Response to review comments of Dr. Heye R. Bogena on the manuscript "Calibration of a large-scale hydrological model using satellite-based soil moisture and evapotranspiration products"

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The authors would like to thank Dr. Heye R. Bogena for his really useful, valuable and productive suggestions on the manuscript. His in-depth review will help us to improve the structure and the overall quality of our manuscript. We have included detailed responses to his comments in the supplementary .pdf file. We have also included a modified version of the original manuscript. Please note the supplement to this comment and the modified manuscript, with modifications in blue.

General comments:

Comment 1:

The motivation for choosing the study area is too weak. Basically the research presented in this study could be accomplished in any catchment. For instance, you could mention the specific challenges for the calibration of hydrological models in such environments.

Answer:

We agree with the reviewer and according to his suggestion, we will include and modify some sentences about the specific challenges for hydrological modelling in ungauged basins as follows:

P2L4-9:"… Ungauged or poorly gauged river basins also include those basins where data are inaccurate, scarce, intermittent or collected at different temporal resolutions, leading to the problem that it is not clear how to integrate these data consistently into hydrological models (Winsemius et al., 2009). As a result, the limited availability and poor quality of data induces large uncertainty in model outputs from these river basins (Seibert and Beven, 2009). Developing novel strategies to enhance available datasets and hydrological models is one of the key strategies when working in ungauged basins (Hrachowitz et al., 2013). …"

We will also include more information about particularities of the Oum Er Rbia basin to improve the motivation behind the selection of this study area:

P3L8-13: "… with a good coverage of in-situ hydro-meteorological data. In the present study area, the Oum Er Rbia river basin located in Morocco, ground observations are spatially sparse and limited in number classifying it as a poorly-gauged river basin. The region frequently suffers from water scarcity and droughts and water availability is the main factor influencing socio-economic development, mostly driven by the agriculture (Houdret, 2009). The studies of Ouatiki et al. (2017), Tramblay et al. (2012) and Tramblay et al. (2016) are testimony to the relevance of this area. Therefore, developing new strategies to model this watershed is highly relevant to improve water management and assessment of the water availability within the basin. …"

Comment 2:

The introduction is repetitive and too long. Please rewrite in a more focussed way and describe more clearly the structure of the paper.

Answer:

We will modify the introduction to clarify the contents and structure of the manuscript as follows:

P2L1-P4L4: "1. Introduction

To assess and manage the available water resources within a river basin, good estimates of hydro-meteorological data, such as precipitation, temperature and streamflow, are required. Yet many river basins around the world still have a limited number of in-situ observations, being either ungauged (Sivapalan et al., 2003) or poorly gauged (Loukas and Vasiliades, 2014). Ungauged or poorly gauged river basins also include those basins where data are inaccurate, scarce, intermittent or collected at different temporal resolutions, leading to the problem that it is not clear how to integrate these data consistently into hydrological models (Winsemius et al., 2009). As a result, the limited availability and poor quality of data induces large uncertainty in model outputs from these river basins (Seibert et al., 2009). Developing novel strategies to enhance available datasets and hydrological models is one of the key strategies when working in ungauged basins (Hrachowitz et al., 2013).

To overcome the lack of hydro-meteorological data, a promising approach is the use of the recently developed global earth observations and reanalysis products to supplement the available data. In the last decades, radar and satellite technologies have improved and have become more broadly available providing diverse hydro-meteorological datasets at finer spatial and temporal resolutions: precipitation -CMORPH (Joyce et al., 2004); TRMM (Huffman et al., 2007); etc.-, soil moisture -AMSR-E (Njoku et al., 2003); ESA-CCI (Dorigo et al., 2015); etc.-, total water storage -GRACE (Tapley et al., 2004); etc.-, evapotranspiration -SEBAL (Bastiaanssen et al., 1998); MOD16 (Nishida et al., 2003); GLEAM (Miralles et al., 2011b); etc.-, etc.

Previous studies have demonstrated the possibility of using these global datasets to better understand the hydrological processes in a river catchment (Kite and Droogers, 2000; Vereecken et al., 2008; Seneviratne et al., 2010; Hafeez et al., 2011) and to improve streamflow model estimates through assimilation (e.g. surface soil moisture – Parajka et al., 2006; Brocca et al., 2012; López López et al., 2016 – or snow cover – Roy et al., 2010; Thirel et al., 2013 –) and/or calibration techniques or a-priori determination of model parameters (e.g. Jacobs et al., 2003; Beck et al., 2009). Calibration approaches based on multiple remotely sensed variables have some advantages in comparison with traditional calibration approaches using only observed and modelled hydrographs in a limited number of locations. Fenicia et al. (2007) and Gupta et al. (2008) recognized that traditional calibration may lead to over-parameterization, i. e. similar model results are obtained with more than one parameters combination, whereas calibrating to multiple variables – step-wise calibration – may partly resolve the problem of non-uniqueness and it helps to a better understanding of the processes happening within the catchment.

Several studies have investigated calibration approaches based on variables different to streamflow. Campo et al. (2006) used soil moisture information from radar images from

ERS-2 sensors to parameterize the hydrological model MOBIDIC. Immerzeel and Droogers (2008) calibrated the hydrological model SWAT based on satellite evapotranspiration from MODIS satellite images. Lo et al. (2010) improved the parameter estimation of the Community Land Model 3.0. using GRACE total water storage data while Isenstein et al. (2015) calibrated the VIC hydrological model using snow covered area from MODIS satellite data. Others have combined remotely sensed variables with in-situ streamflow observations for calibration. In Rientjes et al. (2013), the HBV model was calibrated on satellite based evapotranspiration from MODIS and streamflow. Wanders et al. (2014) calibrated model parameters of LISFLOOD based on discharge and soil moisture observations acquired by AMSR-E, SMOS and ASCAT while Sutanudjaja et al. (2014) calibrated the large scale model PCR-GLOBWB using streamflow and soil water index information derived from the ERS scatterometers. At a global scale, Beck et al. (2016a) used parameter regionalization to calibrate a HBV model. However, the simultaneous use of more than one environmental variable different to streamflow for calibration is rare. A calibration approach using various variables, independently and in combination with streamflow observations, may further improve model performance and contribute to a better understanding of hydrological processes. In the present study, this is tested by comparing multiple calibration scenarios based on evapotranspiration, soil moisture and discharge data.

The previously mentioned calibration experiments were performed for well studied river basins, such as the Rhine-Meuse river basin, with a good coverage of in-situ hydro-meteorological data. In the present study area, the Oum Er Rbia river basin located in Morocco, ground observations are spatially sparse and limited in number classifying it as a poorly-gauged river basin. The region frequently suffers from water scarcity and droughts and water availability is the main factor influencing socio-economic development, mostly driven by the agriculture (Houdret, 2009). The studies of Ouatiki et al. (2017), Tramblay et al. (2012) and Tramblay et al. (2016) are testimony to the relevance of this area. Therefore, developing new strategies to model this watershed is highly relevant to improve water management and assessment of the water availability within the basin.

This study aims to calibrate a large-scale hydrological model (PCR-GLOBWB 2.0, https://github.com/UU-Hydro/PCR-GLOBWB_model, Sutanudjaja et al., 2016) using soil moisture and evapotranspiration observations alone and to compare its discharge estimates to those obtained when the model is traditionally calibrated to streamflow data. We use the evapotranspiration product generated by an enhanced version of the GLEAM model (GLEAM v3.0; Martens et al., 2016b) in combination with the surface soil moisture product from ESA CCI (Dorigo et al., 2015). Both products are derived from satellite data. Furthermore, the influence of precipitation forcing is considered and three different global precipitation products are used and inter-compared: ERA-Interim reanalysis data (EI, Dee et al., 2011), WATCH Forcing Data methodology applied to ERA-Interim reanalysis data, (WFDEI, Weedon et al., 2014) and Multi-Source Weighted-Ensemble Precipitation data by merging gauge, satellite and reanalysis data (MSWEP, Beck et al., 2016c).

Five different calibration approaches are performed by using five calibration scenarios that include streamflow, soil moisture and evapotranspiration: (i) reference scenario using the hydrological model with the standard parameterization, (ii) calibration using in-situ observed discharge time series, (iii) calibration using GLEAM actual evapotranspiration time series, (iv) calibration using ESA CCI surface soil moisture time series and (v) step-wise calibration using GLEAM actual evapotranspiration and ESA CCI surface soil moisture time series. The above is repeated for each of the selected global precipitation product. A priori, it is expected that calibrating to streamflow observations yields the best discharge estimates, and that the step-wise calibration using soil moisture and evapotranspiration provides better results than the calibration scenarios based only on soil moisture or evapotranspiration.

The novel aspects and new contributions of this work include the use and comparison of three different and recently generated global precipitation products, the exploration of calibration techniques based on earth observations of soil moisture and evapotranspiration and their application into a large-scale hydrological model to provide streamflow estimates in the ungauged river basin of Oum Er Rbia in Morocco. Furthermore, understanding the potential gain of calibrating large-scale models to remotely sensed observations may have benefits for water resources management in data-poor river basins globally.

