models apply different mechanisms in land surface modelling, giving cross-section of different comparison aspects, including small scale versus large scale, coupled versus uncoupled, distributed versus lumped and etc. The Noah LSM is a land model of the NCEP (National Centers for Environmental Modelling Prediction) operational regional and global weather and climate models (Betts et al. 1997; Chen et al. 1996; Chen et al. 1997; Ek et al. 2003). The Mosaic model is a land model for the NASA global climate model (Koster and Suarez 1996; Koster and Suarez 1994), which has been replaced by the Catchment land surface model for the recent upgrade of NASA's GOES-5 system. The VIC model is built as a macroscale semi-distributed model, which solves full water and energy balances (Liang et al. 1994). The SAC model is designed as a semi-distributed hydrological model (Koren et al. 1999) based on a lumped conceptual hydrological model (Burnash et al. 1973); and it has been used widely for small-basin flood forecasting. The first two models emerged within the surface vegetation-atmosphere transfer (SVAT) scheme for coupled atmospheric modelling with a focus on the energy and water flux exchange between the atmosphere and the land, with little calibration. Whereas, the last two models were originally designed within the hydrology community as uncoupled hydrological models with a focus on flood simulation and considerable calibration (Xia et al. 2014). Through developments, Mosaic, Noah and VIC have been widely applied as both coupled and uncoupled for all spatial scales. As a result, all three models are considered as both SVATs and semi-distributed hydrological models (Mitchell et al. 2004).

2.3 Translation of observed and simulated soil moisture data to common soil layers

It is impossible for a direct comparison between all sources of soil moisture because they all have different soil depths. The Noah model includes four soil layers, with 0-10 cm, 10-40 cm, 40-100 cm and 100-200 cm respectively. Whereas Mosaic model is designed with three soil layers: 0-10 cm, 10-60 cm and 60-200 cm. Moreover there are three soil layers used in VIC model, with a 10 cm top layer and spatially varying thicknesses for the other two layers. On the other hand, the SAC model is a storage-type model, which is conceptually different from the other three models. It has a two-layer structure, and each layer consists of tension and free water storage. The free water storage of the lower layer is further divided into two sub-storages that control supplemental (fast) and primary (slow) ground water flows. As a result, the SAC model has no specified soil layers. In order to solve the inconsistency problem of soil layers, the methods described in Xia et al. (2014) are applied in this study, where the distribution of Noah's soil layers is used as a benchmark due to its uniform soil layers and maximum number of soil layers across all models. The Mosaic soil data and in-situ observations are transferred to the Noah soil layers by a simple linear interpolation approach. Furthermore the VIC soil moisture data are converted to the Noah soil layers by computing the weighted average of soil moisture in each VIC layer that intersected with the Noah layers. Moreover when the bottom VIC layer is shallower than the lowest Noah layer, then the VIC soil moisture value is assumed to be the same down to the depth of the lowest Noah layer. For SAC, a post-processed soil moisture product with the same soil layer as Noah can be downloaded from the NOAA/NCEP/EMC website (ftp://nomad6.ncep.noaa.gov/pub/raid2/wd20yx/nldas/Postprocessed_SAC/).

2.4 The XAJ hydrological model

There are numerous hydrological models available globally and in this study, a widely used model XAJ is adopted; and a very informative and readable account is given by Zhao (1980). The model has been widely applied to various basins around the world (Chen et al. 2013; Shi et al. 2011; Zhao 1992; Zhao et al. 1995). The XAJ model is a relatively simple conceptual lumped rainfall-runoff model; its main hypothesis is the runoff generation on repletion of storage, which means that runoff is not generated until the soil water content of aeration zone reaches the field capacity. The structure of XAJ model includes an evapotranspiration unit, a runoff production unit and a runoff concentration unit. The model includes three soil layers (upper, lower and deep) which represent the three soil moisture storage components. The runoff component is also known as a water balance model which simulates lumped values of runoff with given rainfall and potential evapotranspiration datasets. The simulated effective rainfall (runoff) is then routed as flow through a routing model to the basin outlet, among which the Muskingum routing method is applied in this study. The model formulations are well suited for automatic parameter estimations. The three-layer SMDs are calculated to determine the effect of drying and wetting on the basin soil water storage.

