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Natural Hazards and Earth System Sciences
Discussions

Challenges in flood modelling over data scarce regions: how to exploit globally available soil moisture products to estimate antecedent soil wetness conditions in Morocco

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Abstract: The Mediterranean region is characterized by intense rainfall events giving rise to devastating floods. In Maghreb countries such as Morocco, there is a strong need for forecasting systems to reduce the impacts of floods. The development of such a system in the case of ungauged catchments is complicated but remote sensing products could overcome the lack of in-situ measurements. The soil moisture content can strongly modulate the magnitude of flood events and consequently is a crucial parameter to take into account for flood modeling. In this study, different soil moisture products (ESA-CCI, SMOS, SMOS-IC, ASCAT satellite products and ERA5 reanalysis) are compared to in-situ measurements and one continuous soil moisture accounting (SMA) model for basins located in the High-Atlas Mountains, upstream of the city of Marrakech. The results show that the SMOS-IC satellite product and the ERA5 reanalysis are best correlated with observed soil moisture and with the SMA model outputs. The different soil moisture datasets were also compared to estimate the initial soil moisture condition for an event-based hydrological model based on the Soil Conservation Service Curve Number (SCS-CN). The ASCAT, SMOS-IC and ERA5 products performed equally well in validation to simulate floods, outperforming daily in situ soil moisture measurements that may not be representative of the whole catchment soil moisture conditions. The results also indicated that the daily time step may not fully represent the saturation state before a flood event, due to the rapid decay of soil moisture after rainfall in these semi-arid environments. Indeed, at the hourly time step, ERA5 and in-situ measurements were found to better represent the initial soil moisture conditions of the SCS-CN model by comparison with the daily time step. The results of this work could be used to implement efficient flood modelling and forecasting systems in semi-arid regions where soil moisture measurements are lacking.

Keywords: Soil moisture, floods, Morocco, ERA5, Rheraya, Issyl, High Atlas

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1 Introduction

The Mediterranean region is characterized by intense rainfall events generating floods with a very short response time (Gaume et al., 2004; Merheb et al., 2016; Tramblay et al., 2011). The socio-economic consequences of these floods are very important in terms of fatalities or damages to the infrastructures in particular for Southern countries (Vinet et al., 2016). This highlights the need for forecasting systems to reduce the impacts of floods. Unfortunately, the development of such systems is very complicated in the case of ungauged catchments (Creutin and Borga, 2003) such as in North Africa and requires remote sensing products to overcome the lack of in situ measurements. Furthermore, while several studies have been focused on northern Mediterranean catchments for flood modelling, only a few studies are available on southern basins, yet those probably the most vulnerable to floods.

The Moroccan catchments are exposed to intense flash floods, such as the event of August 17, 1995 in the Ourika river where the max discharge reached in 45 minutes a peak discharge of 1030 m3/s causing extensive damages and more than 200 casualties (Saidi et al., 2003). Few studies have been carried out in Morocco to minimize the impact of floods by improving the forecasting systems, either by event-based modeling of floods (El Alaoui El Fels et al., 2017; Boumenni et al., 2017; El Khalki et al., 2018) or by hydro-geomorphological approaches (Bennani et al., 2019) to identify the areas at risk of flooding. The severity of floods in these semi-arid regions is controlled by several factors including precipitation intensity, soil permeability, steep slopes and soil moisture content at the beginning of event (El Khalki et al., 2018; Tramblay et al., 2012). In Mediterranean regions, the soil moisture content varies between events and is known to strongly modulate the magnitude of floods (Brocca et al., 2017; Tuttle and Salvucci, 2014) and particularly to be useful for flood modeling and forecasting systems (Brocca et al., 2011; El Khalki et al., 2018; Koster et al., 2009; Marchandise and Viel, 2010; Tramblay et al., 2012). However, studies in North African basins are lacking to document the rainfall-runoff relationship with soil moisture during floods (Merheb et al., 2016).

In most Mediterranean regions and particularly in North Africa, only a few measurements of soil moisture are available. To represent spatial variability, several measurement at different locations are needed due to the potentially large spatial variability of soil moisture for a wide range of scales (Massari et al., 2014; Schulte et al., 2005; Western and Blöschl, n.d.). However, even the in-situ data may not represent the spatial variability over a very wide area in the case of large basins. On the contrary, satellite soil moisture products provide coverage of the earth's surface by microwave sensors. There are two types of microwave sensors, active and passive, noting: 1) The Advanced Scatterometer (ASCAT) soil moisture product is on board MetOp with good radiometric accuracy and stability. This product provides a spatial resolution of 25 km with a temporal resolution of 1 day since January 2007

(Wagner et al., 2013). 2) The Soil Moisture and Ocean Salinity Mission (SMOS) product, which begins in January 2010 with a spatial resolution of 50km (Kerr et al., 2012). The improvement of the robustness of satellite soil moisture products can be achieved by merging passive and active microwave sensors as initiated and distributed by ESA-CCI (European Space Agency Climate Change Initiative) (Liu et al., 2011) providing data from 1978 to 2018. However, remote sensing products might suffer from several problems in complex topography or very dense vegetation and snow cover (Brocca et al., 2017). For this reason and before any use the data, it is necessary to validate them (Al-Yaari et al., 2014; Van doninck et al., 2012; Ochsner et al., 2013), either by in-situ measurements, if they exist, or by using Soil Moisture Accounting models (Javelle et al., 2010; Tramblay et al., 2012) to simulate soil moisture in the ungauged basins.

In this context, with an increasing number of satellite products becoming available to estimate soil moisture, clear guidelines and recommendations about the most suitable products to estimate the initial soil moisture content prior to floods are lacking for the semi-arid basins of North Africa. The purpose of this study is to compare different satellite soil moisture products with in-situ soil moisture measurements and the recently developed ERA5 reanalysis to estimate the initial soil moisture before flood events. The goal is to identify the best products to be used for flood modelling that could improve forecasting systems. This comparison is performed for two basins representative of medium-size catchments of North Africa that are the most sensitive to flash flood events. The validation of the different soil moisture products is made with a Soil Moisture Accounting (SMA) model, to test the capabilities of the different soil moisture products for the sake of estimating the initial conditions for an event-based hydrological model for floods. The paper is organized as follow: In section 2, an overview of the study area and all used data (hydro-meteorological and soil moisture products). Section 3 explains the methods adopted in this paper. Section 4 presents the results. The conclusion and perspectives are given in the last section.

2 Study area and data

2.1 Rheraya and Issyl catchments

The Rheraya research catchment (Jarlan et al., 2015) is located in the Moroccan High Atlas Mountains (Figure 1) with an altitude ranging from 1027 to 4167m and an area of 225km². The climate in the basin is semi-arid, strongly influenced by altitude, with a mean annual precipitation of 732mm, including 30% as snow in altitudes above 2000m (Boudhar et al., 2009). The geology is characterized by volcanic formations that are considered impermeable in the highest elevation areas, while the lowest elevation areas are made of granites with clays and marls. In the highest elevation areas very steep slopes are found with an average of 19% (Chaponnière et al., 2008). The vegetation cover is only

Natural Hazards and Earth System Sciences
Open Access
Discussions

located in the lowest areas with a concentration of cultivated areas found along the river channel. These natural conditions favor runoff generation. There is very low human disturbance for runoff, with only some local water uptake in the lower part of the river.

The Issyl basin (Figure 1) is located in the foothills of the Moroccan High Atlas Mountains with an altitude ranging from 632 to 2300m, an area of 160 km², and a mean annual precipitation of 666mm. It is an ephemeral river with discharge occurring only after rainfall events. The climate is semi-arid to arid and the downstream part of the basin reaches the city of Marrakech. The geological formations in this downstream are alluvial conglomerates that are relatively permeable. The upstream of the basin consists of clays and calcareous marl. The basin area includes agricultural activities that are irrigated in the downstream part of the basin. The irrigation comes from *seguias*, earthen-made channels that traditionally draw their water supply from the river itself, by building small diverting dams on the side of the river (Pérennès, 1994). The *seguias* channels are usually filled up during floods, and water is distributed to the neighboring agricultural parcels. The map on the *seguias* in the Issyl basin can be seen in Figure 1, covering the northern part of the basin. The system is unmonitored and in a context of high evaporation rates the portion of runoff diverted from the stream is not quantified. Due to the temporary nature of *seguias*, they can be partially destroyed during large floods and consequently their hydraulic properties and the amount of water collected can be modified over time.