This manuscript first describes the study area, then the methodology, including the hydrological model, the data, the calibration and validation strategy and the performance metrics. Subsequently, results are presented, starting with the inter-comparison of precipitation products and following with calibration and validation results. This manuscript ends with discussion and conclusions."

Comment 3:

A justification for using 6 performance metrics for the precipitation evaluation is missing. Since only the performance metrics NSE and KGE are used for the model validation analysis, I suggest to limit the precipitation data evaluation also to these metrics.

Answer:

We agree with the reviewer that not all the performance metrics considered for precipitation evaluation are significant for the inter-comparison of the precipitation products. Therefore, and according to the reviewer's suggestion, we will reduce the number of performance metrics. We will use KGE as the main performance indicator. As KGE can be considered a weighted evaluation of NSE, r and Percent Bias (Gupta et al., 2009), we will also include the latter three metrics to analyse the importance of each component. These metrics will be added because similar values of KGE and NSE were found for EI and MSWEP precipitation datasets. Hence, r and Percent Bias will be used to analyse their differences in further detail. Better performance in terms of r was obtained with MSWEP and lower PBias values were found with EI. The analysis of these results, shown in Figure 4 (which will be also modified), is missing in the manuscript. We will modify the manuscript as follows (see comment 7):

P10L25-P11L3: "… Moreover, various performance metrics between the interpolated and in-situ ground data were calculated and shown in Figure 4. Overall, EI and MSWEP provide a better fit to the station data compared to WFDEI, with higher KGE_{precip}, NSE_{precip} and r_{precip} than WFDEI. When comparing EI with MSWEP, similar values of KGE_{precip} and NSE_{precip} were found, whereas higher differences exist in r_{precip} and $PBias_{precip}$. In terms of correlation MSWEP shows the best performance, but EI shows the lowest Percent Bias at both weather stations, with a value of less than 10 % . Only two weather stations were found within the basin for the previous analysis. These measurements were considered too scarce to cover the basin and to discard the precipitation product with the lowest performance (WFDEI). Therefore, the three global precipitation products were used to calibrate PCR-GLOBWB under the five calibration scenarios. ..."

Comment 4:

The presentation of the results needs to be improved. It is very difficult to keep the attention to the text, because the text is difficult to comprehend and the results are merely listed. Also a critical in-depth discussion of the results is largely missing.

Answer:

We will improve section 4. Results in different ways to facilitate its reading and comprehension. Initially, we will structure it in different subsections, starting with the inter-comparison results of precipitation products (subsection 4.1.) (before placed in subsection 3.2. Data), following with calibration results (subsection 4.2.) and ending with validation results (subsection 4.3.). The structure will be as follows:

4. Results

 4.1. Inter-comparison of precipitation products (see comment 3 and 7)

 4.2. Calibration results

  4.2.1. Calibration using in-situ observed discharge time series (S1)

  4.2.2. Calibration using GLEAM actual evapotranspiration time series (S2)

  4.2.3. Calibration using ESA CCI surface soil moisture time series (S3)

  4.2.4. Step-wise calibration using GLEAM actual evapotranspiration and ESA CCI surface soil moisture time series (S4)

 4.3. Validation results

At the same time, section 5. Discussion will be deleted and incorporated into a last section called Discussion and conclusions, where the results will be critically discussed (see comment 29).

Moreover, figures will be improved (see comments 16, 31, 32 and 33) together with their analysis (see comments 17-28).

Detailed comments (P: page, L: line or lines):

Comment 5:

P3L18: GLEAM is a comprehensive model for the estimation of terrestrial evaporation and root-zone soil moisture from satellite data. Please clarify

Answer:

The review is right. Indeed the GLEAM is a model that estimates the different components of terrestrial evaporation. We will clarify this aspect in section 1. Introduction as follows:

P3L16-17: "… to streamflow data. We use the evapotranspiration product generated by an enhanced version of the GLEAM model (GLEAM v3.0; Martens et al., 2016b) in combination …"

This will be also clarified in section 3.2.3. Evapotranspiration data and in section 3.2.4. Soil moisture data as follows:

P7L6-10: "… 1980-2014. To generate the GLEAM evapotranspiration product, the GLEAM model separately estimates the different components of terrestrial evaporation, including transpiration, interception loss, bare-soil evaporation, snow sublimation and open-water evaporation. To this end, it consists of four modules: the evaporation module, the stress module, the soil-water balance module and the rainfall interception model (Martens et al., 2016a). GLEAM evapotranspiration (0.25^o x 0.25^o) was interpolated …"

P7L20: "…. Similarly to GLEAM evapotranspiration, ESA CCI SM product …"

Comment 6:

P7L3-20: This section is copious and repetitive. Please rewrite in a more clear and concise way.

Answer:

We agree with the reviewer's comment and this section will be rewrite as follows:

P6L9-27: "… The meteorological data required to force PCR-GLOBWB are air temperature, precipitation and reference potential evapotranspiration. Air temperature and precipitation were obtained from the WATCH Forcing Data methodology applied to ERA-Interim reanalysis data (WFDEI) at an original spatial resolution of 0.5^o x 0.5^o (Weedon et al., 2014). Reference potential evapotranspiration was obtained through the FAO Penman-Monteith equation. Precipitation, air temperature and reference potential evapotranspiration were downscaled from the original spatial resolution to a 0.08^o x 0.08^o grid. Precipitation and air temperature were downscaled using precipitation and temperature lapse rates derived from the 10' CRU-CL2.0 data (New et al., 2002) through a linear regression analysis (Sutanudjaja et al., 2011). Reference potential evapotranspiration was downscaled using the e2o-downscaling-tools (Schellekens and Sperna Weiland, 2017; Sperna Weiland et. al. 2015).

To test model sensitivity to precipitation, air temperature and reference potential evapotranspiration were fixed and two additional global precipitation products were used: (i) ERA-Interim reanalysis data (EI) from the European Centre for Mediumrange Weather Forecasts (ECMWF) at the original spatial resolution of 0.5^o x 0.5^o (Dee et al., 2011) and (ii) Multi-Source Weighted-Ensemble Precipitation data (MSWEP) by merging gauge, satellite and reanalysis data at the original spatial resolution of 0.25^o x 0.25^o (Beck et al., 2016c).

The three global precipitation products were inter-compared and interpolated to the two weather station locations found inside the Oum Er Rbia basin (http://www.wmo.int/pages/themes/climate/), Beni Mellal and Kasba Tadla (Figure 1). Nash-Sutcliffe efficiency (NSE), Kling-Gupta efficiency (KGE), Pearson's correlation coefficient (r) and Percent Bias (PBias) between the interpolated and in-situ ground daily data were calculated. A description of the performance metrics with their mathematical formulation is included in section 3.4. These metrics were selected to have detailed information about differences between precipitation products. …"

Comment 7:

P7L32-P8L6: This section should be placed in the results section. Please indicate the temporal resolution of the data from the rainfall gauging stations. In addition it is not clear to me, why you need to six performance metrics for the precipitation validation. Also, just listing the values of the metrics is not sufficient

Answer:

We think that moving this subsection to section 4. Results is a good suggestion to improve the structure and analysis of the results. Following the reviewer's suggestion the inter-comparison of the three global precipitation products will be placed in section 4. Results, subsection 4.1. Inter-comparison of precipitation products (see comment 4). We will indicate the daily temporal resolution of the precipitation validation (P6L29). We will reduce the number of performance metrics and we will improve the analysis of these metrics (see comment 3). Therefore, this section will be modified as follows:

P10L16-P11L2: "4.1. Inter-comparison of precipitation products

To inter-compare the precipitation products, the annual mean precipitation for the study time period (1979-2010) for each forcing dataset was calculated (Figs. 3a, 3b and 3c). In addition to the spatial resolution difference, MSWEP is able to capture the rainfall pattern over the Atlas Mountains rather well, which is only roughly distinguished by WFDEI and unrecognized by EI. The finer spatial resolution and the combination of reanalysis, satellite and in-situ data are probably the reasons for its more plausible spatial pattern. Furthermore, climatology of precipitation products was analyzed (Fig 3d). WFDEI ranges from 4.5 mm in July to 57 mm in February, whereas EI and MSWEP show a lesser variability with precipitation values from 10.5 mm in July to 42.6 mm in November. Smaller differences between WFDEI and EI and MSWEP are observed during the summer months. EI and MSWEP show similar temporal precipitation patterns. Annual mean precipitation over the entire basin obtained with MSWEP (355.15 mm) is approximately 80 mm higher than with EI (276.67 mm). Similar annual median values are obtained with the three global precipitation products, although the distribution of WFDEI highly differs from the other two products.