3. Results and discussion

3.1 XAJ simulation for SMD estimation

For calibration of the XAJ model, two years of data (January 1, 2010-December 31, 2011) are used, while the remaining one year (January 1, 2012-December 31, 2012) data are used for validation purpose. The calibration procedure focuses especially on the modelling of actual evapotranspiration and the distribution of total runoff (e.g. surface runoff, interflow and groundwater) in the XAJ model; as well as a good agreement between the estimated and observed flow. The performance of the model is determined by the Nash-Sutcliffe Efficiency (*NSE*) (Nash and Sutcliffe 1970) as an objective function, because it is the most common and important performance measure used in hydrology. The observed and simulated flow time series are compared over the complete monitoring period. As a result, the overall performance indicates a *NSE* value of 0.86 for the calibration and 0.83 during the validation. The time series between rainfall and flow during the calibration and validation periods are shown in Fig. 3. The modelling outcome demonstrates that the XAJ model tends to match the measured flow rather well while there is only a slight underestimation during the calibration. On the other hand, at some parts of the validation the flow simulation deviates slightly from the observed flow, especially at the low-flow parts of the hydrograph. Nevertheless, both *NSE* values are sufficiently high for an acceptable hydrological model.

3.2 NLDAS-2 LSMs simulated soil moisture

It is extremely difficult to compare model generated soil moisture with ground observations because there are no direct measurements of the area averaged soil moisture. Nevertheless, an attempt has been made to compare the NLDAS-2 multi-model simulated soil moisture products with the observations. In order to reduce the spatial difference as small as possible, we only use the NLDAS-2 grid cell that is closest to the Asheville 13 S station in this section. Pearson product moment correlation coefficient ($r_{pearson}$) is used for the comparison. The three-year daily soil moisture variations from the four LSMs and the observations for four individual soil layers are shown in Fig. 4. The results reveal a generally clear seasonal fluctuation at all the soil layers during the monitoring period. However, it is obvious that VIC and Noah models present less seasonal variation when compared with the measured soil moisture and the other two models for the top layer. One possible reason could be explained by the fraction of bare soil within a grid cell in Xia et al. (2014). Furthermore, all those models tend to overestimate soil moisture for the top soil layer (except for SAC) and underestimate soil moisture for the bottom two layers. In particular, the SAC model significantly underestimates soil moisture between 10 cm and 100 cm. Similarly, the VIC generated soil moisture in the bottom layer is excessively dryer than the other three models. One possibility is that the lowest soil layer in VIC is around 1.5 m and soil moisture values are extrapolated to 2 m through post-processing, which could produce some errors. Generally speaking, all the models indicate high correlation for all the four soil layers (>0.64), except for VIC in the top 10 cm where less seasonal variation is observed (0.40). Overall, Mosaic and SAC show higher correlations in the top two layers, whereas Noah and VIC exhibit better similarities to the observations in the bottom two layers.

3.3 Evaluation of five soil moisture products against XAJ simulated three-layer SMDs

Firstly, it is necessary to carry out an overall assessment by comparing with the summation of the three-layer XAJ SMDs. For this purpose, all five sources of soil moisture products are transformed to four soil layers (0-50 cm, 0-100 cm, 0-150 cm, 0-200 cm) by applying a simple linear interpolation approach. As illustrated in Fig. 5, all those soil moisture products seem to follow the summation of SMDs quite well. So when soil dries in the summer, SMD rises significantly; whereas when soil gets wetter during rainy seasons, SMD tends to be around zero. Specifically, all soil moisture products are able to capture individual rainfall events rather reactively. However the SAC model shows slow recovery for both wetting and drying processes, indicating stronger variation persistence than other models, such as the unreasonable significant increase of soil moisture during October 2011. The reason may be due to the improper maximum water capacity parameter set in the SAC model (Xia et al. 2014). As a result, this leads to relatively weaker correlations compared with the other soil moisture products, as revealed in Table 1. Moreover, $r_{pearson}$ become stronger for all soil moisture products when soil layer becomes thicker. To further check the linear and nonlinear relationships, the spearman rank correlation coefficients ($r_{spearman}$) (Chen et al. 2013) are also generated, which yield nearly similar trends and values, revealing that there are no strong nonlinearity. The best performances are all observed in the 0-200 cm layer, with the Mosaic model at -0.95, followed by VIC (-0.89), observations and Noah (-0.84), and SAC (-0.79).