2.2 Hydro-meteorological data

In the Rheraya basin, we used 8 rainfall stations, 5 of them from the data network of the Joint International Laboratory Télédétection et Ressources en Eau en Méditerranée semi- Aride ‘’LMI TREMA’’ (Jarlan et al., 2015; Khabba et al., 2013) and the remaining ones from the Tensift Hydraulic Basin Agency. The data is covering from 2008 to 2016. For the Issyl basin, only 2 rainfall stations are available from the Tensift Hydraulic Basin Agency, covering the years from 2010 to 2015. In this type of basin, the spatial variability of rainfall is very important (Chaponnière et al., 2008). The hydrometric data was provided by radar installed in each basin’s outlet. The data is covering only the year 2014 for Rheraya, since the sensor was installed at the end of 2013, and the years 2010 to 2015 for Issyl. The discharge data is provided with a time step of 10min converted into hourly time step as for rainfall.

The discharge data is missing in some events that are not selected. For this reason we considered only the events with complete discharge data. Some of the flood events considered in this study (Table 1) occurred in winter season, where rainfall can be in the form of snow above 2000m elevation. According to El khalki et al.(2018) the snow doesn’t contribute to runoff during winter season in the Rheraya basin, where only 17% of basin area is occupied by snow. The runoff coefficients calculated

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Preprint. Discussion started: 12 May 2020

for each selected events are ranging from 13.1 to 34.1% for Rheraya and from 1.2 to 7.2% for Issyl. This indicates the important role of initial conditions in both basins, with a much higher infiltration capacity in the Issyl basin in addition to potential water loss due to irrigation. We used 5 temperature stations located in the Rheraya basin and one temperature station located in the Issyl basin with an hourly time step to calculate the average temperature over each basin, ranging from 2008 to 2016. This data enabled us to calculate potential evapotranspiration (PET) with Oudin formula (Oudin et al., 2005) requiring temperature only.

2.3 Soil moisture data

We used 7 different types of soil moisture data over the Rheraya basin and 6 types in the Issyl basin due to the absence of measurements in this basin. Covering the same period of rainfall data mentioned in the 2.3 section, we used:

1. In-situ measurement with three Thetaprobes at 5cm and 30cm depth in the Rheraya basin, located at the SMPR7 station (Figure 1).
2. Simulated soil moisture from a Soil Moisture Accounting model (SMA)
3. ASCAT satellite soil moisture
4. SMOS satellite soil moisture
5. SMOS-IC satellite soil moisture
6. ESA-CCI satellite soil moisture
7. ERA5 reanalysis soil moisture

2.3.1 In-situ measurements

Soil moisture measurements are available at one location with three Thetaprobes at two different depths (5cm and 30cm). In this study we used Thetaprobes with 5cm depth, which is comparable with the depths of satellite products (Massari et al., 2014). The site is located in Rheraya basin, with an altitude of 2030m and a slope of 30% (Figure 1). The data is covering the time period from 2013 to 2016, with 30min time step converted to daily time step.

2.3.2 Soil moisture accounting model

The SMA is a continuous Soil Moisture Accounting model that can be used in the absence of soil moisture data to represent the degree of saturation for flood modeling (Anctil et al., 2004; Tramblay et al., 2012). In this study, a simplified version of the SMA model is used, adopting the same approach used by Tramblay et al. (2012) and Javelle et al. (2010). The SMA calculates the level of the soil reservoir (S/A), ranging between 0 and 1, by calibrating its single parameter, A, which represents the

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

reservoir capacity. An interpolated daily rainfall dataset created by the Inverse Distance method and evapotranspiration data computed from daily maximum and minimum temperature with the Hargreaves-Samani equation (Hargreaves and Samani, 1982) are used as inputs to the SMA model.

2.3.3 Soil moisture products

In this study we used three different types of satellite products and a Reanalysis product: an active product (ASCAT), two variants of a passive product (SMOS and SMOS-IC), a product that combines the two active and passive products (ESA-CCI) and ERA5 product:

1. The Advanced SCATterometer (ASCAT) is a Soil Moisture product, onboard Metop-A and Metop-B and a Metop-C satellite is a C-band (5.255 GHz) scatterometer onboard the Metop satellite series. It has a spatial sampling of 12.5 km and 1 to 2 observations per day (Wagner et al., 2013). The SM product was provided within the EUMETSAT project (http://hsaf.meteoam.it/) denoted as H115.
2. The Soil Moisture and Ocean Salinity (SMOS) mission is a radiometer operating at L band (1.4 GHz), providing Soil Moisture data with ~50km as spatial sampling and 1 observation per 2/3 days (Kerr et al., 2001). Centre Aval de Traitement des Données SMOS (CATDS, https://www.catds.fr/) provided the version RE04 (level3) for this study. This version is gridded on the 25km EASEv2 grid.
3. The Soil Moisture and Ocean Salinity INRA-CESBIO (SMOS-IC) is an algorithm designed by Insitut National de la Recherche Agronomique (INRA) and Centre d'Etudes Spatiales de la Biosphère (CESBIO) for a global retrieval of Soil Moisture and L-VOD. Two parameters of inversion of the L-MED model are used in the SMOS-IC (Wigneron et al., 2007) with a consideration of the pixel as homogeneous. This version is 105 and has a spatial sampling of 25km with EASEv2 Grid (Fernandez-Moran et al., 2017).
4. The ESA-CCI soil moisture product (http://www.esa-soilmoisture-cci.org/) regroups active and passive microwave sensors to measure soil moisture, giving three type of products: Active, Passive and Combined (Active + Passive). In this paper, the ESA-CCI V4.5 – Combined product is used (Dorigo et al., 2017; Gruber et al., 2017, 2019). The product has been validated to be useful by 600 ground-based measurement points around the globe (Dorigo et al., 2015), as well as it was compared with ERA-Interim products (Albergel et al., 2013). In the field of hydrological modeling, several global studies have used the ESA-CCI product to initiate the hydrological model (Dorigo et al., 2012, 2015; Massari et al., 2014) at the scale of Morocco (El Khalki et al., 2018). We extracted for each basin the pixel that corresponds to it.

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

5. ERA5 (Copernicus Climate Change Service (C3S), 2017) developed by European Centre for Medium-Range Weather Forecasts (ECMWF), it is the latest version of atmospheric reanalysis available for public since February 2019. The ERA5 replaced ERA-Interim with improvement at different scales, particularly, a higher spatial and temporal resolution, and a better global balance of precipitation and evaporation. The spatial resolution is 31km instead of 79km, hourly resolution is used instead of 6 hours, and the covered period will be extended to 1950 in future. The ERA5 product was applied in some recent studies in hydro-climatic field (Albergel et al., 2018; Hwang et al., 2019; Mahto and Mishra, 2019; Olauson, 2018). We selected the volumetric soil water of the first soil layer. This new product is tested in our study for the first time in Morocco. An alternative dataset, ERA5-Land using an improved land-surface scheme with a spatial resolution of 10km, was also tested, providing the same results as ERA5 since there is a strong correlation between soil moisture simulated by the two products.

3 Methods

3.1 Evaluation of different soil moisture datasets

In-situ data preparation consists of averaging the 5cm depth probes in order to get a single value to work with and take into account the plot-scale variability of the measurements. This data is considered as a reference for soil moisture data in the Rheraya basin, so that all the other soil moisture products are compared to it. The different soil moisture products are compared to the observed soil moisture over the entire period and also on a seasonal basis.

The SMA model is used to represent the soil moisture aggregated at the catchment scale. The rationale behind the use of such model here is that continuous rainfall and temperature series are often available in monitored catchments, unlike soil moisture, and a calibrated SMA model can sometimes palliate the lack of soil moisture measurements (Tramblay et al., 2012). For the SMA model, the A parameter, representing the soil water holding capacity, is calibrated to obtain the best correlation between observed and simulated soil moisture (S/A). The calibration with observed data can only be performed in the Rheraya basin where soil moisture is measured. In addition to this calibration, other values of A, ranging between 1 and 1000, are tested in the SMA model to maximize the correlations with the different soil moisture products. The choice of this approach is to check if there are any possible uncertainties that can be related to the in-situ soil moisture measurements, located on a steep slope plot that may not fully represent the average soil moisture conditions over the whole basin. In the case of the Issyl basin, since there is no observed soil moisture data, the model is run for a range of different

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

values of the A parameter. The best value of the A parameter is selected as the one yielding the best correlations with the different satellite products.

