We are thankful to all reviewers for their valuable and constructive feedback which helped us to improve the manuscript. In response, aside from several minor corrections, we have introduced the following main changes to the paper:

(1) We have considerably expanded the methodology section to clarify the model characteristics and its calibration process. In addition, we have added more discussion along with the relevant references to compare the outcome of this study with existing comparative precipitation assessments.

(2) Motivated by the reviewers' ideas, we have developed and expanded our analyses in two main directions by introducing; i) daily-scale results to compare the propagation of rainfall uncertainty across different time scales, and ii) a mean ensemble of the individual precipitation products to explore its potential to reduce uncertainty in runoff simulations.

The results show that our findings on the climate-dependent propagation of precipitation uncertainty are valid across daily and monthly time scales, and that the mean precipitation ensemble yields runoff simulations which agree better with observations than for any individual precipitation product.

Please note that we additionally corrected (i) Figures 3 and 4 to show results for May-September as indicated in the caption, while previously it was erroneously April-October, and (ii) the considered catchments to be consistently determined through the criterion of NSE(runoff)>0.36, resulting in a slight increase in the number of considered catchments.

Reviewer #1

Summary:

The manuscript has evaluated different precipitation products to understand the uncertainty propagation into the water cycle, specifically streamflow and evapotranspiration. The manuscript evaluated the different products by forcing a lumped model with the different precipitation products and evaluating the outputs, streamflow and evapotranspiration in >200 catchments across Europe.

Overall I think the paper has a good language style and is rather easy to read. I think the study has to be improved in elaboration of the methodology and discussion on different assumptions and how it performs and complements other comparative studies. At this stage I do not believe this study is easily reproducible and this should be the aim of the methodology to a certain extent.

A1: We thank the reviewer for notifying the fluency of the manuscript and have considered the points as mentioned in the following.

General comments:

In the introduction I would also include existing studies that compare precipitation products directly or indirectly and show explicitly need for this gap that you are filling. I would include a discussion on how the results from this study performs with the existing studies you will mention in the introduction with comparative investigations. The discussion should also include some assumptions and why these where made and how you justify them with references to literature.

A2: We have added more references and put our results in context of earlier studies throughout the manuscript:

- Results and discussion (lines 123-126):

"It is related to the fact that most of the considered catchments are located in relatively wet climate (aridity<1) such that soils are often saturated, triggering a rather direct runoff response to precipitation (Ghajarnia et al., 2020). Also, in these climate regimes ET is typically energy-controlled rather than water-controlled (Koster et al., 2004, Pan et al., 2019; Zheng et al., 2019; Denissen et al., 2020), leading to the observed low sensitivity of ET to precipitation (uncertainty)."
- Results and discussion (lines 185-188):
"The weaker performance in cold climate, which is also present in the case of E-OBS, might be related to smaller gauge network density, and more complex topography in colder areas (Beck et al., 2017b; Ziese et al., 2018)."
- Conclusions (lines 206-208):
"Thereby the products differ mostly with respect to the temporal dynamics rather than the overall amount of precipitation (Sun et al., 2018; Fallah et al., 2020)."
- Conclusions (lines 224-225):
"Another important outcome of our analyses is that ET simulations are mostly insensitive to precipitation uncertainty in European climate, confirming previous studies (Bhuiyan et al., 2019; Zheng et al., 2019)."

Evaluation or validation of the ET simulations with respect to the available gridded ET datasets may be quite interested to see. Several studies exist where different ET products have been compared for Europe at the basin scale as well as at the European scale and would be valuable to see what might come from this comparison to a 'reference'.

A3: We thank the reviewer for this interesting suggestion. Please note, however, Fig.3 shows that there is no strong relationship between precipitation inputs and ET simulations. Because of this, we cannot re-do the analysis from Figure 5 for ET. Similarly, we also cannot assess the validity of existing ET datasets. To clarify this point, we have updated the manuscript:
- Results and discussion (lines 153-154):
"This is, however, not possible in the case of ET due to the lacking relationship between ET and the precipitation forcing in our study region (Figure 3)."
- Conclusions (lines 225-228):
"However, in warmer and drier regions such as the Middle East, Central North America or Australia, the link between ET and precipitation should be stronger. Wherever available in these regions, ET measurements can and should be used for indirect evaluation of large-scale precipitation products to complement the results in this study where we focused more on comparatively wet regions."

Which calibration method was used, what specific software or was it manual? There should be a certain level of reproducibility possible using the methodology described currently this is not possible as many things are not mentioned. Please elaborate your methodology to include for example:

- Description of how your catchments were selected

- A more detailed description of the model used or where we can find this description

- A description of the model setup, show a schematic of the model architecture.

- A description of the calibration methodology

o What method was used

o which parameters were adjusted

o maybe a map with NSE results from the different catchments.

Are your input precipitation datasets open accessible and available? Show in your table
1 where people can access these datasets.

A4: Addressing the reviewers' comments, more information is added regarding our data and methodology, in particular to more comprehensively describes the selection of catchments, the model, and the calibration method. Also, the access links to the precipitation datasets are provided in the acknowledgment section; all data are publically accessible.

- Data and methodology (lines 69-73):

"We use here the model version introduced by Orth and Seneviratne 2015 which is adapted to the daily time scale by addition of a streamflow recession parameter and an implicit form of the water balance equation. Note that the basic concept and the governing equations of runoff and ET formation used here are well established and employed in many similar conceptual models, such as HBV (Bergström 1995; Orth and Seneviratne, 2015)."