Following the aforementioned assessment, a more comprehensive evaluation is implemented. This evaluation is based on the correlations between five sources of soil moistures at four individual layers (0-10 cm, 10-40 cm, 40-100 cm, 100-200 cm) and the XAJ three-layer SMDs. As shown in Table 2, for the XAJ SMD in the upper layer (layer one), there are good agreements with all the soil moisture products in 0-10 cm, except for the VIC model. The VIC simulated soil moisture in the top layer gives only -0.38 $r_{pearson}$, hence it has little usage for hydrological modelling. Moreover the VIC simulated soil moisture and the in-situ observations are not logically linked with the XAJ model by layer order, e.g. their layer two is matched with XAJ layer one with higher correlations; whereas other products follow the corresponding orders more clearly. For XAJ layer one, the best correlation is gained from the SAC model in 0-10 cm ($r_{pearson}$ = -0.77). For XAJ SMD in the lower layer (layer two), there exist much stronger relationships with all the soil moisture products in layer four (100-200 cm). The highest correlation is obtained in the VIC bottom layer ($r_{pearson}$ = -0.90). Moreover it is a surprise that the point based observation in 100-200 cm also attains a high correlation at $r_{pearson}$ = -0.86 with the XAJ layer two SMD. One possible reason is that soil moisture fluctuations become more stable in the deeper soil layers than in the shallower soil layers, hence even a point based measurement is able to capture the deep soil moisture variations for the entire basin. Surprisingly, all soil moisture products show very poor relationships with the XAJ SMD at deep layer (layer three). The highest correlation is obtained only at $r_{pearson}$ = -0.49 for Mosaic model in 100-200 cm and the result from Spearman correlation ($r_{spearman}$ = -0.34) is equally poor, suggesting that the overall correlations for the XAJ deep layer are weak. The reason for the poor results is that the XAJ model runs with real soil depth which can be much deeper than 2 m in this region. In another word, the lowest soil depth in all the soil moisture products would be too shallow for hydrological applications at certain basins. This is a common weakness. Since water balance below 2 m has been neglected in both land surface modelling and in-situ measurements, it is difficult nowadays to monitor the soil moisture status in a deeper level. Nevertheless it is strongly suggested that the layers of LSMs should be dependent on the saturation of soil at a region and should be tailored for different user communities.

4. Conclusion and discussion

Soil moisture is a key variable in hydrological modelling, especially for real-time flood forecasting. This is because in real-time modelling, SMD can drift away due to the error accumulations (especially after a long period of low flows (Ottlé and Vidal-Madjar 1994)). Accurate soil moisture datasets generated by LSMs have the potential to avoid such time drifts. In order to realize so, the primary step is to assess the accuracy of the soil moisture products, by using the long-term historical hydrological modelled soil moisture outputs. If there is sufficient amount of useful soil moisture information to the hydrological modelling; it is then possible to utilize such information in real-time flood forecasting by data assimilation (e.g. Kalman filter, 3DVAR and 4DVAR Kalman filters) or model state updating methodologies. It has been recognized that the NLDAS-2 data is very useful for numerical weather prediction models; however no particular attention is given for their application in hydrological models. Therefore in this study we carry out for the first time a comprehensive hydrological evaluation of five soil moisture products (i.e. the NLDAS-2 multi-model simulated soil moistures: Noah, VIC, Mosaic and SAC; and a ground observation), against a widely used hydrological model (XAJ) as a benchmark, to assess their potential usage in the operational hydrology.

Overall, all products have good agreements with the hydrological soil moisture simulation, with superior performance obtained from the SAC model and the VIC model. However it has been found that a direct replacement of the XAJ SMDs with these soil moisture products derived SMDs (or a simple regression of those products with XAJ SMD), can result in a rather poor performance in the flow modelling. The explanation is as follows. The operational hydrological model such as XAJ tends to do well in real time flood forecasting if the antecedent soil moisture is accurately represented in the model prior to an incoming flood causing storm. However, it has been found that in practice, it is common to observe that overestimation or underestimation of flood peaks occurs often. A main reason for this is because the accumulated errors from the evapotranspiration estimation cause the time drift in the model's soil moisture state variable so that it is no longer an accurate reflection of the true soil moisture condition. Such an issue is more evident after a long dry period in summer. The intended use of those alternative soil products is to help duty hydrologists detect and correct the drift (the alternative soil moisture data may not suffer from the same error). This is not an easy task because more detailed research is needed to find out the prevailing conditions for those drifts to occur and their characteristics so that appropriate corrections could be implemented using alternative soil moisture products.

In addition the NLDAS-2 forcings are still new, and further studies are clearly necessary to evaluate them at a wider range of basins covering more climate types and land cover/land uses. Furthermore more studies are also needed to consider information from other data sources to improve the soil moisture accuracy. Another complementary data source is the remote sensing soil moisture products by microwave and visible light/ infrared bands, which have been extensively used over the last two decades. Therefore, the data fusion between model based soil moisture and remote sensing based soil moisture may provide the optimal soil moisture estimation for hydrological purpose.