The values from ASCAT and SMA are given in percentage (values are ranging between 0 and 1) while SMOS, SMOS-IC, ERA5, ESA-CCI and observations are in $m^3\ m^{-3}$. To allow a comparison for all soil moisture datasets a rescaling procedure is needed. Before applying the rescaling procedure, according to Albergel et al. (2010), a 95% confidence interval is chosen to define the higher and lower values to exclude any abnormal outliers using equation 1 and 2. The resulted data is then rescaled to their own maximum and minimum values considering the whole period using the equation 3. The issue in the validation of satellite soil moisture products and reanalysis product with in-situ measurements is the spatial resolution (Jackson et al., 2010). Several studies mentioned that, in the case of the temporal stability introduced by Vachaud et al. (1985), one in-situ measurement point can represent the soil moisture condition of a larger area (Brocca et al., 2009b, 2010; Loew and Mauser, 2008; Loew and Schlenz, 2011; Martínez-Fernández and Ceballos, 2005; Miralles et al., 2010; Wagner et al., 2008). According to (Massari et al., 2015), the coarse satellite observations can be beneficial for small basins, in the case if the in-situ observation falls in the satellite product pixel. This means that the in-situ measurements can represent a good benchmark (Liu et al., 2011). In this study we considered the in-situ measurement as a benchmark to validate different soil moisture products.

$$\mathrm{Up_{SM}} = \mu_{\mathrm{SM}} + 1.96\sigma_{\mathrm{SM}}, \tag{1}$$

$$\mathrm{Low_{SM}} = \mu_{\mathrm{SM}} - 1.96\sigma_{\mathrm{SM}}, \tag{2}$$

Where Up_{SM} and Low_{SM} are the limits of the confidence interval (the upper and the lower 95%)

$$\mathrm{SM} = \frac{\mathrm{SM} - \mathrm{Low_{SM}}}{\mathrm{Low_{SM}} - \mathrm{Up_{SM}}}, \tag{3}$$

3.2 Extended collocation analysis:

An alternative technique to validate soil moisture products when ground truth is missing is the use of Triple Collocation (TC) analysis (Gruber et al. 2016b). TC analysis requires the availability of three datasets with mutually independent errors and linear additive error model between the measurement systems and the unknown truth:

$$\mathrm{X} = \alpha + \beta \mathrm{S} + \varepsilon, \tag{4}$$

where X is the soil moisture estimate, S is the true soil moisture, α and β are additive and multiplicative biases, respectively. Eventually, ε is the zero-mean random error.

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

To build such a triplet, satellite and ground-based datasets can be combined with modeled soil moisture fields from reanalysis (e.g., ERA5). The reanalysis datasets ingest a number of satellite, atmospheric and ground observations which can potentially undermine their independence with respect to other members of the triplets. This creates doubts about the satisfaction of the null cross-correlation assumptions required to apply TC (Stoffelen, 1998). In a preliminary analysis (not shown), we used TC to characterize the error variance of the different soil moisture datasets by using different triplet combinations of the products. However, we observed substantial differences among the selected triplets likely due to error co-dependence. Based on that, we assumed the existence of non-null error cross correlation for the selected triplets (e.g. ERA5, SMOS and ASCAT).

When more than three products are available (i.e., N), the error can be estimated using an Extended Collocation (EC) approach (Gruber et al. 2016). The same assumptions for TC also apply for EC, but the number (N >3) datasets constitutes an over-constrained system, allowing the designation of N-3 non-zero error covariance terms which can be estimated with a least-squares solution (Pierdicca et al. 2015). Therefore, the zero TC assumption can be relaxed to allow non-zero correlation among N-3 data product pairs. For N = 4, the X, Y, Z, W measurement systems and assuming that non-zero EC exists only between X and Y, the least-squares solution for the QC problem is given by:

$$M=\begin{bmatrix}\sigma_X^2\\ \sigma_Y^2\\ \sigma_Z^2\\ \sigma_W^2\\ \sigma_{XY}\\ \sigma_{XZ}\sigma_{XW}/\sigma_{ZW}\\ \sigma_{YZ}\sigma_{YW}/\sigma_{ZW}\\ \sigma_{XZ}\sigma_{ZW}/\sigma_{XW}\\ \sigma_{YZ}\sigma_{ZW}/\sigma_{YW}\\ \sigma_{XW}\sigma_{ZW}/\sigma_{XZ}\\ \sigma_{YW}\sigma_{ZW}/\sigma_{YZ}\\ \sigma_{XZ}\sigma_{YW}/\sigma_{ZW}\\ \sigma_{XW}\sigma_{YZ}/\sigma_{ZW}\end{bmatrix} A=\begin{bmatrix}1000010000\\0100001000\\0010000100\\0001000010\\0000100001\\1000000000\\0100000000\\0010000000\\0010000000\\0001000000\\0001000000\\0000100000\\0000100000\end{bmatrix} S=\begin{bmatrix}\beta_X^2\sigma_T^2\\ \beta_Y^2\sigma_T^2\\ \beta_Z^2\sigma_T^2\\ \beta_W^2\sigma_T^2\\ \beta_X\beta_Y\sigma_T^2\\ \sigma_{\varepsilon_X}^2\\ \sigma_{\varepsilon_Y}^2\\ \sigma_{\varepsilon_Z}^2\\ \sigma_{\varepsilon_W}^2\\ \sigma_{\varepsilon_X\varepsilon_Y}\end{bmatrix}, \qquad (5)$$

where σ_T^2 is the true soil moisture variance, σ_ε^2 is the variance of the random error, and σ_(ε_X ε_Y) is the error covariance between X and Y.

And the least squares solution for the parameters in S is given as:

$$\hat{S}=(A^TA)^{-1}A^TM, \qquad (6)$$

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

Which provide the error variance of each dataset as long as the error covariance terms. More details on the method and its mathematical derivation can be found in Gruber et al. (2016).The error variance provided by EC can also be expressed in normalised form as Signal-to-Noise Ratio (SNR). This overcomes the dependency on the chosen scaling reference and allows to compare the error variances between the data sets. SNR is usually given in decibel, which can be easily interpreted: a value of zero means that the signal variance is equal to the noise variance, and every 3dB increase(decrease) implies a doubling (halving) of the signal variance compared to the noise variance. The SNR (expressed in dB) can be computed using the following formulation:

$$SNR[db] = 10 \log \frac{\beta_i^2 \sigma_\theta^2}{MSE_i}, \tag{7}$$

with i, j in [X, Y, Z] and $i \neq j$.

In some special cases, the MSEi can become negative and the SNR cannot be expressed in dB (logarithm of a negative number is undefined). The reason is that the relation of the covariances between the data sets become larger than the actual signal variance (e.g. #XY #XZ/#Y Z > #2X), which can be related numerical problems, wrong estimation of the covariances or a violation of the underlying assumptions of the error model in general.In our study we used two different configurations of the EC techniques. In particular, for the Issyl basin no in situ observations are available so we used quadruple collocation analysis with quadruplets constructed with ASCAT, SMOS, ERA5 and SMA and ASCAT, SMOS-IC, ERA5 and SMA. The choice of these quadruplets was based on the assumption of non-zero correlation between SMOS products and ERA5 so in the process we also estimated σ_(SMOS-ERA) (not shown). Similarly, for Rheraya we applied the methods by using five different datasets and assuming SMOS and ERA products and SMA and in situ observations characterized by non-null error cross-correlations. For both basins we used either SMOS or SMOS-IC in the configurations.

3.3 Event-based hydrological model for floods

In this study, we used the Soil Conservation Service Curve Number (SCS-CN) model for each basin, implemented in the hydrologic Engineering System - Hydrologic Modeling System ‘’HEC-HMS’’ software (US Army Corps of Engineers, 2015). This model is known by its widespread popularity and to the simplicity of the application method (Miliani et al., 2011). SCS-CN is often used in the semi-arid context (Brocca et al., 2009a; El Khalki et al., 2018; Tramblay et al., 2010; Zema et al., 2017). Our methodology is based on the use of SCS-CN model as a production function to compute net rainfall, by manually calibrating the Curve Number parameter (CN), the value of CN is non-

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

dimensional ranging from 0 (dry) to 100 (wet). The potential maximum retention, S, is related to CN as follows:

$$S = \frac{25400}{CN} - 254\,, \tag{8}$$

The transformation of precipitation excess into runoff is provided by Clark Unit hydrograph model (transfer function). The calibration procedure is based on calibrating the Clark Unit hydrograph model parameters; Storage Coefficient (Sc) and Time of Concentration (Tc). The two functions (production and transfer) are calibrated separately to avoid the parameter dependence.

The validation procedure is based on two steps; first, testing the relationship between soil moisture data (In-situ, SMA, ERA5, ASCAT, SMOS, SMOS-IC and ESA-CCI), at two different timescales (daily and hourly) and the S parameter of the event-based model of all the flood events. The hourly time step concerns only the in-situ data and ERA5 by choosing the soil moisture state 1 hour before the starting time of rainfall for each event. Only the ERA5 product can be used in the Issyl basin at the hourly time step due to the absence of observed data. Then, the soil moisture products that are well correlated with S parameter are used to validate the model by calculating the S parameter from the linear equation obtained between soil moisture and S, using the leave-one-out resampling procedure; each event is successively removed and a new relationship between the remaining event is re-computed. The estimated S parameter for a given event is then used in the SCS-CN model in validation. For the Clark Unit Hydrograph model, the average of the Sc and the Tc parameters are used in validation.