Moreover, various performance metrics between the interpolated and in-situ ground data were calculated and shown in Figure 4. Overall, EI and MSWEP provide a better fit to the station data compared to WFDEI, with higher KGE_{precip}, NSE_{precip} and r_{precip} than WFDEI. When comparing EI with MSWEP, similar values of KGE_{precip} and NSE_{precip} were found, whereas higher differences exist in r_{precip} and $PBias_{precip}$. In terms of correlation MSWEP shows the best performance, but EI shows the lowest Percent Bias at both weather stations, with a value of less than 10 % . Only two weather stations were found within the basin for the previous analysis. These measurements were considered too scarce to cover the basin and to discard the precipitation product with the lowest performance (WFDEI). Therefore, the three global precipitation products were used to calibrate PCR-GLOBWB under the five calibration scenarios."

Comment 8:

P9L3: Why did you use the first three layers? Given the extremely low penetration depth of the C-band data used for the ESA CCI SM product, you should only compare to the first layer. The depth of this layer needs to match the penetration depth of the C-band data, i.e. 2 cm.

Answer:

According to P7L27-28: "ESA CCI surface soil moisture observations were compared to simulated soil moisture with the first of the three vertical soil layers in PCR-GLOBWB." To clarify this and following the reviewer's suggestion, we will include a note as follows:

P7L23-24: "… ESA CCI surface soil moisture observations were compared to simulated soil moisture of the first of the three vertical soil layers in PCR-GLOBWB (top 5 cm of soil). …"

Comment 9:

P9L5-8: In my opinion this procedure leads to an untrustworthy and unsound comparison of simulated and observed soil moisture. A direct comparison of model results and observed data is a prerequisite for an unbiased and unadorned evaluation of the simulation results.

Answer:

Following the reviewer's suggestion, we produced two figures with the original and the rescaled simulated soil moisture time series before and after the mean-standard deviation matching technique is applied (see comment 25). This rescaling approach applied to surface soil moisture have been previously used in several studies to overcome the existent uncertainties in satellite observations and model estimates (Koster et al., 2009; Renzullo et al., 2014; Su et al., 2013). However, we agree with the reviewer that other possible approaches could have been investigated including an analysis of the optimal soil depth in the model corresponding to the depth for satellite measurements. Due to computational time limitations and to avoid numerical stability problems derived from the daily temporal resolution, we decided to follow a mean-standard deviation matching technique.

Comment 10:

P9L15-34: This section is copious and repetitive. Please rewrite in a more clear and concise way.

Answer:

We will modify the section as follows:

P8L5-19: "… Alternative single objective calibration approaches based on discharge, actual evapotranspiration and surface soil moisture and a multiobjective calibration approach based on actual evapotranspiration and surface soil moisture were inter-compared. Five different calibration scenarios were carried out. Calibration scenario S0 represents the reference calibration scenario, which was not locally calibrated for the Oum Er Rbia basin, but uses a-priori model parameters derived from vegetation, soil properties and geological information at a global scale (latest model version of PCR-GLOBWB). Calibration scenario S1 aims to calibrate the hydrological model using in-situ discharge observations, following the traditional calibration approach. Calibration scenarios S2 and S3 use GLEAM actual evapotranspiration and ESA CCI surface soil moisture time series for calibration, respectively. Calibration scenario S4 represents the multiobjective calibration approach and it consists of a step-wise calibration scheme that attempts to combine the strengths of calibration scenarios S2 and S3. Step one is simply scenario S2, where all the model parameters are allowed to be adjusted based on GLEAM actual evapotranspiration. In step two, those parameters that are clearly identified by calibration scenario S2 are held constant and the remaining parameters are allowed to be adjusted according to ESA CCI surface soil moisture, calibration scenario S3.

The five calibration scenarios were analysed for each of the three global precipitation products to study their impact on model parameters calibration and model performance. The calibration scenarios are described in Table 2, including the scenario identifier. …"

Comment 11:

P10L2: Why did you choose KGE for this analysis?

Answer:

Traditional calibration and evaluation approaches of hydrological models with observed data use Mean Squared Error (MSE) and Nash-Sutcliffe efficiency (NSE) as the objective functions to maximize. However, Gupta et al., (2009) proposed Kling-Gupta efficiency (KGE) as an alternative criterion to avoid possible problems derived from the use of NSE, such as the underestimation of high values and overestimation of low values. Moreover, KGE can be considered a weighted evaluation of NSE, r and Percent Bias. Based on this, we decided to choose KGE for the analysis of calibration results. We will add a sentence explaining the selection of KGE as follows:

P8L21-23: "… for the calibration scenarios was Kling-Gupta efficiency (KGE), instead of the traditional Mean Squared Error (MSE) or Nash Sutcliffe efficiency (NSE) to avoid underestimating the variability of values (Gupta et al., 2009). The mathematical …"

We will also modify the manuscript as follows:

P15L17-24: "… A possible route to overcome this problem may be to use various performance indicators (for example, KGE, NSE, PBias and r) as objective functions to optimize in each calibration scenario, instead of using a single one. This multiobjective calibration approach may further improve discharge model estimates. …"

Comment 12:

P10L4: In my view, it does not make sense to recalibrate for each precipitation data set. I would be more sensible to use the data that corresponds best with the rainfall gauging station data.

Answer:

As it is indicated in P8L17-19, the analysis of the five calibration scenarios for each global precipitation product, allow us to study their impact on model parameters calibration and model performance. Moreover, we can analyse the influence and/or importance on model performance of the calibration approach in comparison with the precipitation dataset used as forcing.

Furthermore, from the inter-comparison of precipitation products included in section 4.1 (see comments 3 and 7) it was not possible to select only one precipitation product, because MSWEP performed better for some indicators and worse for others in comparison with EI.

On the other hand, only two rainfall stations were found inside the Oum Er Rbia basin, as it is mentioned in section 3.2.1. Meteorological data. These measurements were considered too scarce in number and spatially sparse to cover the entire basin and therefore, to select the best global precipitation product and discard the remaining ones.

We will add a sentence on this aspect in section 4.1. Inter-comparison of precipitation products as follows:

P10L29P11L5-2: "… than 10 % . Only two weather stations were found within the basin for the previous analysis. These measurements were considered too scarce to cover the basin and to discard the precipitation product with the lowest performance (WFDEI). Therefore, the three global precipitation products were used to calibrate PCR-GLOBWB under the five calibration scenarios. ..."

Comment 13:

P10L5: I guess the different Ksat-values correspond to the soil layers S1-3. What about the Ksat-value for S4?

Answer:

Indeed, we also calibrated the K_{sat4}, with the calibration of the baseflow recession coefficient (J). Soil in PCR-GLOBWB is divided into three vertical layers representing the top 5 cm of soil (S1), the following 25 cm of soil (S2) and the remaining 120 cm of soil (S3). Under the third soil layer, there is a groundwater store (S4). The saturated hydraulic conductivities of 1st, 2nd and 3rd soil layers are K_{sat1}, K_{sat2} and K_{sat3}, which controls the vertical fluxes between soil layers and the groundwater store, affecting the groundwater recharge. Baseflow from the active groundwater layer depends on the baseflow recession coefficient (J), which varies in function of the aquifer transmissivity and the aquifer specific yield. Therefore, J is included as a model parameter to calibrate. J is a recession coefficient parameterized based on Kraaijenhoff van de Leur (1958):

$$J = \frac{\pi^2 (KD)}{4 S_y L^2}$$

With KD and S_y indicating aquifer transmissivities and specific yields, and L indicating average flow lengths.

Comment 14:

P10L6: Reference potential ET is not a parameter. Since it varies in time, it is variable.

Answer:

Indeed, reference potential evapotranspiration is a variable and not a model parameter. We calibrated three model parameters and in addition, we also checked the uncertainty of reference potential evapotranspiration following a similar approach with prefactors. We will modify the manuscript to clarify this topic as follows:

P8L25-P9L3: "… To calibrate PCR-GLOBWB for each of the three precipitation products, 81 runs with different parameter values were simulated: minimum soil water capacity (W_{min}), soil saturated hydraulic conductivites ($Ksat_1$, $Ksat_2$ and $Ksat_3$) and baseflow recession coefficient (J). These model parameters, which vary spatially over the basin, influence different model parts of the model behaviour, as it was explained in section 3.1. For the variation of the parameter values, spatially uniform prefactors were used: f_w, f_k and fj (Table 3). The remaining model parameters were kept fixed.

The prefactors to vary model parameter values were referred to the parameters of the S0 calibration scenario. The spatial distribution of the parameters W_{min}, K_{sat} and J used in S0 scenario can be found in Figure A1 of Appendix A.

Furthermore, the uncertainty of reference potential evapotranspiration ($E_{p,0ref}$) was also investigated using a correction prefactor, f_e, to this model variable. Considered values for f_e prefactor are included with the previously mentioned ones in Table 3.