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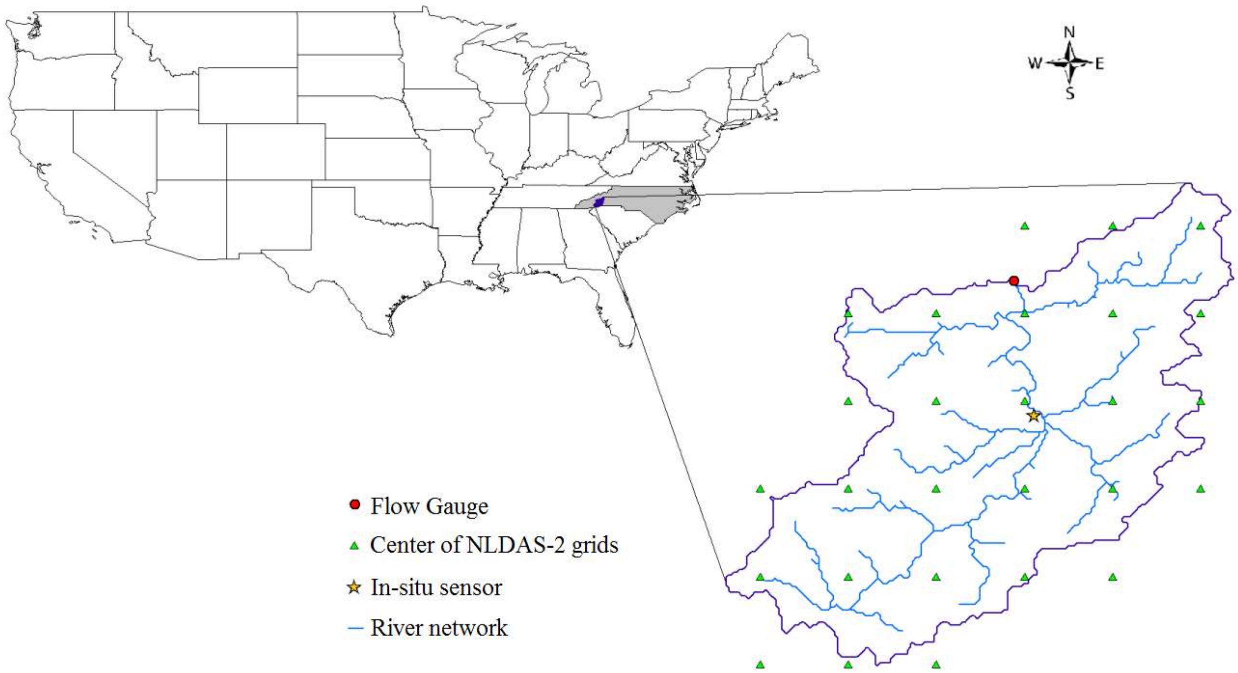

Fig. 1. Location of the French Broad catchment with the flow gauge, NLDAS-2 grids locations, and the in-situ soil moisture measurement station over the river network map.