The correlation coefficient of Pearson equation (9) and the Root Mean Square Deviation (RMSD) equation (10) are used to compare in-situ measurements and humidity modeled by SMA model and the different soil moisture products. For the evaluation of the flows simulated by the flood event model, we compared the simulated discharge with those observed using the efficiency coefficient of Nash-Sutcliffe (Ns) (Nash and Sutcliffe, 1970) equation (11) as well as through the bias on peak flow and on volume equation(12).

$$r = \frac{N\sum SM_{sat}SM_{In-situ} - (\sum SM_{sat})(\sum SM_{In-situ})}{\sqrt{[N\sum {SM_{sat}}^2 - (\sum SM_{sat})^2][N\sum {SM_{In-situ}}^2 - (\sum SM_{In-situ})^2]}}, \tag{9}$$

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(SM_{In-situ} - SM_{sat})^2}{N}}, \tag{10}$$

$$Ns = 1 - \frac{\sum_{i=1}^{n}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{n}(Q_{obs,i} - \overline{Q_{obs}})^2}, \tag{11}$$

$$\mathrm{BIAS_Q} = \frac{(\mathrm{Q_{sim}} - \mathrm{Q_{obs}})}{\mathrm{Q_{obs}}}, \qquad (12)$$

Where $\mathrm{Q_{sim}}$ is the simulated discharge, Q_{obs} is the observed discharge, $SM_{In-situ}$ is the in-situ measurements of soil moisture, SM_{sat} is the soil moisture from satellite or reanalysis and N is the number of values. The Ns ranges between -∞ and 1, the 1 value of Ns indicates that the simulated discharge perfectly match the observed hydrograph

4 Results and discussions

4.1 Relationship between satellite soil moisture data and in-situ measurements

The comparison between measured soil moisture at 5cm depth and the different products of soil moisture show that the SMOS-IC and ERA5 provide the best correlations, with r=0.76 and r=0.67 respectively, but it should be noted that all the correlations with the different products are also significant. Figure 2 shows that SMOS-IC and ERA5 reproduce dry periods well, whereas ERA5 reproduces well wet periods. This result is in accordance with the results of Massari et al. (2014) who found that ERA-Land is well correlated with In-situ data. ASCAT product shows a correlation of r=0.43 which is less than the correlation given in Albergel et al. (2010) who found r values ranging from between 0.59 and 0.64, the lower correlation may be caused by the orography and the coarse resolution. In fact, this results shows that the use of a combined product as ESA-CCI give an obvious advances in term of r values than one single satellite soil moisture product (Ma et al., 2019; Zeng et al., 2015). It should be noted that the soil moisture products have a different percentage of missing data for ASCAT (0%), SMOS (18.7%), SMOS-IC (6.82%), ESA-CCI (46%) and observed soil moisture (12%). The ESA-CCI showed an important percentage of missing values comparing to ASCAT that is integrated in the ESA-CCI product. This due to the filter used in the ESA-CCI product to ensure the data quality, more description can be found in (Dorigo et al., 2017).

4.2 Relationship between the SMA model outputs and soil moisture products

The best correlation between observed soil moisture and the soil moisture level (S/A) modeled by the SMA model is obtained for A=8mm with r=0.86. But it shows higher RMSD than observations (RMSD =0.23) which is due to the overestimation of the wet periods (Figure 3). This can be related to the averaging of rainfall data in the SMA model over the basin which could be higher than rainfall in the soil moisture measurement site. It should be noted that the value of the A parameter is very small by comparing to previous studies (Javelle et al., 2010; Tramblay et al., 2012), indicating a much lower soil storage capacity.

We correlated the SMA model output (for A=8mm) with the Satellite Products of Soil Moisture, and the best correlations are found for SMOS-IC and ERA-5, with r=0.74 and r=0.63 respectively (Figure 4). Other values of A that maximize the correlations with the different soil moisture products have also been tested. Optimal values of A are ranging from 1 mm with ASCAT (with r= 0.4), 8 mm for SMOS (r=0.56), SMOS-IC (r=0.75) and ESA-CCI (r=0.55) up to 16mm for ERA5 (r=0.68). Comparing the Figure 2 and Figure 4 we notice that the soil moisture products better reproduce in-situ measurements than modelled soil moisture with the SMA model, expect for ESA-CCI and SMOS. This improvement is directly related to the SMA model performance, which overestimates soil moisture, and should be compared to Figure 2 where ESA-CCI and SMOS products also overestimate in-situ measurements.

For the Issyl basin, the percentage of missing values is a bit lower than in the Rheraya and also different between the satellite products: ASCAT (0%), SMOS (17.19%), SMOS-IC (9.1%) and ESA-CCI (2.2%). As mentioned above, no observed soil moisture data is available in the Issyl basin to calibrate the A parameter of the SMA model. Therefore, different values of A are tested to correlate the SMA outputs with the different soil moisture datasets. Over all datasets, the value of A best correlated to the majority of soil moisture products is 30mm. The best correlation is given by A=30mm with r=0.78, 0.82 and 0.79 for ASCAT, SMOS-IC and ESA-CCI respectively. As for SMOS and ERA5, the best correlation is given for A=40mm with r=0.7 and A=60mm with r=0.8, respectively. In order to choose a single value of A that represents the basin, we have considered A=30mm, the optimal value yielding the best correlations with the different soil moisture products. Figure 5 shows that the best correlation between satellite products and S/A is obtained with SMOS-IC (r=0.82) and ESA-CCI (r=0.79). As observed over the Rheraya basin, the SMOS-IC and ERA5 products showed a good reproduction for dry periods with a better reproduction of wet periods with ERA5, these results are similar to those of Ma et al. (2019) who found that SMOS-IC performs well in arid zones with a median r value of 0.6. Overall, the higher value for the A parameter found for this basin is coherent with the fact that this basin is located in a plain area with a much higher soil moisture storage capacity than in the mountainous Rheraya basin.

4.3. Comparison of soil moisture datasets by seasons

Seasonal evaluation of satellite soil moisture and reanalysis data shows for the Rheraya basin that during the summer season there are low correlations (average r=0.34) for all the products which is possibly due to very low precipitation amounts mostly as localized convective precipitation (Albergel et al., 2010). On the contrary, better performance are obtained with the SMA model (r=0.59) that considers catchment-scale precipitations. Better correlations are obtained in fall with an average of r=0.61 and 0.58 for the in-situ data and SMA respectively (Table 2). In the winter we found a poor

Natural Hazards and Earth System Sciences
Discussions

correlation using SMOS and ESA-CCI that can be related to the important percentage of missing values. For the Issyl watershed, the satellite products show good correlations with the SMA model outputs (on average r=0.76) except for the SMOS product especially in winter. We also notice a trend of improving correlations by moving from winter to autumn with a similarity between spring and autumn, which is not the case in the Rheraya basin, probably because of different precipitation patterns. The ERA5 overall product shows good correlations for most seasons.

4.4 Extended collocation analysis

Table 3 shows the results obtained for the two basins and two configurations. For Issyl, it can be seen that SMOS-IC is the best performing product with SNR much larger 3DB, followed by ASCAT and SMA. Conversely ERA5 and SMOS are suboptimal having noise variance similar to the signal variance. For Rheraya SMOS-IC is the only product providing SNR>3DB followed by SMOS and ERA5 which are however are still suboptimal. Poor results are found for both SMA, in situ and ASCAT in this catchment. Overall, the results of this complementary analysis confirm the findings of previous sections.

4.5 Calibration of the event-based hydrological model

Calibration results (Table 4) on the individual flood events of Table 1 show that the difference between the values of the potential maximum soil moisture retention (S) of each basin is very important with larger values for the Issyl basin where the soil depth is prominent. We noticed that the temporal variability of soil moisture can be important between two successive events like the events of 02/04/2012 and 05/04/2012 for the Issyl basin. The SCS-CN model reproduces well the floods of the Rheraya basin with average Ns of 0.67 and bias on runoff peak ($BIAS_Q$) of 4% (Table 3). As shown on Figure 6, the SCS-CN model in calibration is able to reproduce the shape of the different flood events even for the most complex ones (21/04/2014 and 22/11/2014). Similarly, for the Issyl basin the SCS-CN model gives good results with average Ns of 0.66 and an average bias on runoff peak of 6.93%. Figure 7 shows the simulated hydrographs which are in good agreement with the observations. The lower Ns coefficients obtained for the 23/01/2014 event in the Rheraya and for the 03/04/2011 and 28/09/2012 events in the Issyl basin are caused by a slight shift in the hydrograph probably due to a time lag in instantaneous precipitation measurements. For the Clark Unit Hydrograph model, the averages of calibrated Tc and Sc parameters are considered for validation (Sc = 1.42 and 2.54 hours and Tc = 2.85 and 3.64 hours for Rheraya and Issyl respectively).