As reference calibration scenario, S0 prefactors are: f_w=1, f_k=0, f_j=1 and f_e=1. The model performances of all the simulations were evaluated for each of the five calibration scenarios to identify the best prefactor sets as the calibrated prefactor sets. …"

Comment 15:

P12L8: Delete "nearly"

Answer:

We will delete "nearly".

Comment 16:

P12L8: Due its complexity, Figure 5 is difficult to comprehend. In particular, the meaning of the dots in the scatterplots stays unclear with regard to what are actually representing (i.e. why is there more than one dot per variant). Since only three different values of the prefactors are considered no continuous scale should be used for the x-axis (otherwise the reader gets puzzled why the dots are not spreading).

Answer:

We agree with the reviewer that Figure 5 is quite complex and difficult to explain and therefore, to understand. We will improve this figure in different ways: we will use different colours and dot shapes to indicate different values of f_e, we will modify the horizontal axis of each scatterplot limiting the tick marks and numbers to the values of the used calibration prefactors and we will change the label of y-axis to indicate when KGE values are based on discharge, actual evapotranspiration and surface soil moisture using subscripts KGE_q, KGE_{evap} and KGE_{sm}. Moreover, to facilitate the comprehension of the scatterplot, we will modify the figure explanation as follows:

P11L5-15: "… Model parameters were calibrated using discharge, evapotranspiration and soil moisture observations through five different calibration scenarios for the time period

1981-1993. Figure 5 shows results of all runs produced in this study for different calibration scenarios based on: in-situ discharge observations (S1) at Ait Ouchene (Figure 5a) and Mechra Eddahk (Figure 5b), GLEAM actual evapotranspiration (S2, Figure 5c) and ESACCI surface soil moisture (S3, Figure 5d). For each sub-figure in Figure 5, KGE results (y-axis) of using the three precipitation products are plotted in different rows (top: EI, middle: WFDEI and bottom: MSWEP) and prefactor values are plotted in different columns (x-axis, 1st column: f_e, 2nd column: f_j, 3rd column: f_k and 4th column: f_w). Each scatterplot contains 81 dots representing each run with a different combination of parameter values. This means that the KGE values are the same in the four scatterplots of a row (y- axis), but in each of these scatterplots, they are plotted against a different prefactor (x-axis). With Figure 5, prefactor, and therefore parameter, ranges leading to better and worse performances can be distinguished, as well as their global optimal values. If no optimal value can be inferred, prefactors from the calibration scenario S0 are maintained (f_e=1, f_j=0, f_k=0 and f_w=1) …"

Comment 17:

P12L10: Please explain in more detail, why these prefactors should be well defined.

Answer:

According to the reviewer's comment, we will improve the explanation of prefactors identifiabilities as follows:

P11L26-30: "… Figures 5a and 5b (calibration scenario S1) are similar. From these figures, f_e (1st column) and f_w (4th column) are well identified by discharge calibration at both gauging stations when forced with any of the three precipitation products. f_e = 1.25 and f_w = 1.25 lead to the highest KGE_q values. However, it is not possible to identify the best prefactors of f_j (2nd column) and f_k (3rd column). There are no clear and distinct maximum values in the scatterplots of these figures, hence f_j = 0 and f_k = 0 are used. …"

Comment 18:

P12L16: "are considered"

Answer:

We will modify this sentence as follows:

P12L21-23: "… Therefore, model run with prefactors f_e = 1.25, f_j = 0, f_k = 0 and f_w = 1 is considered as the calibrated run based on the evapotranspiration performance. …"

Comment 19:

P12L17: Please explain in more detail, why these prefactors should be well defined.

Answer:

Similarly to comment 17, we will include a note as follows:

P12L19-21: "… Figure 5c (calibration scenario S2) indicates that only prefactor f_e (1st column) can be clearly identified (the highest KGE_{evap} values are obtained with f_e=1.25), whereas the remainder of the prefactors (f_j, f_w and f_k) are non identifiable, suggesting that evapotranspiration-based calibration may be unreliable in their identification. Therefore, …"

Comment 20:

P12L23-31: This section is incomprehensible. Please rewrite.

Answer:

We will modify this section as follows:

P13L11-19: "…Calibration scenario S4 attempts to combine the strengths of scenarios S2 and S3. In the first step, the model is calibrated using GLEAM evapotranspiration (S2, Figure 5c). From Figure 5c, only f_e prefactor is well identified (the highest KGE_{evap} value is obtained with f_e = 1.25). In the second step, f_e prefactor that has been identified was held constant and the remaining three prefactors were allowed to be calibrated according to ESA CCI soil moisture (S3, Figure 5d). From Figure 5d, f_w and f_k are identifiable (the highest KGE_{sm} values are obtained with f_w = 1.25 and f_k = 0.25). As a result, for calibration scenario S4, the prefactors identified during the evapotranspiration calibration (S2): f_e = 1.25 and during the soil moisture calibration (S3): f_w = 1.25 and f_k = 0.25 are adopted. This step-wise calibration approach using multiple system variables allow to identify more parameters than when those variables are separately used. Nonetheless, neither of the steps in calibration scenario S4 allow the clear identification of f_j, so its value for the calibration scenario S0 is used, f_j = 0. …"

Comment 21:

P12L34: "scatterplots"

Answer:

We will correct "scatteplots" to "scatterplots".

Comment 22:

P13L3: The scatterplots of Figures 6 and 7 are quite repetitive. I would be enough to present only the NSE and KGE values of all variants and some selected scatterplots in case it is helpful for the discussion of the results.

Answer:

We agree with the reviewer on this matter. We believe that scatterplots of Figures 6 and 7 are helpful for the analysis and the discussion of the results. During the writing of the manuscript, the authors considered to delete Figure 6 and include only scatterplots for Mechra Eddahk station (Figure 7). However, this may give the impression that both discharge stations performs similarly for all calibration scenarios and precipitation products, which is not true. Therefore, we will move Figure 6 from the manuscript and include it to the Supplementary Information.

We will also improve the explanation of Figure 6 and Figure 2 in the Supplementary Information and we will modify the analysis of calibration results of these figures as follows:

P11L16-21: "… Once the best runs for each calibration scenario were identified, their discharge performance was checked at the two gauging stations: Mechra Eddahk, in Figure 6, and Ait Ouchene, in Figure 2 of the Supplementary Information. Observed discharge (y-axis) and estimated discharge (x-axis) are plotted in Figure 6 for the five calibration scenarios. Different rows in Figure 6 indicate the three global precipitation products (top: EI, middle: WFDEI and bottom: MSWEP) and different columns indicate the five calibration scenarios (1st column: S0, 2nd column: S1, 3rd column: S2, 4th column: S3 and 5th column: S4). The performance indicators NSE and KGE for discharge are included in every scatterplot in Figure 6 (NSE_q and KGE_q). …"

P11L31-8: "… From Figure 6 (2nd column), the highest discharge performance is obtained when the model is calibrated with in-situ discharge observations (S1).

For all the calibration scenarios, a few general observations can be made. Scatterplots (Figure 6) highlight an overall better agreement and a lower bias between discharge observations and estimates for the Ait Ouchene (see Figure 2 in the Supplementary Information) than for Mechra Eddahk station. KGEq values at Ait Ouchene station for calibration scenario S0 are lower than for Mechra Eddahk station. …"

P12L24-26: "… From Figure 6 (3rd column), results indicate an increase of KGE_q and NSE_q values when GLEAM evapotranspiration is used for model calibration compared to the reference scenario (S0, 1st column of Figure 6). However, higher model performance values are obtained when calibrating based on in-situ discharge observations (S1, 2nd column of Figure 6). …"

P13L1-4: "… From Figure 6 (4th column), scatterplots indicate an improvement in the correspondence between observed and estimated discharge compared to the non-calibrated scenario (S0, 1st column of Figure 6). Similarly to calibration scenario S2 (3rd column of Figure 6), this improvement is lower than when the model is calibrated based on ground discharge observations (S1, 2nd column of Figure 6). …"

Comment 23:

P13L6-7: This is very obvious and provokes the question why you are using the poorer precipitation data sets for the model calibration analysis at all.

Answer:

This aspect has been already addressed in comment 12. Only two rainfall stations were found inside the Oum Er Rbia basin. These measurements were considered too scarce in number and spatially sparse to cover the entire basin and therefore, to select the best global precipitation product and discard the remaining ones. We will modify the manuscript as follows:

P12L7-16: "… Scatterplots (Figure 6) also show that estimated discharges are closer to observed discharges at both gauging stations when PCR-GLOBWB is forced with EI precipitation. Moreover, scatterplots indicate a worse agreement and a tendency to overestimate discharge when WFDEI and MSWEP are used. KGE_q values for the reference calibration scenario S0 at Mechra Eddahk are 0.607, 0.325 and 0.561 when EI, WFDEI and MSWEP are used as forcing data respectively. These performance discrepancies are related with the differences between EI, WFDEI and MSWEP precipitation products discussed in section 4.1. The lower quality of WFDEI in this region compared with the other precipitation datasets may be a possible reason of the lower discharge performance. When MSWEP was compared with in-situ precipitation data, performance in terms of correlation was higher than EI. However, EI showed less bias. The higher performance of discharge estimates when PCR-GLOBWB is forced with EI may be due to this bias difference and that the validation is carried out at a monthly temporal resolution, reducing the impact of correlation. …"

Comment 24:

P13L26: You should first introduce the motivation for presenting these figures.