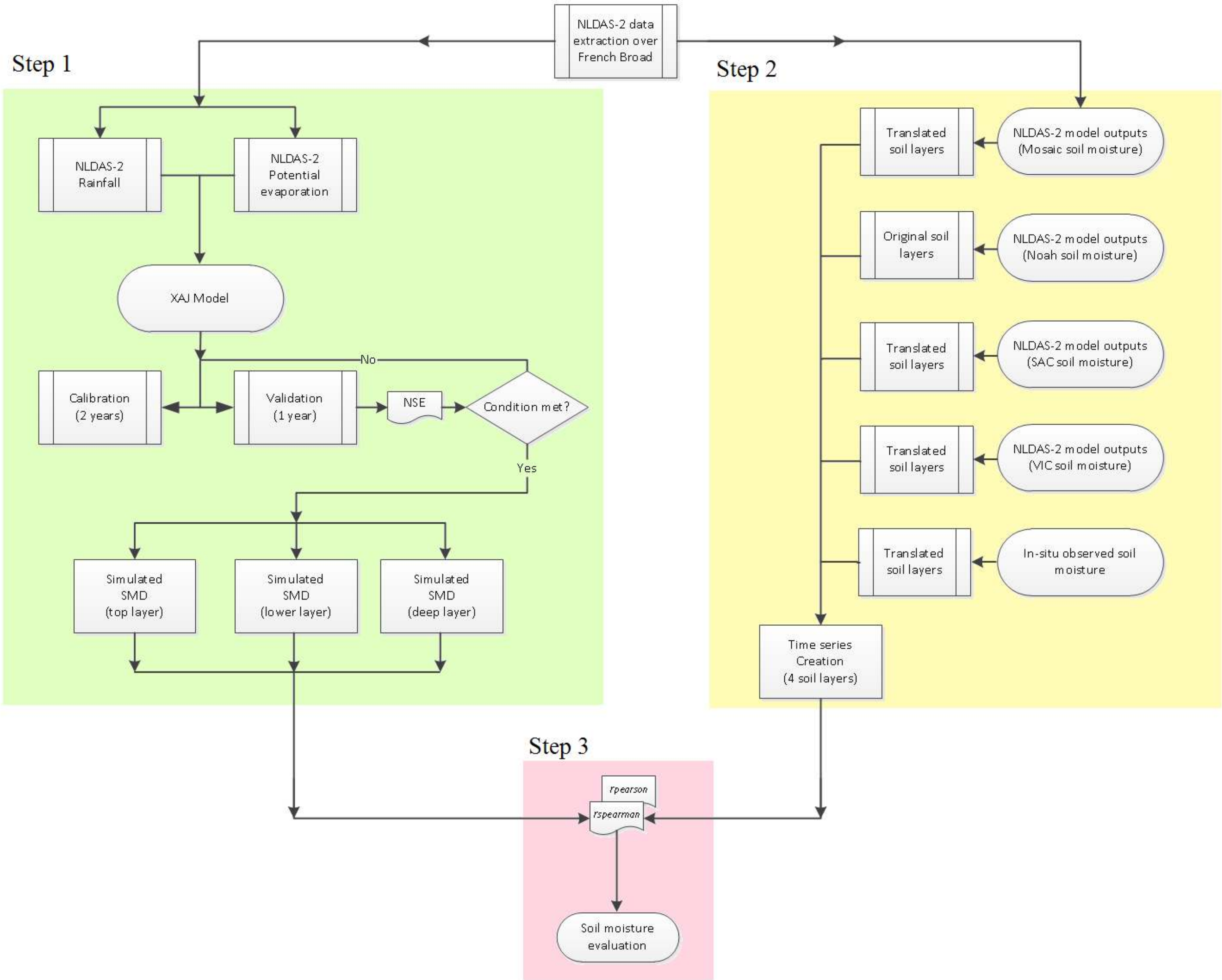

Fig. 2. Flowchart depicting the methodology used in this study. In step 1: NLDAS-2 precipitation and potential evapotranspiration datasets are used to drive the XAJ model, and the performance of the model is determined by the *NSE* coefficient as its objective function. Both calibration and validation *NSE*s have to be sufficiently high for an acceptable hydrological model (i.e. above 0.80). Once the condition is met, the three-layer SMDs are then generated. In step 2: soil moisture datasets are collected and translated into a common soil-layer system, by using the distribution of the Noah's soil layers as a benchmark. The time series of each soil moisture datasets are generated accordingly. In step 3, the five sources of soil moisture products are evaluated hydrologically by statistical indicators.