The S parameters of the hydrological models, for the two basins, are then compared to the soil moisture products. For the Rheraya basin, there are significant correlations of the S parameter with in-

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

situ soil moisture data, ERA5 and SMOS-IC (Table 5). The correlations using observed soil moisture, ESA-CCI and SMOS data can be computed with only 8 and 6 events respectively, due to the presence of missing values. The time step of the soil moisture data in the Rheraya basin seems to play a key role in the representation of soil moisture conditions. Indeed, the daily time step shows a weakness to effectively represent the antecedent soil moisture conditions in the SCS model, which indicates the rapid change of soil moisture content in such a semi-arid mountainous basin. For the Issyl basin, ESA-CCI is the only satellite product that is significantly correlated to the S parameter at the daily time step. The ERA5 product is also significantly correlated with the S parameter but at the hourly time step. The daily output of the SMA model is also able to estimate the initial condition of the model for the Issyl basin, with a correlation of -0.69 with S. Interestingly, the SMA model does not provide a good performance in the Rheraya basin. It can be due to the fact that in such a mountainous basin, there is a strong spatial variability of rainfall and it is difficult to obtain reliable precipitation estimates for continuous simulations (Chapponiere et al., 2005).

4.6 Validation of the event-based hydrological model

The validation of the event-based hydrological model is performed on the events of Rheraya and Issyl using only the soil moisture datasets that show relatively good correlations with the initial condition (S) of the model from Table 6. These products include SMOS-IC, ERA5 and observed soil moisture for the Rheraya, and ESA-CCI, ERA5, SMOS and SMA for Issyl. The validation of the event-based model is performed with S calculated from the linear equation obtained from the correlation analysis between the different soil moisture products and the calibrated parameter S. The validation results show that for the Rheraya basin the events are well validated using both daily (Figure 6) and hourly (Figure 7) time step of soil moisture products. The best validation result at the daily time step is obtained with SMOS-IC with an average Ns of 0.58 for all events (median Ns =0.63). This result should be compared with the results found in the previous sections where SMOS-IC showed the best correlations with observed soil moisture. ASCAT and ERA5 show similar results in term of average Ns (~0.45). On the contrary, the daily observed soil moisture shows a lower performance with an average Ns of 0.25 (median Ns =0.49). The hourly time step enhanced the performance of the model, with an average Ns using the ERA5 product of 0.64 (median Ns = 0.73) and also a better performance with the hourly in-situ data with mean Ns = 0.54 (median Ns = 0.61). These results show that the hourly time step better represents the saturation content before the flood events in this bassin. For the Issyl, the validation results are quite different (Figure 8). For only 5 events (the 03/04/2011, 02/05/2011, 19/05/2011, 05/04/2012 and 25/03/2015) the event-based model can be validated using the ERA5 hourly data with an average Ns coefficient of 0.46, while for all other events and with different soil moisture products the Ns coefficients are negative and the hydrographs not adequately reproduced. These validation results should be put in perspective with the fact that the Issyl basin has a

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

land use characterized by agricultural activities with possible large water uptake in the diver channel during floods for irrigation. Some simple methods to compensate for the water losses due to irrigation, such as the application of a varying percentage of runoff added to the observed discharge to compensate the part of water lost for irrigation, have been tested but with no improvement of the results. This is probably because the quantity taken for irrigation is not constant from one event to another depending on the farmer needs, as shown by field surveys, and this amount may also depend on discharge thresholds.

5 Conclusions

This study performed an evaluation of different soil moisture products (ASCAT, ESA-CCI, SMOS, SMOS-IC and ERA5) using in-situ measurements and a Soil Moisture Accounting model (SMA) over two basins located in the Moroccan High Atlas in order to estimate the initial soil moisture conditions before flood events. There is a knowledge gap on the evaluation of soil moisture products in North Africa (Jiang and Wang, 2019) that the present study aimed to fill. The results indicated that the SMOS-IC product is well correlated with both the in-situ soil moisture measurements and simulated soil moisture from the SMA model over the two basins. Beside satellite products, the new ERA5 reanalysis reproduced also well the in-situ measurements over the mountainous basin, which indicates the robustness of this product to estimate soil moisture in these semi-arid environments. The seasonal analysis showed increasing correlations coefficients, from winter to autumn, for all the soil moisture products when compared to observations, which encourages the use of these remote sensing products for flood forecasting because the majority of events occur in autumn and early winter in these regions (El Khalki et al., 2018). The extended collocation analysis show coherent results with the correlation results with the SMOS-IC providing the best results for the Issyl and Rheraya basins. One of the main finding of the present study is that different products, in particular SMOS-IC, ASCAT and ERA5, are efficient to estimate the initial soil moisture conditions in an event-based hydrological model, that could improve the forecasting capability in data-scare environments.

This study also showed that the hourly temporal resolution for soil moisture may provide a better estimate of the initial soil moisture conditions for both basins. Indeed, the use of hourly in-situ soil moisture measurements and ERA5 provided better performance to estimate the initial condition of the hydrological model. These results indicate that the temporal variability of soil moisture in these semi-arid basins under high evapotranspiration rates can be very important causing a quick decay of soil moisture following a rainfall event. For this type of basin or others under even more arid conditions, the use of soil moisture products with an hourly temporal resolution could be required to estimate with accuracy the soil moisture content prior to flood events. This constitute a research challenge to monitor soil moisture at the sub-daily timescale without ground measurements, since most remote sensing products at present are not available at the hourly time step. As shown by this study, atmospheric reanalysis coupled with a land surface model, such as ERA5, could provide a valuable alternative, in particular since the resolution of these products is constantly improving along with a more realistic representation of water balance.

For the catchment that is the most influenced by agricultural activities, the Issyl basin located nearby Marrakech, the water uptake for irrigation made difficult the validation of the hydrological model. The model overestimates runoff for some flood events, since the water uptake during floods from the river channel by small artisanal structures is not monitored and thus cannot be represented in the hydrological model. This example show the difficulty in the implementation of a flood forecasting system in such basin without a good knowledge on the human influences on river discharge. This situation is not a particular case but deemed common in semi-arid areas where rivers with a high risk of flooding are also a substantial water resource for agriculture. Therefore, as shown by our results, a hydrological model that is not accounting for water use and irrigation may not be efficient at reproducing flood events in an operational context. The resolution of this issue would requires the development of an irrigation monitoring system, that would need intensive field surveys and mapping but also the agreement of the local farmers that benefit from this system.

This study is a first step towards the development of operational flood forecasting systems in semi-arid North Africa basins highly impacted by floods. Indeed, the evaluation of the most suitable satellite or reanalysis products to estimate soil moisture for the monitoring of the basin saturation conditions before floods is a necessary first step prior to implement flood warning systems based on rainfall and soil moisture thresholds or coupled hydrometerological modelling (Javelle et al., 2010; Norbiato et al., 2008). One important aspect that should be addressed in further research aiming at developing a flood forecasting system is the selection of soil moisture data based on the latency of these products. For instance the ERA5 reanalysis is available within 5-days latency when ASCAT or SMOS satellite products could be available with 3-hours latency. Prior to these developments, this type of evaluation should be generalized in Morocco and other sites in North Africa where soil moisture measurements are available, for the development of reliable flood forecasting systems using the outputs of meteorological models in combination with the soil moisture state.

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https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

Natural Hazards and Earth System Sciences
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Discussions

TABLES

Table 1: Characteristics of the selected flood events.