Answer:

According to the reviewer's comment and considering the new structure of the results section, we will include a short paragraph explaining the motivation of Figures 7 and 8. We will also modify the analysis of Figures 7 and 8 as follows:

P13L28-P14L9: "… Once the model had been calibrated for each calibration scenario and each precipitation product, comparisons between estimates (before and after the calibration) and observations of actual evapotranspiration, surface soil moisture and discharge were carried out for the validation time period (1994-2011). To perform the analysis of these results, time series plots are included in Figures 7 and 8.

In Figure 7a, simulated actual evapotranspiration time series of the reference run (S0, red dashed line) and the step-wise calibrated run (S4, purple dashed line) are plotted against GLEAM actual evapotranspiration observations (black line). Similarly as Figure 7a, Figure 7b shows simulated surface soil moisture of the reference run (S0, red dashed line) and the step-wise calibrated run (S4, purple dashed line) plotted against ESA CCI surface soil moisture time series (black line). The rescaled soil moisture time series (after mean-standard deviation matching technique applied, see section 3.2.4) are shown. In Figure 7c, estimated discharge of the reference run (S0, red dashed line) and the step-wise calibrated run (S4, purple dashed line) are plotted against discharge observations (black line) at Mechra Eddahk. KGE values for actual evapotranspiration, surface soil moisture and discharge are included in Figures 7a, 7b and 7c. For the sake of simplicity, only results when the model is forced with MSWEP precipitation are shown.

Similarly to Figure 7, Figure 8 shows simulated evapotranspiration (Figure 8a), surface soil moisture (Figure 8b) and discharge (Figure 8c) against observations. However, in Figure 8, estimates of the discharge-calibrated run (S1, red dashed line) and the step-wise calibrated run (S4, purple dashed line) are plotted against observations (black line). …"

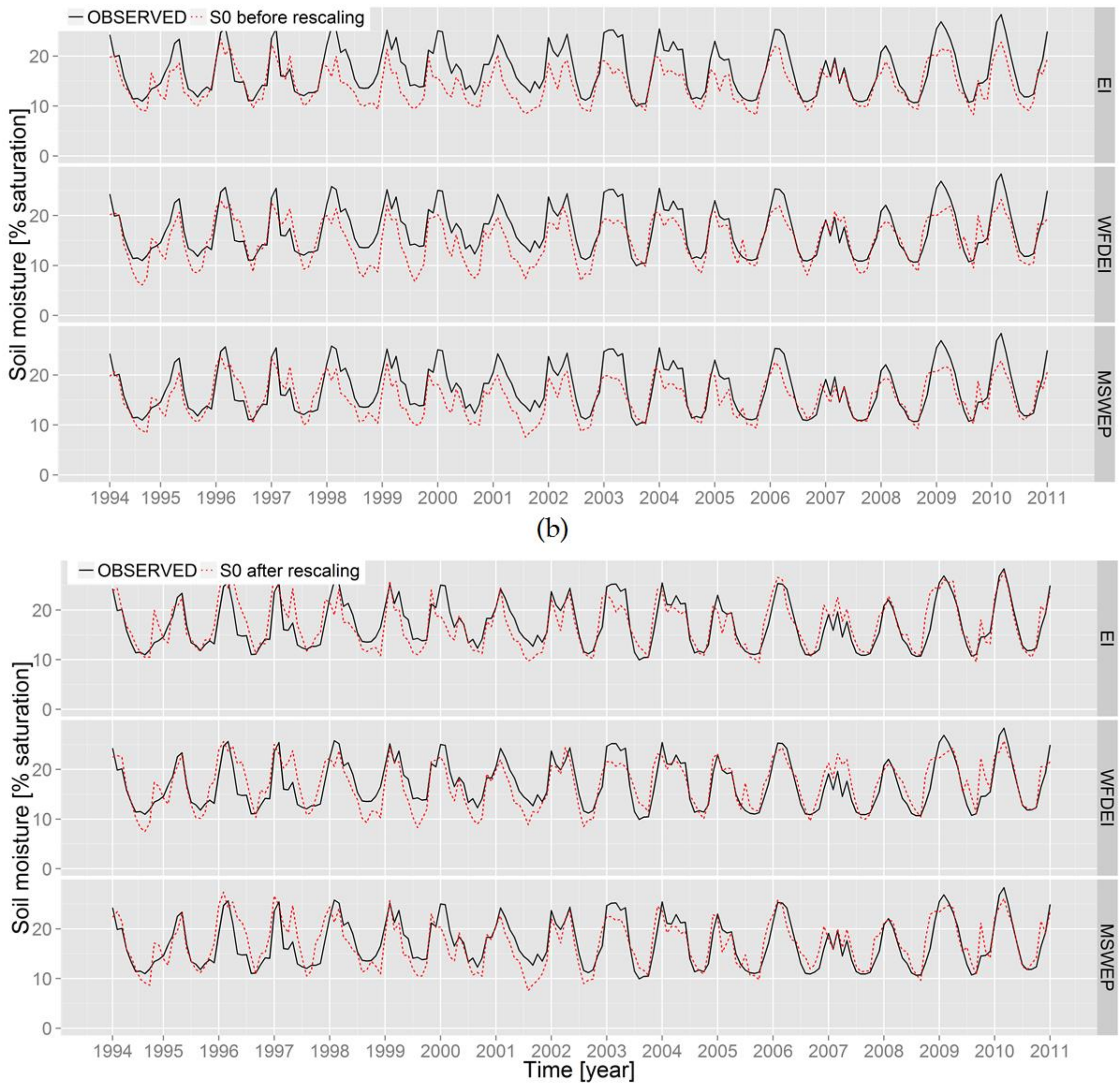
Comment 25:

P13L35: I would rather like to see the unscaled results, because this procedure embellishes the model results.

Answer:

According to the reviewer's suggestion, we produced two figures with the original and the rescaled simulated soil moisture time series before and after the mean-standard deviation matching technique is applied.

(a)



From these figures, the bias correction is observed between the rescaled and the original soil moisture time series. However, the inclusion of this fourth line (non-rescaled soil moisture) in the time series graphs of Figures 7 and 8 would difficult their interpretation and we believe that adding a new figure to the manuscript with original soil moisture time series would not improve the results analysis. Therefore, we will include it in Figure 1 of the Supplementary Information. We will also modify the manuscript as follows:

P8L1-3: "… When comparing the original and the rescaled soil moisture, it is observed that the mean-standard deviation technique effectively removes the biases between the simulated and observed soil moisture time series (see Figure 1 of the Supplementary Information). …"

Comment 26:

P14L9-10: You could simply check using the measured precipitation data.

Answer:

Only two rainfall stations were found inside the Oum Er Rbia basin. These measurements were considered too scarce in number and spatially sparse to cover the entire basin and therefore, to check the global precipitation products (see comments 12 and 23). Moreover, the lack of fit can be also due to model structural deficiencies. We will modify this section as follows:

P14L15-17: "… 1997. This lack of fit may be due to errors in the precipitation data, because higher discharge differences are shown when WFDEI and MSWEP products are used in comparison to EI product. Other possible reasons may be related with model structural deficiencies. When…"

Comment 27:

P14L30: See comment P13L6-7

Answer:

According to the reviewer's comment, we will delete the sentence: "This is a consequence of the precipitation discrepancies analysed in section 3.2.1."

Comment 28:

P15L8-9: So wouldn't it be more sensible to use multi-objective function calibration procedure?

Answer:

A multiobjective calibration approach using various objective functions, such as KGE, NSE, NSE for low flows, NSE for high flows, etc., may be an alternative route to calibrate model parameters. We will include a short paragraph on this topic in section 4.3. Validation results as follows:

P15L17-19: "… in terms of discharge. A possible route to overcome this problem may be to use various performance indicators (for example, KGE, NSE, RMSE and r) as objective functions to optimize in each calibration scenario, instead of using a single one. This multiobjective calibration approach may further improve discharge model estimates. …"

We will also discuss this topic in section 5. Discussion and conclusions as follows:

P16L5-6: "… a multiobjective calibration approach to streamflow observations could be followed. Similarly to Fenicia et al. (2007), multiple objective functions may be optimized in sequential steps for high flows, low flows and timing. …"

Comment 29:

P15L10: The discussion chapter is largely a summary of the results (first half) and an outlook, which should be placed in the conclusion chapter. In order to reduce redundancy, I suggest skipping this chapter and moving parts to the results and conclusion chapters.