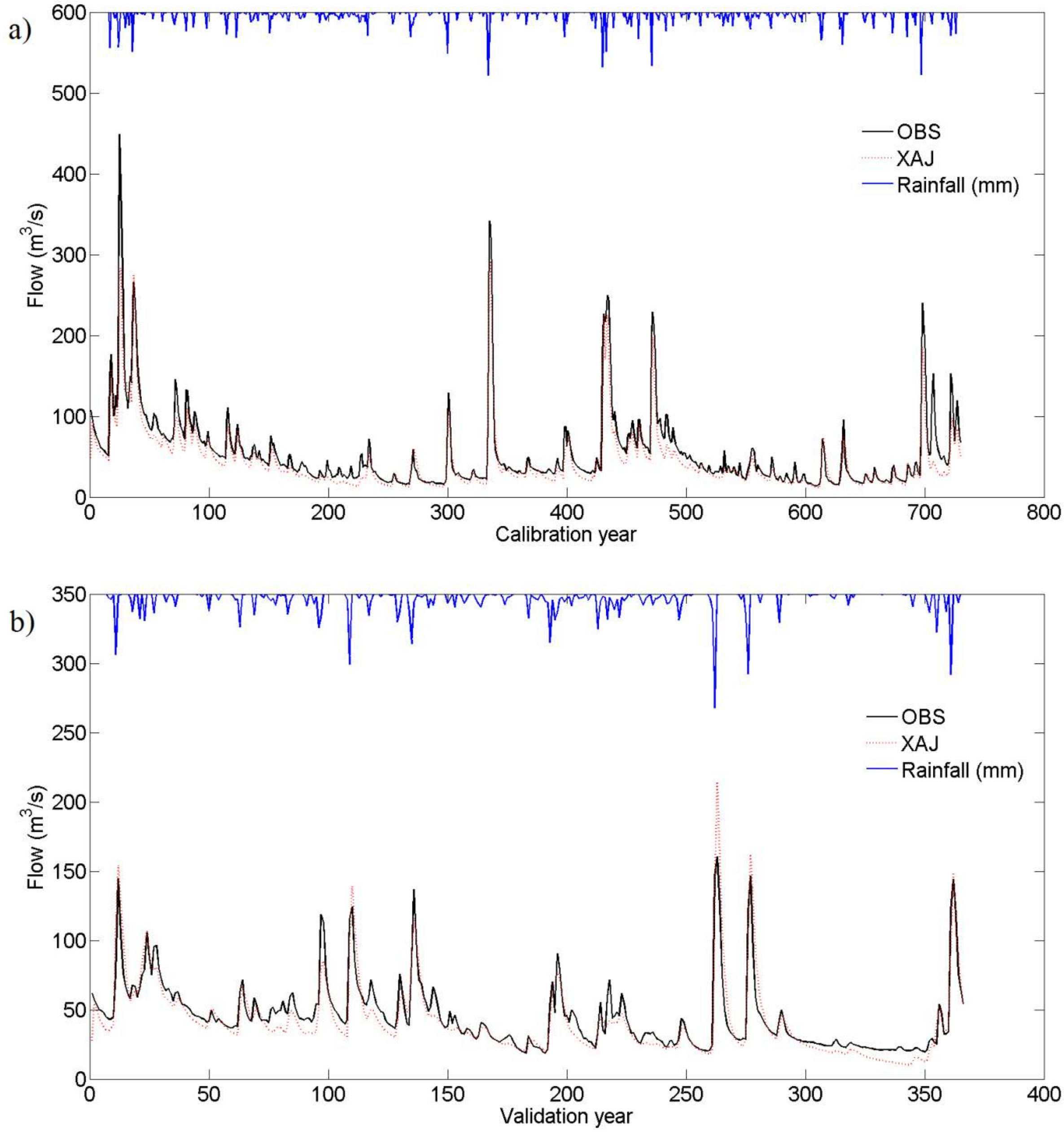

Fig. 3. Daily rainfall and flow time series during calibration and validation with the hydrograph generated from XAJ for: (a) two year calibration, *NSE* = 0.86; (b) one year validation, *NSE* = 0.83.