	Max Discharge [m^3/s]	Volume [10^3 m^3]	Precipitation Volume [10^3 m^3]	Runoff Coefficient [%]
Rheraya				
23/01/2014	17.1	459.2	2749.5	16.7
29/01/2014	39.7	602.8	2632.5	22.9
10/02/2014	19.2	543.2	2904.7	18.7
11/03/2014	19	557	1633.5	34.1
21/04/2014	38.2	1070	5431.5	19.7
21/09/2014	24.4	440.6	3363.8	13.1
05/11/2014	46.5	1027	5737.5	17.9
09/11/2014	42.2	869.3	4575.2	19
22/11/2014	99.5	3868.9	17586	22
28/11/2014	76.4	3797.2	11940.8	31.8
Issyl				
25/03/2011	63.8	385.28	27520	1.4

03/04/2011	16.6	550.656	30592	1.8
29/04/2011	19.7	246.4	11200	2.2
02/05/2011	17.1	303.36	10112	3.0
16/05/2011	45.8	361.12	9760	3.7
19/05/2011	27.6	315.392	7168	4.4
06/06/2011	18.3	212.352	5056	4.2
02/04/2012	16.8	216.576	18048	1.2
05/04/2012	20	543.744	7552	7.2
28/09/2012	22.7	126.72	7040	1.8
05/04/2013	15.4	365.376	16608	2.2
28/11/2014	37.2	489.6	28800	1.7
25/03/2015	16.2	767.424	18272	4.2

Table 2: Results of correlation analysis between soil moisture data and in-situ measurements and SMA model (significant correlations are represented in bold)

		Winter	Spring	Summer	Fall
		Rheraya			
In-situ	SMA A=8mm	**0.82**	**0.83**	**0.67**	**0.75**
ASCAT	In-situ	**0.47**	-0.03	0.18	**0.70**
	SMA A=8mm	**0.32**	0.09	**0.54**	**0.65**
SMOS	In-situ	0.01	**0.68**	**0.61**	0.16
	SMA A=8mm	-0.09	**0.75**	**0.58**	**0.54**
SMOS-IC	In-situ	**0.80**	**0.68**	**0.45**	**0.85**
	SMA A=8mm	**0.80**	**0.72**	**0.62**	**0.57**
ESACCI	In-situ	0.12	0.28	**0.41**	**0.60**
	SMA A=8mm	0.15	**0.30**	**0.67**	**0.51**
ERA5	In-situ	**0.74**	**0.73**	0.04	**0.73**
	SMA A=8mm	**0.86**	**0.76**	**0.54**	**0.65**
Mean	In-situ	0.43	0.47	0.34	0.61
	SMA A=8mm	0.41	0.52	0.59	0.58
		Issyl			
ASCAT	SMA A=30mm	**0.77**	**0.86**	**0.70**	**0.90**
SMOS		**0.39**	**0.76**	**0.47**	**0.74**

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

SMOS-IC		**0.85**	**0.81**	**0.56**	**0.93**
ESACCI		**0.70**	**0.89**	**0.77**	**0.89**
ERA5		**0.88**	**0.82**	**0.70**	**0.88**
Mean	SMA A=30mm	0.72	0.83	0.64	0.87

Table 3: Signal to noise ratio for Rheraya and Issyl basins. The SNT = 0 : Error variance, SNR > 3 Signal variance double the noice variance (very good) and SNR < 3 Signal variance half noice variance (not good).

	ASCAT	SMOS	SMOS-IC	ERA5	SMA
Rheraya	-5.55		7.54		-1.99
	-6.16	4.31		1.16	-1.10
Issyl	4.23	1.90		2.33	5.03
	4.28		8.12	2.33	4.99

Table 4: Calibration results of SCS-CN model, S is the potential maximum soil moisture retention, $BIAS_Q$ is the difference between the observed and calibrated peak discharge of the event, $BIAS_V$ is the difference between the observed and calibrated volume of the event.

Rheraya					**Issyl**				
Events	**S[mm]**	**Ns**	**$BIAS_Q$ [%]**	**$BIAS_V$ [%]**	**Events**	**S[mm]**	**Ns**	**$BIAS_Q$ [%]**	**$BIAS_V$ [%]**
23/01/2014	19.1	-0.58	1.18	-5.76	25/03/2011	679.8	0,83	29,94	-13,5
29/01/2014	24.5	0.87	6.43	29.14	03/04/2011	730.5	0,02	-12,05	27,93
10/02/2014	34.6	0.71	-4	2.85	29/04/2011	218.1	0,83	0	10,36
11/03/2014	9.5	0.61	-17.39	2.57	02/05/2011	113	0,91	-0,58	44,39
21/04/2014	55.8	0.73	6.41	2.3	16/05/2011	176.5	0,61	17,69	-26,31
21/09/2014	34.6	0.77	27.08	-6.87	19/05/2011	136.7	0,87	1,09	9,64
05/11/2014	39.6	0.97	15.38	0.88	06/06/2011	108.8	0,75	0	-5,38
09/11/2014	40.7	0.83	6.3	-0.32	02/04/2012	440.3	0,56	0	15,26
22/11/2014	43.1	0.78	-5.06	2.38	05/04/2012	125.1	0,56	13,5	-1,91
28/11/2014	71.6	0.97	3.66	-6.22	28/09/2012	159.7	0,11	32,16	23,41
					05/04/2013	388.2	0,9	6,49	-4,16

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

				28/11/2014	254	0,74	1,88	0,71
				25/03/2015	356.6	0,89	0	12,32
Mean	0.67	4	2.09	Mean		0,66	6,93	7,14
Median	0.77	4.98	1.59	Median		0,75	1,09	9,64

Table 5: Correlation between soil moisture products and the S parameter of the SCS-CN hydrological model

	Rheraya		**Issyl**	
	S	**Number of events**	**S**	**Number of events**
In-situ [Daily]	-0.71	8	-	-
In-situ [Hourly]	-0.83	8	-	-
SMA A=8mm	-0.32	10	-	-
SMA A=30mm	0.02	10	-0.69	13
ASCAT	-0.55	10	-0,29	13
ESA-CCI	-0,29	8	-0.66	11
SMOS	0.12	6	-0,59	6
SMOS-IC	-0.81	10	-0.34	13
ERA5 [Daily]	-0.46	10	-0.37	13
ERA5 [Hourly]	-0.80	10	-0.63	13

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

Table 6: Performance of the SCS-CN model in term of Nash Coefficient for the Rheraya and Issyl events, using the daily or hourly time steps for the different soil moisture products.

	Daily							Hourly	
	ASCAT	**ESA-CCI**	**SMOS**	**SMOS-IC**	**ERA5**	**In-situ**	**SMA 30mm**	**ERA5**	**In-situ**
					RHERAYA				
Min	-0.15	-	-	-0.04	-0.73	-1.88	-	-0.01	0.15
Mean	0.48	-	-	0.58	0.45	0.25	-	0.64	0.54
Median	0.57	-	-	0.63	0.66	0.49	-	0.73	0.61
Max	0.85	-	-	0.84	0.82	0.83	-	0.81	0.71
					ISSYL				
Min	-	-56041	-1938.07	-	-	-	-96.08	-114.6	-
Mean	-	-14138.2	-324.3	-	-	-	-24.77	-16.74	-
Median	-	-254.85	-1.8	-	-	-	-2.46	-0.85	-
Max	-	-2.10	-0.52	-	-	-	-0.78	0.83	-