Answer:

We believe that the reviewer is right and we will modify these sections. We consider that there are aspects, such as the possibility of other calibration approaches: multiobjective calibration, scaling relationships, catchments classification schemes, etc. or the potential use of other satellite products for hydrological modelling that are of interest of discussion. Therefore, and following the reviewer's suggestion, we will delete section 5. Discussion and we will modify section 6. Summary and conclusions to Discussion and conclusions to avoid repetitions as follows:

"5. Discussion and conclusions

This study investigates alternative routes to calibrate the large-scale hydrological model PCR-GLOBWB using earth observations globally available for the data-poor river basin of Oum Er Rbia in Morocco. Three global precipitation products, EI, WFDEI and MSWEP, are inter-compared and applied to force PCR-GLOBWB. Five different calibration scenarios are followed where GLEAM actual evapotranspiration and ESA CCI surface soil moisture data are used to identify model parameters with the aim to improve discharge estimates. In-situ discharge observations are also used for calibration, as they are traditionally used to calibrate hydrological models.

Results show that GLEAM actual evapotranspiration and ESA CCI soil moisture observations may be used to calibrate determined PCR-GLOBWB model parameters. GLEAM actual evapotranspiration can be used to calibrate the reference potential evapotranspiration (f_e), affecting the water exchange between the top soil layer and the atmosphere and hence the soil water balance. ESA CCI soil moisture data can be used to calibrate the minimum soil water capacity (f_w) and the saturated hydraulic conductivities of the soil layers (f_k), determining the surface runoff generation response, the shallow sub-surface flow and the groundwater recharge. However, calibration using only GLEAM evapotranspiration or only ESA CCI soil moisture can result in more than one parameters combination to be optimal in terms of discharge (overparametrization or equifinality problem). To overcome this problem, a step-wise calibration scenario based on both observations, evapotranspiration and soil moisture, can be included, allowing the identification of the optimal values of f_e, f_w and f_k. Nonetheless, neither of these observations can be used to calibrate the baseflow from the active groundwater layer (f_j). To identify baseflow recession coefficient parameter (f_j) a multiobjective calibration approach to streamflow observations could be followed. Similarly to Fenicia et al. (2007), multiple objective functions may be optimized in sequential steps for high flows, low flows and timing.

Spatially uniform prefactors for the entire Oum Er Rbia basin were used for the variation of the parameter values in this study. Developing novel calibration strategies where prefactors and so, model parameters vary with soil type, land use, elevation and/or other characteristics within the basin would be a promising research route to investigate. Furthermore, the present work inter-compare five calibration scenarios using a brute force method, where several combinations of parameters values are tested and the best performing is selected. A suggestion for future studies may be to use an Ensemble Kalman Filter to calibrate the hydrological model, as previously presented in literature (Moradkhani et al., 2005; Wanders et al., 2014). Furthermore, the validation of this study was carried out exclusively on streamflow. Other validation approaches, including the empirical orthogonal functions, wavelet analysis or their combination, may be another promising way towards a more in-depth validation of distributed hydrological models (Mascaro et al., 2015; Koch et al., 2015; Fang et al., 2015).

A step-wise calibration approach based on GLEAM actual evapotranspiration and ESA CCI soil moisture results in discharge estimates of acceptable accuracy (Moriasi et al., 2007), compared to discharge estimates derived from a model that has been calibrated to in-situ discharge measurements. Traditional calibration to in-situ discharge measurements results in the highest model performance, as expected. A model calibrated only on evapotranspiration or soil moisture observations achieves a lower discharge performance than when they are used together.

In the inter-comparison between the three global precipitation products, WFDEI shows the lowest performance, whereas EI and MSWEP perform quite well. Apart from the in-situ discharge calibration scenario, the highest discharge improvement is obtained when the two latter forcing data are used in combination with a step-wise calibration approach based on evapotranspiration and soil moisture observations.

Results indicate that precipitation impact on streamflow estimates is more significant than the one derived from calibrating model parameters, thus the lower quality of WFDEI compared to EI and MSWEP, decreases model performance and calibration is biased in order to compensate precipitation errors. Further investigation of the effect of precipitation errors on model efficiency, but also on model parameters estimation may be an interesting route for hydrological research (Andréassian et al., 2004; Looper et al., 2012).

Although there is still room for further research, this study shows that globally available earth observations, such as evapotranspiration or soil moisture, can be used to further parameterize large-scale hydrological models providing reasonable discharge estimates at regional or basin scale. In principle, these calibration approaches can be applied and investigated in other basins without or with limited in-situ ground hydro-meteorological data (ungauged basins), not only to estimate discharge, but also to improve the understanding of the hydrological processes in the basin. Results suggest the potential of using other satellite products for hydrological modelling studies, including soil moisture products such as AMSR-E (Njoku et al., 2003) and SMOS (Kerr et al., 2001), evapotranspiration products such as SEBAL (Bastiaanssen et al., 1998) and MOD16 (Nishida, 2003), total water storage products such as GRACE (Tapley et al., 2004), etc. Future studies may investigate step-wise calibration approaches using the combined information from multiple hydrological system variables. By incorporating several data products, different parts or components of the model can be optimized to increase the overall model performance. Another approach could be to calibrate the model to different variables with multiple objective functions - multiobjective calibration- (Gupta et al., 1998; Khu and Madsen, 2005; Fenicia et al., 2007). Alternatively, these hydro-meteorological data which are globally available may be used to identify and develop relationships between different basins using similarities, classification and scaling frameworks, as presented in previous studies (Samaniego et al., 2010b; Kumar et al., 2013)."

Comment 30:

P16L12: Another promising way towards a more in-depth validation of distributed models are the empirical orthogonal functions analysis and the wavelet coherence analysis (e.g. Fang et al., 2015).

Answer:

We will include a paragraph about alternative ways for validation of distributed hydrological models (see comment 29):

P16L15-18: "… Furthermore, the validation of this study was carried out exclusively on streamflow. Other validation approaches, including the empirical orthogonal functions, wavelet analysis or their combination, may be another promising way towards a more in-depth validation of distributed hydrological models (Mascaro et al., 2015; Koch et al., 2015; Fang et al., 2015) …"

Figures:

Comment 31:

Figure 3: The precipitation field seems to be shifted (the highest precipitation amounts are expected in the Atlas mountain ranges, see e.g. Chehbouni et al., 2008). You should add dots in the lower graphic.

Answer:

We will correct the precipitation shift mistake in Figures 3a, 3b and 3c. We will include dots in Figure 3d and therefore, produce a new complete Figure 3.

Comment 32:

Figure 5: The scatterplots are too crowed and difficult to read.

Answer:

This comment has been already addressed in comment 16.

Comment 33:

Figures 6-10: Always indicate that you are showing monthly values, e.g. "Monthly observed discharge".

Answer:

According to the reviewer's comment, we will modify Figures 5, 6, 7, 8 and 9 to indicate that the temporal resolution is always monthly.

Additional modifications

For the results analysis consistency of the manuscript, we will replace RMSE with PBias in Figure 9. The text will be also modified accordingly.

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Additional modifications in figures and figures to be included