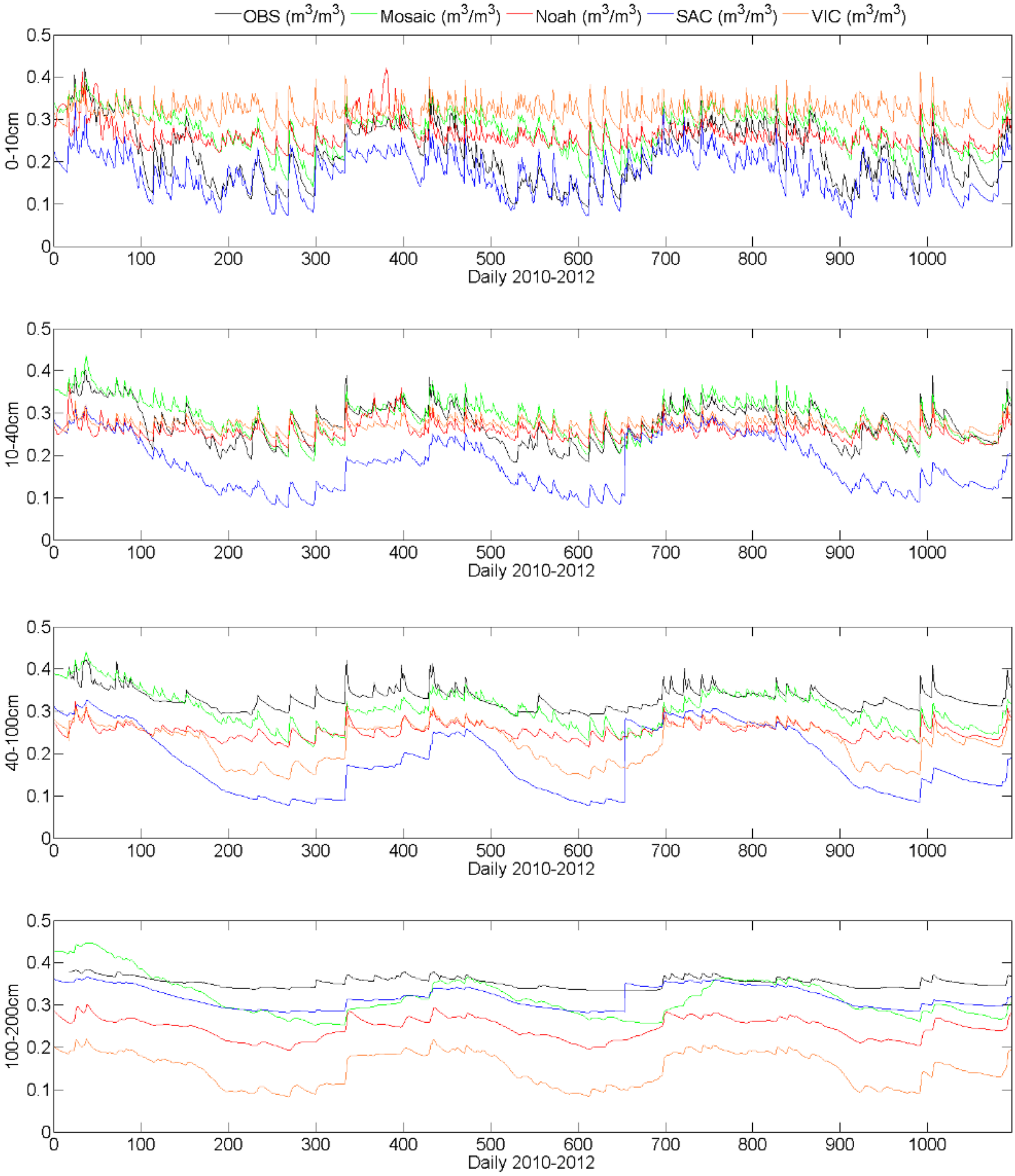

Fig. 4. Daily volumetric (m^3/m^3) soil moisture variations at individual soil layers: 0-10 cm, 10-40 cm, 40-100 cm, 100-200 cm; for in-situ measurements, NLDAS-2 driven Mosaic, Noah, SAC and VIC simulated soil moisture values. The correlation coefficients ($r_{pearson}$) between the measured and the simulated soil moisture variations are calculated: for Mosaic are as 0.82, 0.81, 0.74 and 0.73 for the four soil layers accordingly; for Noah are 0.65, 0.69, 0.81 and 0.87 accordingly; for SAC are 0.85, 0.78, 0.66 and 0.72 accordingly; and for VIC are 0.40, 0.64, 0.76 and 0.90 accordingly.