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Discussions

FIGURES

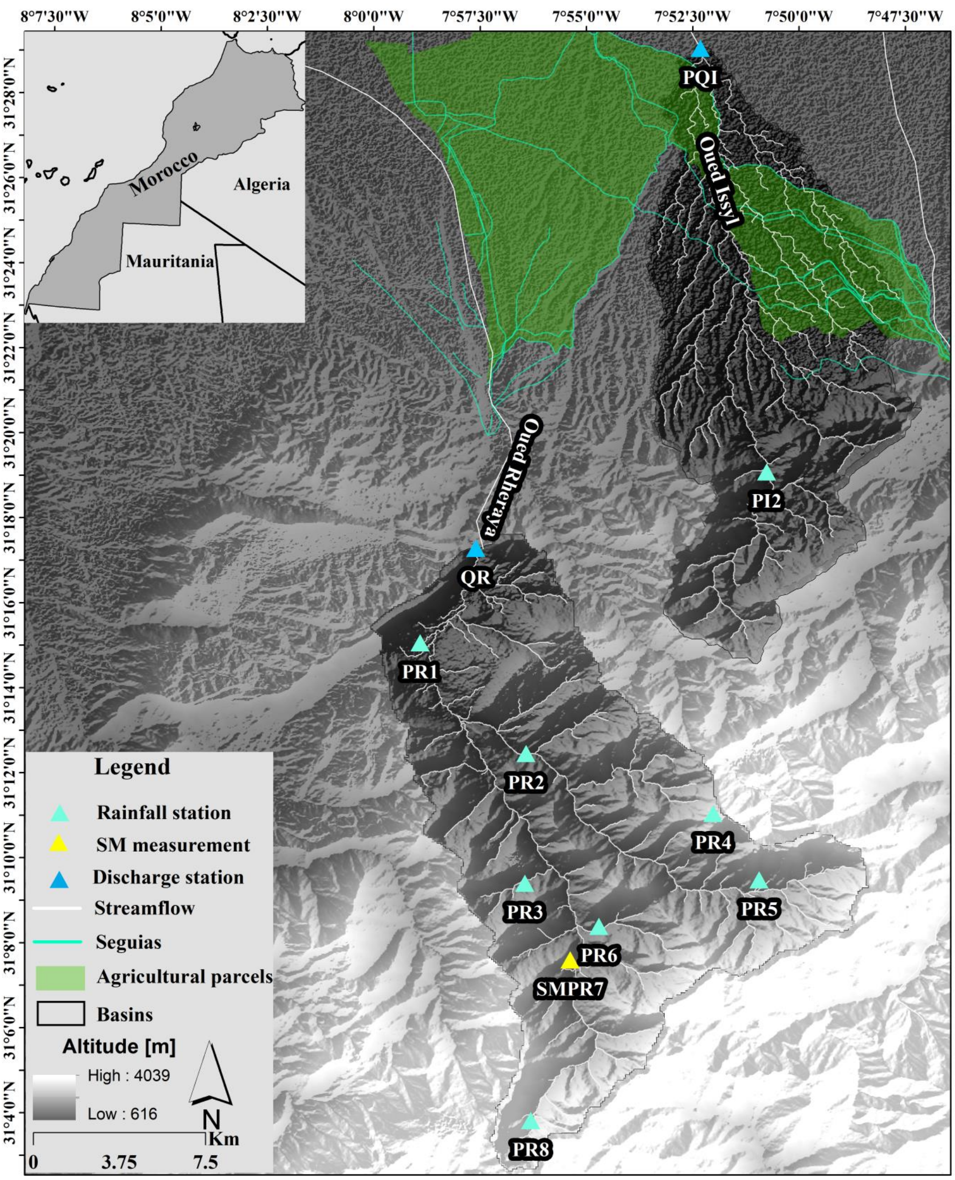

Figure 1: Location of Rheraya and Issyl basins, the seguias network, the agricultural parcels and the hydro-meteorological network – PR: Rainfall station in Rheraya, SMPR: Soil moisture measurement+ Rainfall station in Rheraya, PQI: Rainfall and discharge station in Issyl, QR: Discharge station in Rheraya.

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

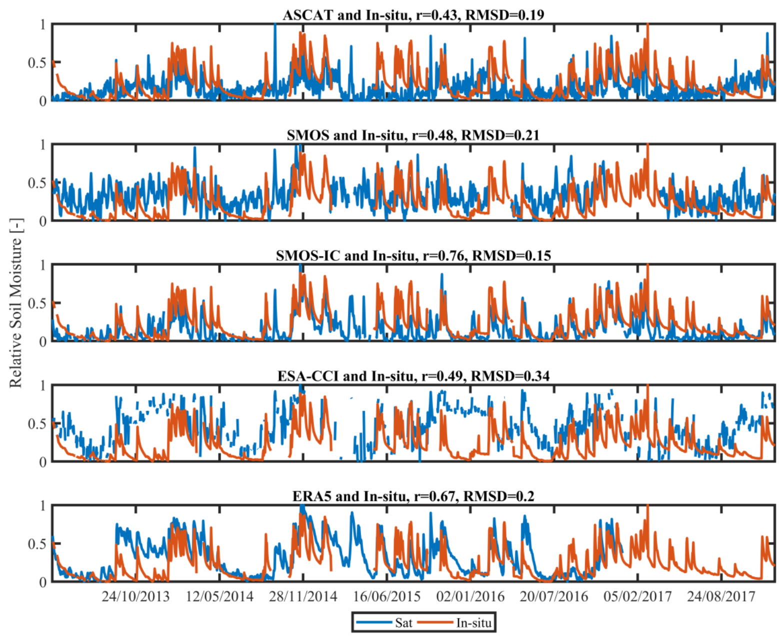

Figure 2: Correlation between measurements of soil moisture (5cm depth) and different products of soil moisture (Rheraya basin).

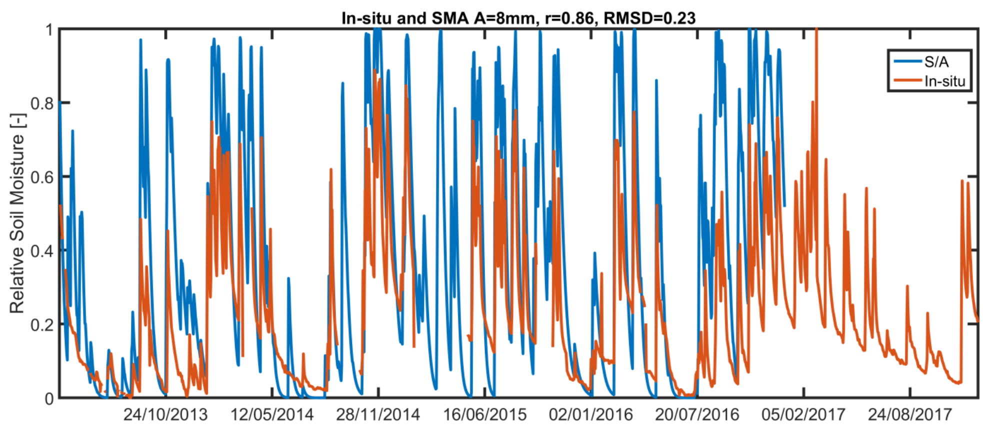

Figure 3: Relationship between S/A and observed soil moisture data between 08/04/2013 and 31/12/2016 for different values of A (Rheraya basin).

https://doi.org/10.5194/nhess-2020-119
Preprint. Discussion started: 12 May 2020

Natural Hazards and Earth System Sciences
Discussions

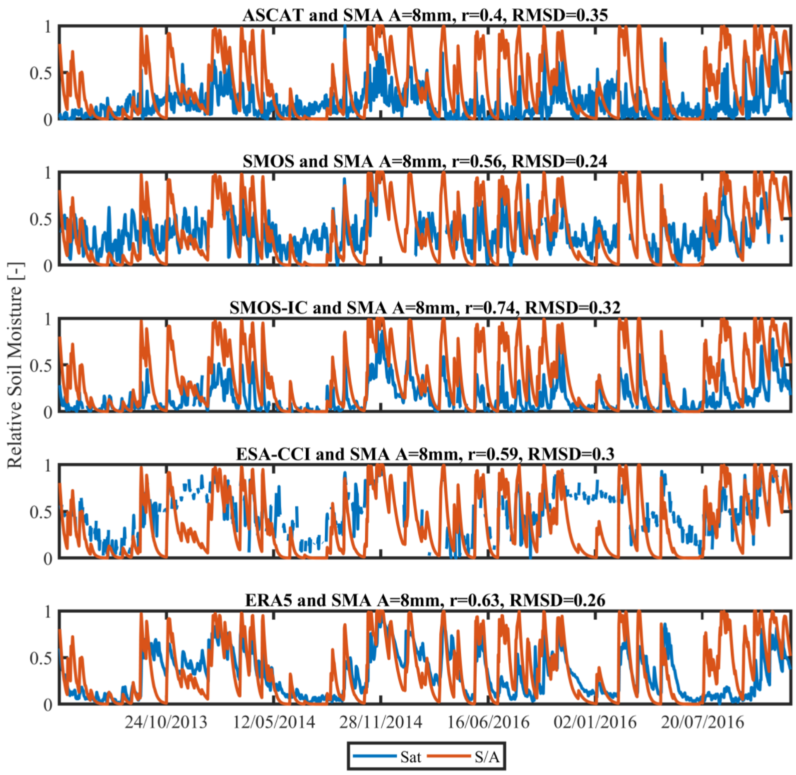

Figure 4: Relationship between satellite products of soil moisture and ERA5 with and SMA outputs between 08/04/2013 and 31/12/2016 over the Rheraya basin.