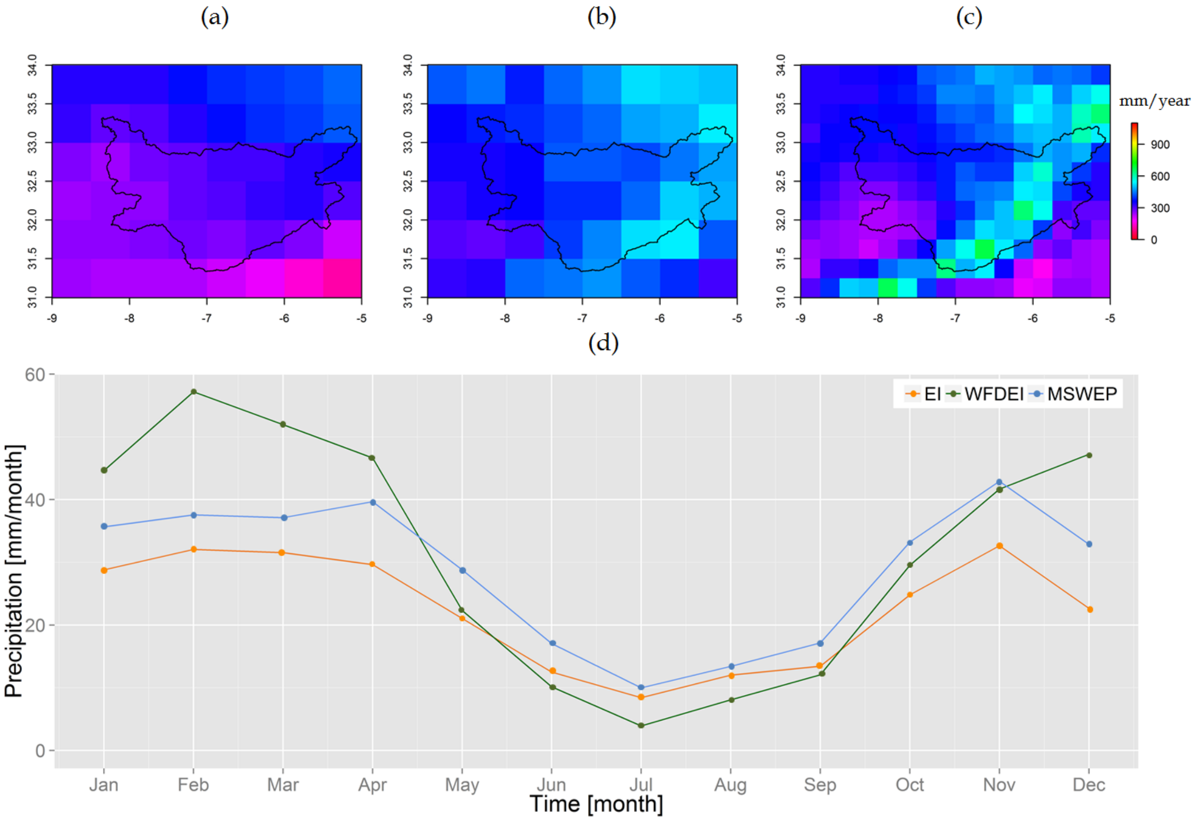

Figure 3. *(a) EI annual mean precipitation, (b) WFDEI annual mean precipitation and (c) MSWEP annual mean precipitation for 1979-2010 time period and (d) climatology of EI, WFDEI and MSWEP precipitation products.*

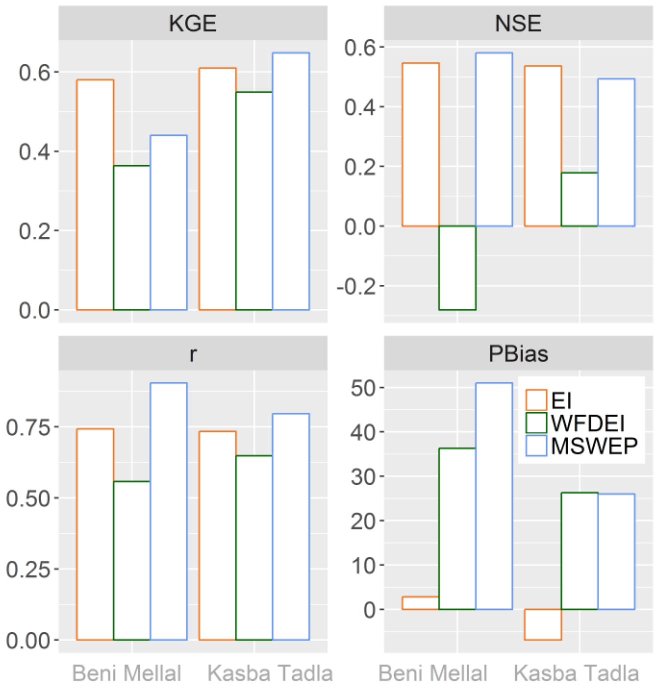

Figure 4. *Performance metrics of daily EI, WFDEI and MSWEP precipitation products at Beni Mellal and Kasba Tadla weather stations, including Kling-Gupta efficiency (KGE), Nash-Sutcliffe efficiency (NSE), Pearson's correlation coefficient (r) and Percent Bias (PBias).*

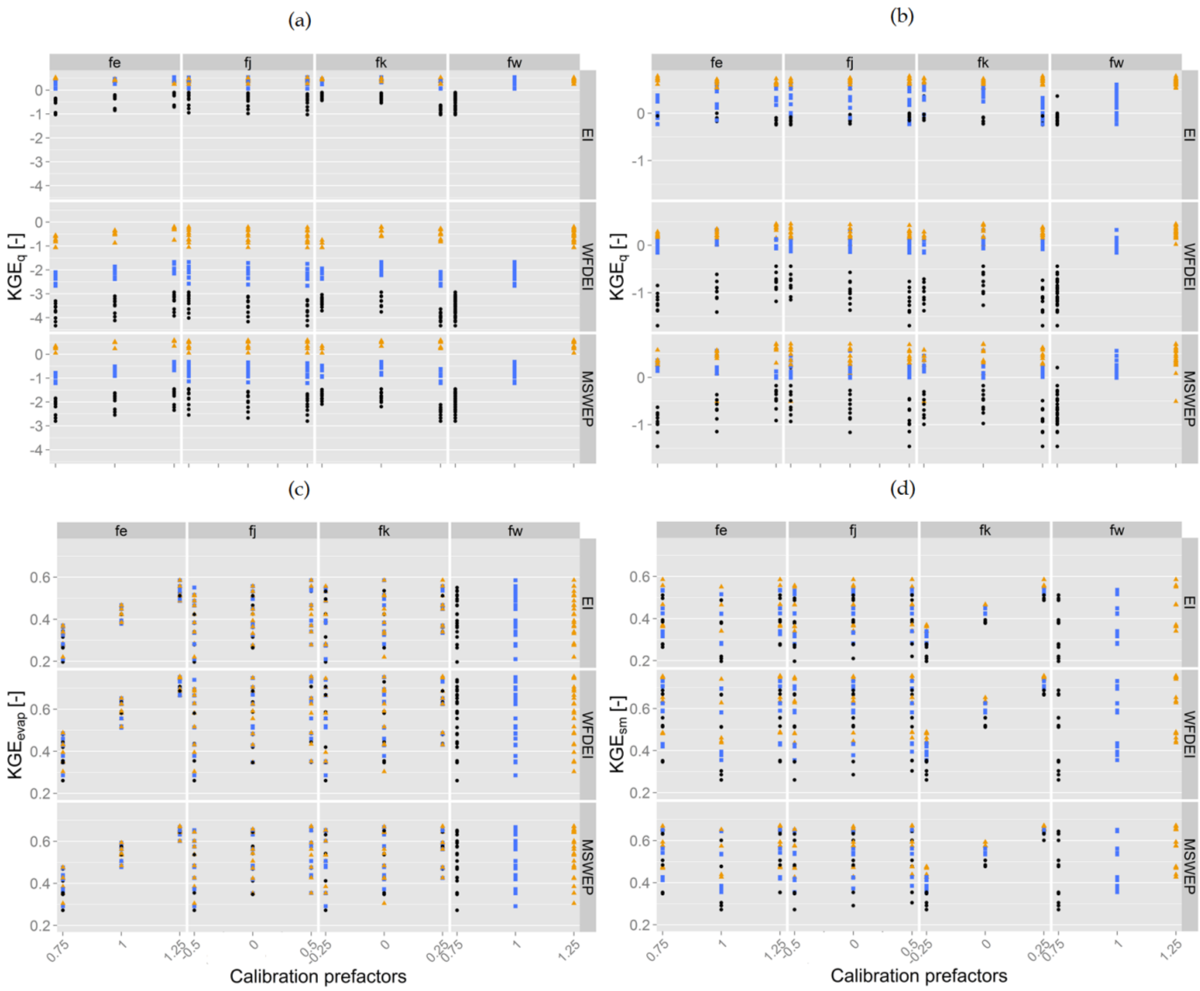

Figure 5. *Scatterplots of discharge performance indicator KGE based on the monthly observations versus prefactors f_e, f_j, f_k and f_w for the calibration scenarios S1 ((a) Ait Ouchene (b) Mechra Eddahk), S2 (c) and S3 (d). In each sub-figure, columns indicate the different calibrated prefactors and rows indicate the three global precipitation products used as model forcing. Different colours and dot shapes indicate different f_w values.*