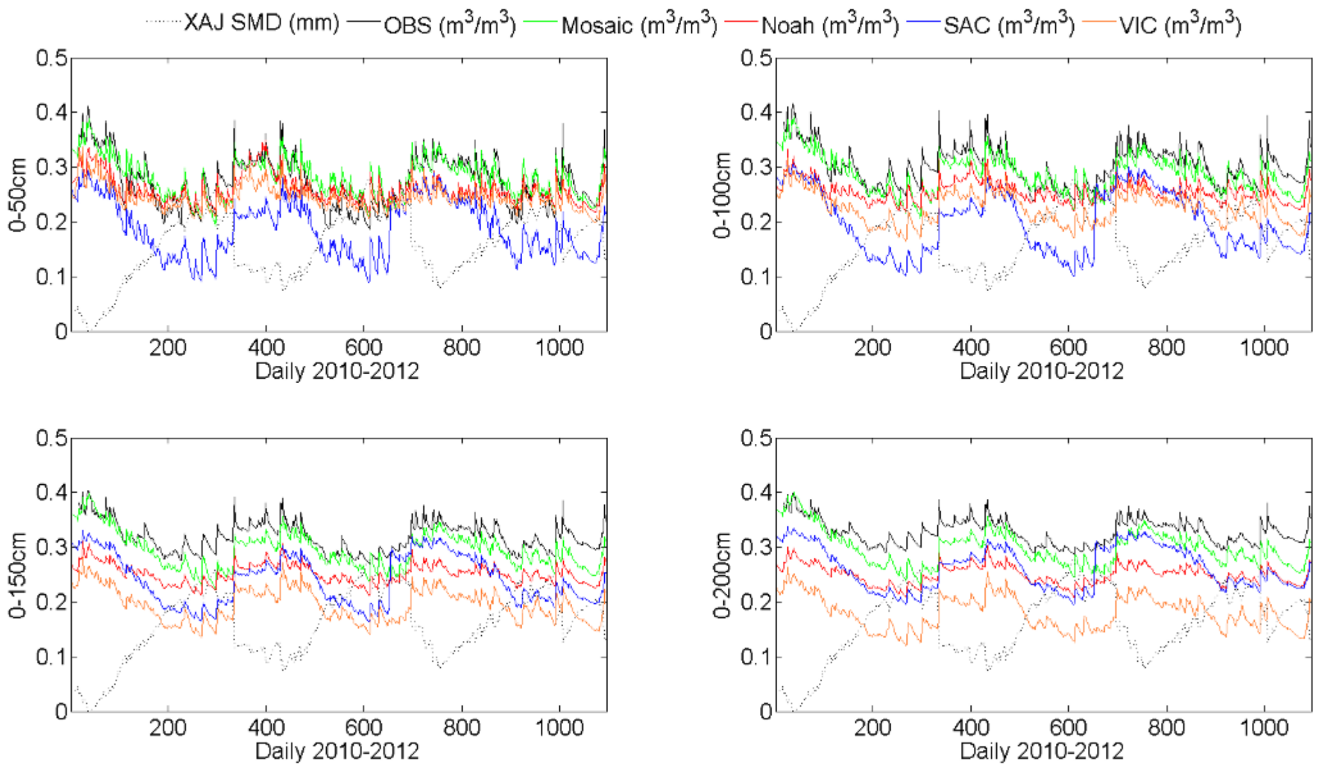

Fig. 5. Time series for volumetric (m^3/m^3) soil moisture contents (observations, Mosaic, Noah, SAC and VIC) at four soil layers: 0-50 cm, 0-100 cm, 0-150 cm, 0-200 cm, with the summation of three-layer XAJ soil moisture deficits (SMDs; mm).

Table 1. Daily soil moisture correlations between observed, LSMs simulated soil moistures (m^3/m^3) and the summation of XAJ generated soil moisture deficits SMDs (mm) for the period January 1, 2010 to December 31, 2012.

Soil layers (cm)	OBS	Mosaic	Noah	SAC	VIC
$r_{pearson}$					
0-50	-0.79	-0.87	-0.69	-0.78	-0.70
0-100	-0.80	-0.91	-0.75	-0.79	-0.86
0-150	-0.82	-0.94	-0.83	-0.79	-0.88
0-200	-0.84	-0.95	-0.84	-0.79	-0.89
$r_{spearman}$					
0-50	-0.77	-0.86	-0.67	-0.76	-0.68
0-100	-0.78	-0.89	-0.73	-0.78	-0.85
0-150	-0.81	-0.92	-0.83	-0.78	-0.87
0-200	-0.83	-0.93	-0.85	-0.78	-0.87

Table 2. Daily soil moisture correlations between the five soil moisture products (observations, Mosaic, Noah, SAC and VIC) at four individual soil layers (0-10 cm, 10-40 cm, 40-100 cm, 100-200 cm) and the XAJ simulated three-layer SMDs (upper, lower and deep layers) for the period January 1, 2010 to December 31, 2012. U is the upper XAJ soil layer, L is the lower XAJ soil layer and D is the deep XAJ soil layer.

Soil layers (cm)	OBS			Mosaic			Noah			SAC			VIC		
	U	L	D	U	L	D	U	L	D	U	L	D	U	L	D
$r_{pearson}$															
0-10	-0.61	-0.79	-0.16	-0.65	-0.73	-0.25	-0.67	-0.47	-0.13	**-0.77**	-0.57	0.03	-0.38	-0.08	-0.06
10-40	-0.64	-0.76	-0.15	-0.65	-0.76	-0.26	-0.61	-0.54	-0.16	-0.55	-0.82	-0.08	-0.60	-0.40	-0.21
40-100	-0.60	-0.75	-0.17	-0.51	-0.82	-0.38	-0.52	-0.61	-0.12	-0.34	-0.86	-0.13	-0.52	-0.89	-0.16
100-200	-0.47	-0.86	-0.27	-0.29	-0.82	**-0.49**	-0.38	-0.85	-0.12	-0.33	-0.86	-0.13	-0.50	**-0.90**	-0.19
$r_{spearman}$															
0-10	-0.63	-0.77	0.03	-0.68	-0.73	-0.12	-0.78	-0.46	0.08	**-0.81**	-0.56	0.18	-0.42	-0.07	-0.09
10-40	-0.66	-0.77	0.03	-0.66	-0.75	-0.12	-0.68	-0.53	-0.03	-0.57	-0.81	0.06	-0.65	-0.33	-0.04
40-100	-0.58	-0.80	0.00	-0.52	-0.83	-0.22	-0.52	-0.63	-0.05	-0.35	-0.85	-0.03	-0.52	-0.88	-0.09
100-200	-0.44	-0.85	-0.13	-0.27	-0.85	**-0.34**	-0.38	-0.86	-0.07	-0.35	-0.85	-0.03	-0.50	**-0.89**	-0.10