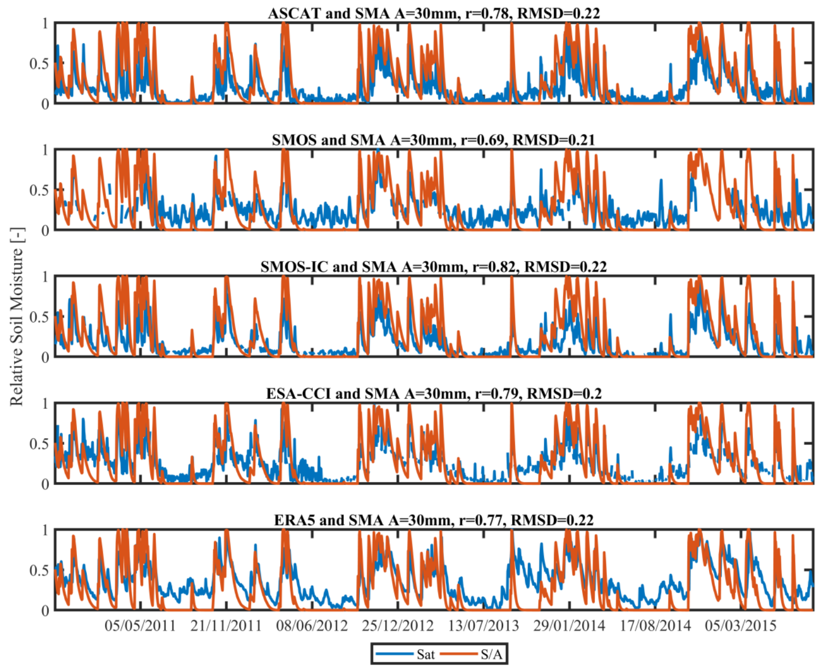

Figure 5: Relationship between Satellite products of soil moisture and SMA outputs for A=30mm between 18/10/2010 and 20/08/2015 in the Issyl basin

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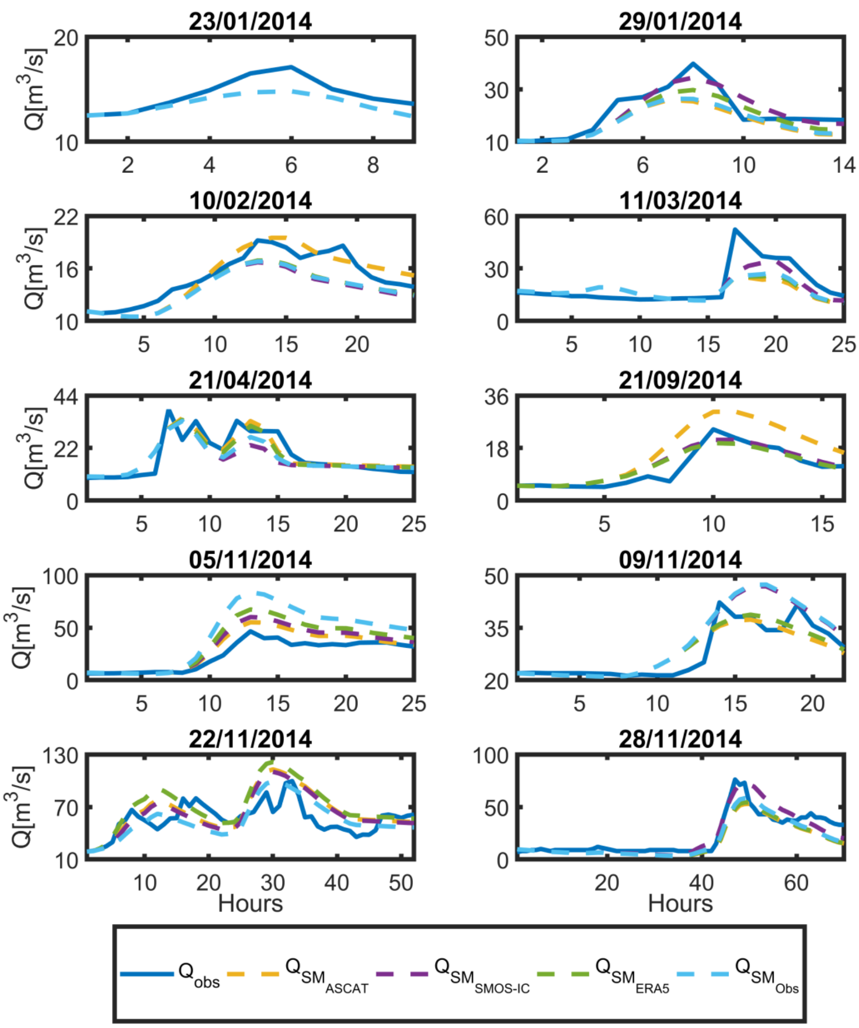
Preprint. Discussion started: 12 May 2020



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1006 **Figure 6: Validation results of flood events simulated for the Rheraya using different soil moisture**
1007 **products with a daily time step. The observed hydrograph (Q_{obs}) is compared to the simulated**
1008 **hydrographs using ASCAT, SMOS-IC, ERA5 and in situ data.**

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Preprint. Discussion started: 12 May 2020

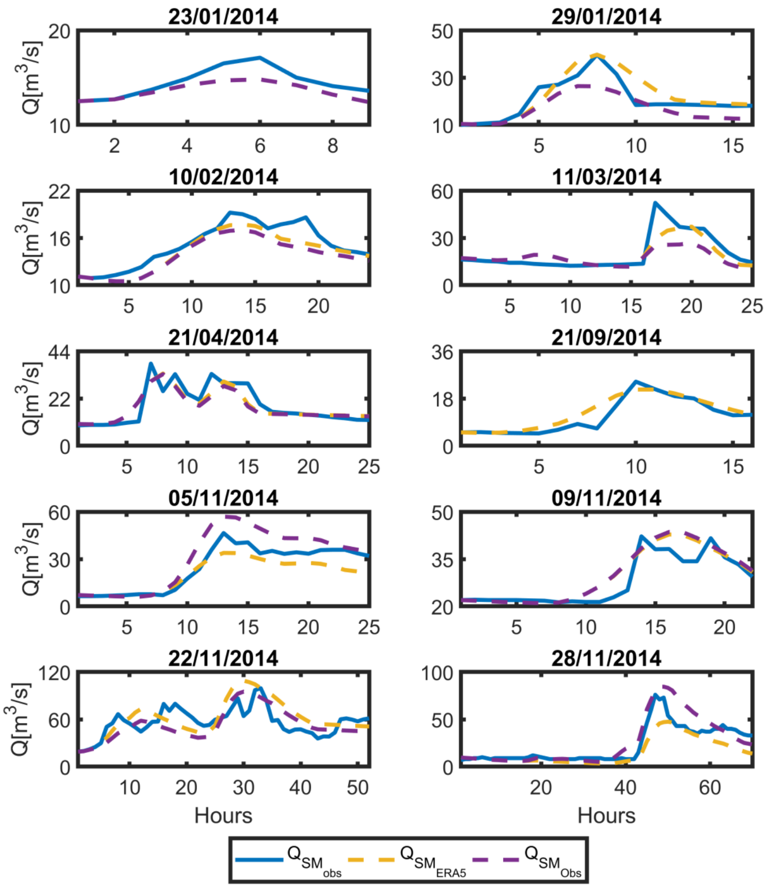

Figure 7: Validation of the flood events simulated for the Rheraya using ERA5 and in situ soil moisture with hourly time step.

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Preprint. Discussion started: 12 May 2020

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Open Access
Discussions

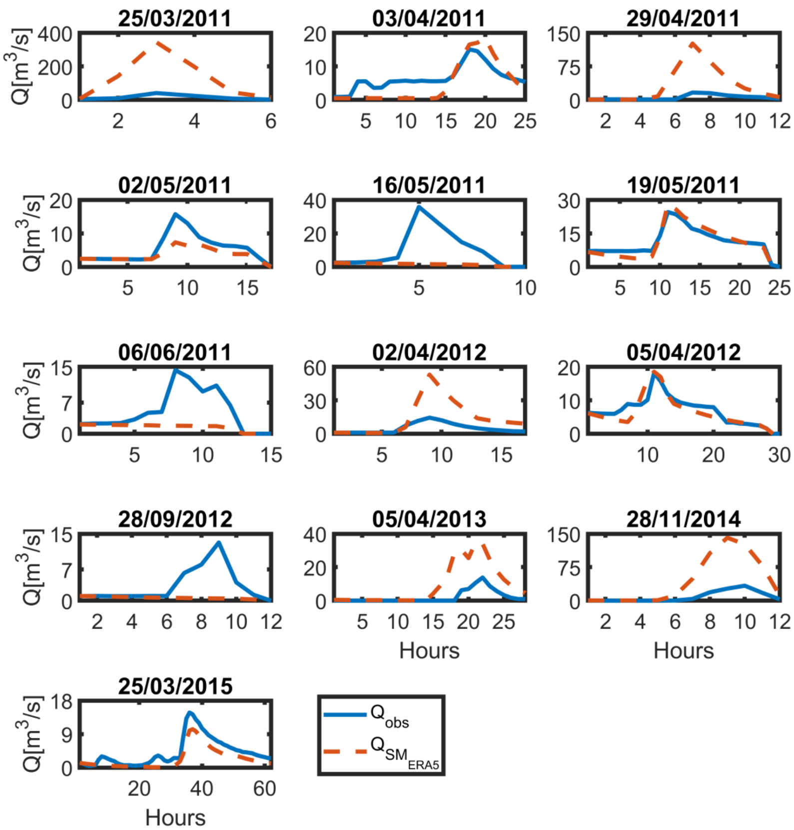

Figure 8: Validation result of flood events for the Issyl using ERA5 with hourly time step