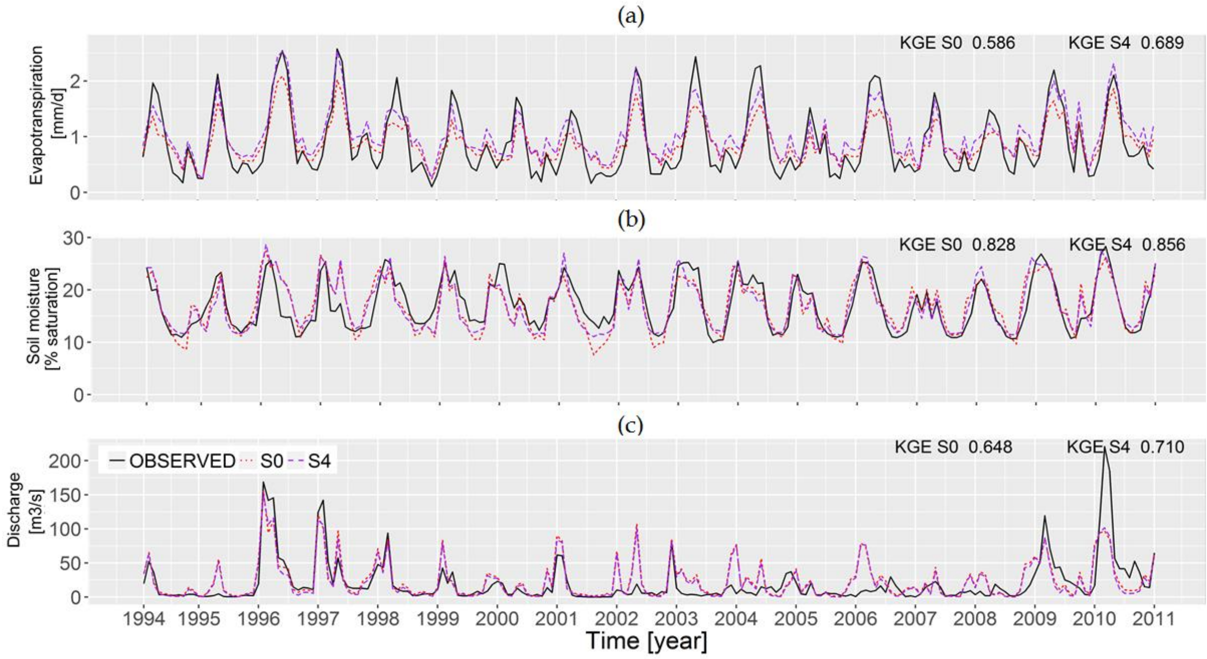

Figure 7. *(a) Monthly GLEAM actual evapotranspiration (black) and estimated actual evapotranspiration (red and purple) time series. (b) Monthly ESA CCI soil moisture (black) and estimated soil moisture (red and purple) time series. (c) Monthly observed discharge (black) and estimated discharge (red and purple) time series. The red dashed lines represent estimates from calibration scenario S0 (reference scenario). The purple dashed lines represent the calibrated time series from calibration scenario S4 which are taken from the runs that yield the best simulations. Estimated time series over the entire Oum Er Rbia basin for the validation time period obtained with MSWEP precipitation are shown.*

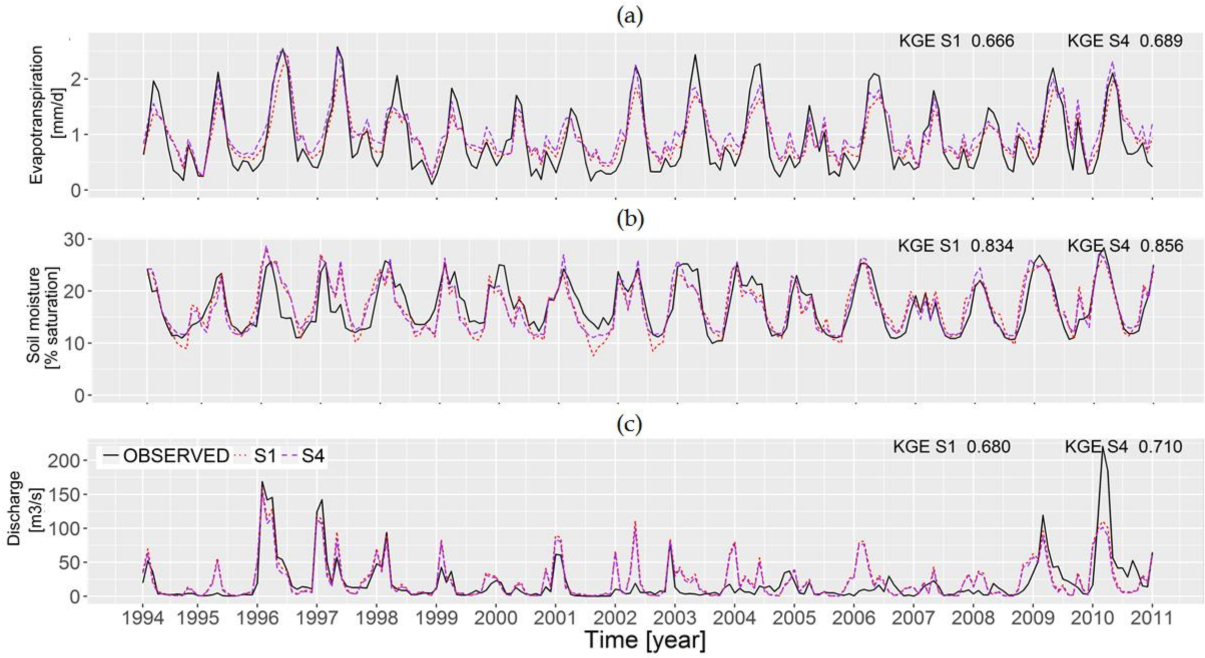

Figure 8. *(a) Monthly GLEAM actual evapotranspiration (black) and estimated actual evapotranspiration (red and purple) time series. (b) Monthly ESA CCI soil moisture (black) and estimated soil moisture (red and purple) time series. (c) Monthly observed discharge (black) and estimated discharge (red and purple) time series. The red dashed lines represent estimates from calibration scenario S1. The purple dashed lines represent the calibrated time series from calibration scenario S4 which are taken from the runs that yield the best simulations. Estimated time series over the entire Oum Er Rbia basin for the validation time period obtained with MSWEP precipitation are shown.*

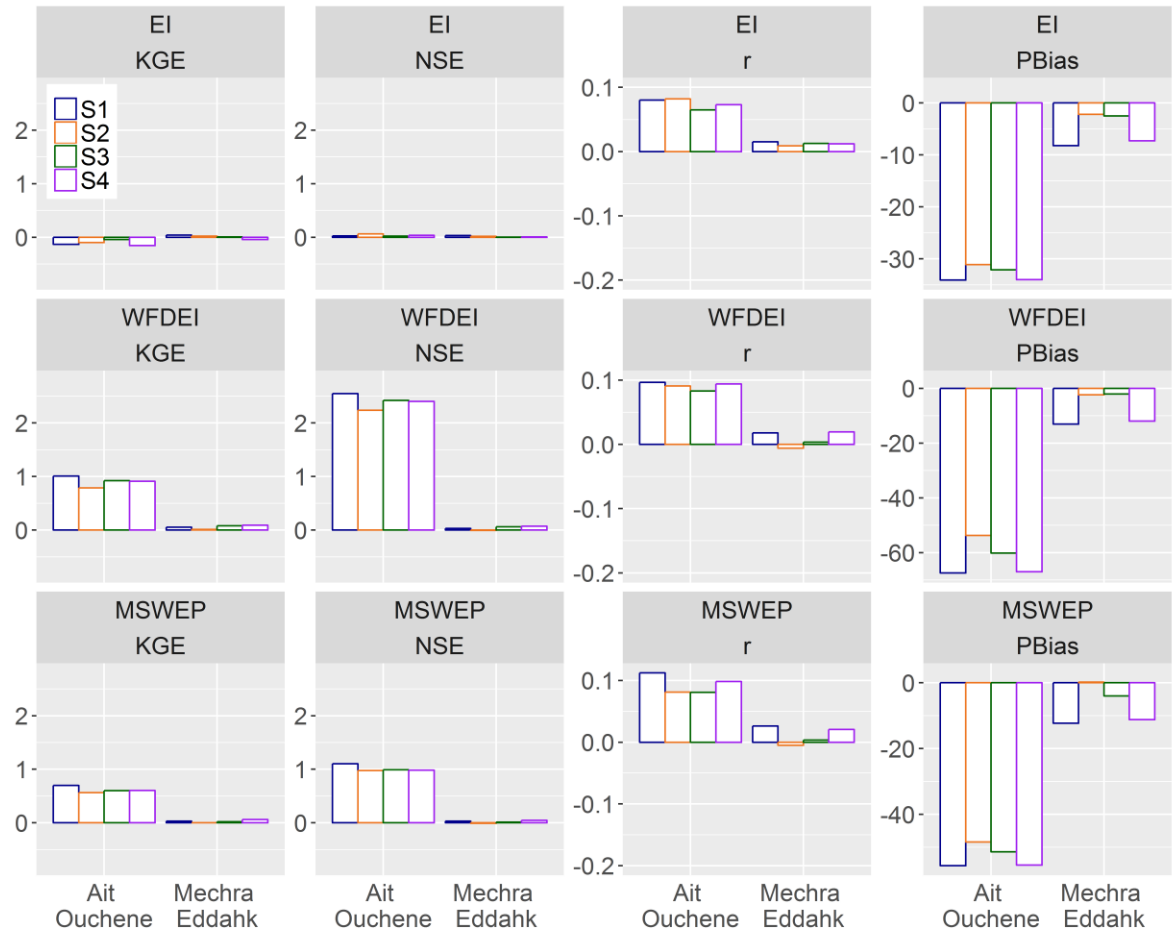

Figure 9. *KGE, NSE, r and PBias variations comparing monthly discharge estimates of calibration scenarios S1, S2, S3 and S4 with S0. Rows indicate the three global precipitation products and columns indicate the performance metrics.*