- Data and methodology (lines 101-103):

"Note that we perform only calibration of the model, and no validation. This is because we focus on the influence of the precipitation forcing on the modelled runoff performance, and not on the simulation capacity of the model outside training conditions which has been shown in previous studies (e.g. Orth et al. 2015)."

- Data and methodology (lines 89-94):

"The simple water balance model employed in this study includes six adjustable parameters: water-holding capacity, inverse streamflow recession time scale, runoff ratio exponent, ET ratio exponent, maximum evaporative fraction, and a snow melting parameter (as in Orth and Seneviratne 2015, see also Table S1). For model calibration, 500 parameter sets are tested which are randomly sampled from the entire parameter space using Latin Hypercube Sampling (LHS; McKay et al., 1979). The ranges for each parameter within this parameter space are obtained from O et al., 2020 (see also Table S1). This way, we performed 500 corresponding simulations for each catchment over the entire considered time period 1984-2007."

- Data and methodology (lines 109-112):

"The model parameters are thereby obtained from the above-mentioned calibration using E-OBS precipitation. As this can potentially introduce biases into our results, we additionally calibrated the model using GPCC V.2018 precipitation data to derive alternative parameters with which we re-computed the main analyses."

It would also be a good idea to list the catchments and some of their details in the supplementary notes so that readers can identify these catchments. Where did you get the data for streamflow (GRDC?) This needs to be mentioned.

A5: We have updated the manuscript in lines 84-87 to clarify the origin of the data. For further details on individual catchments, we refer to the original study by Stahl et al. 2010.

- Data and methodology (lines 84-87):

"The streamflow data were collected from the European water archive, national ministries and meteorological agencies and from the WATCH project. These daily data are available for the period 1984-2007… More details on the data and catchments can be found from Stahl et al., 2010."

- Acknowledgment (lines 248-251):

"Further, we are thankful for streamflow data from a dataset compiled by Stahl et al., 2010, who collected data from the European water archive ([http://www.bafg.de/GRDC/], accessed 9 December 2019), from national ministries and meteorological agencies, as well as from the WATCH project ([http://www.eu-watch.org], accessed 9 December 2019)."

Maybe it would be interesting to see results of an ensemble precipitation product that could be used to possibly adjust for the differences in the different products. This could result in overall better performance. It would be nice addition to add an ensemble of your products and see how this performs against the individual products.

A6: Many thanks for this suggestion. We have implemented it and conducted an analysis based on the precipitation ensemble mean. As the reviewer was suspecting, the ensemble yields better agreement between modelled and observed streamflow than any of the individual products. The results are displayed in figures 5 and S7-S10. Discussion on the results can be found in sections:

- Results and discussion (lines 165-167):

"The precipitation ensemble outperforms all individual products, highlighting the usefulness of multi-source and multi-product approaches in the derivation of suitable precipitation datasets for hydrological modelling."

- Conclusions (lines 210-212):

"We further find that the ensemble mean of the considered precipitation datasets outperforms the individual datasets, suggesting that such approaches are promising to obtain more reliable precipitation forcing for hydrological modelling as shortcomings in individual datasets seem to cancel out to some extent when used within an ensemble."

Specific comments:

P2L65 – what is the difference between this version of the model you are using and the one you describe initially?

A7: In the new version, a new streamflow recession parameter and an implicit form of the water balance equation have been implemented.

- Data and methodology (lines 69-71):

"We use here the model version introduced by Orth and Seneviratne 2015 which is adapted to the daily time scale by addition of a streamflow recession parameter and an implicit form of the water balance equation."

P3L87 : : :'temperature is derived: : :"

A8: Corrected (line 105) as "temperature is taken from the E-OBS"

P3L99 which month do the points represent? The same for each catchment or different?

A9: It is pointed at lines 129-130.

"We compute the median of the standard deviations from catchments within each regime, considering all respective warm season months."

How did you choose the month?

A10: We chose the months "May-September" (now explained at lines 113-114)

"All analyses are performed during the warm season (May-September) to minimise the impact of snow and ice even though snow melting can locally affect streamflow even in the warm season (Jenicek et al. 2016)."

Calibration is done for model forced with E-OBS precipitation data and you find the model forced with E-OBS data to be the most accurate when comparing streamflow simulated and observed results. Even though you conduct a calibration with small differences in the outputs I think it is important to compare the streamflow results from the second calibrated model (forced with GPCC precipitation data) forced with all precipitation products with observed streamflow results to see if you get similar rankings across catchments.

A11: We confirmed that there is little difference between the E-OBS calibrated and GPCC V.2018 calibrated models in terms of the precipitation data rankings across catchments. Moreover, our main findings regarding the climate-dependent propagation of precipitation uncertainty are not affected by the selection of data for model calibration, as shown in the main figures 4, 5 compared to Supplementary figures S4, S9.

- Data and methodology (lines 109-112):
"The model parameters are thereby obtained from the above-mentioned calibration using E-OBS precipitation. As this can potentially introduce biases into our results, we additionally calibrated the model using GPCC V.2018 precipitation data to derive alternative parameters with which we re-computed the main analyses."
- Results and discussion (lines 142-148):
"Further, we repeat the uncertainty propagation analysis using (i) model parameters obtained from calibration with GPCC V.2018 precipitation forcing instead of E-OBS precipitation (Figure S4)… We find that Figures S4-S6 show similar patterns as in Figure 4, which confirms that our findings are robust with respect to the methodological approach, particularly in terms of the precipitation dataset employed for model calibration,…"
- Results and discussion (lines 174-177):
"In addition, we re-compute Figure 5 using all months of the year (Fig. S8), and GPCC-derived SWBM parameters (Fig. S9), which both largely confirm the described results. Note that, not surprisingly, model calibration with a particular precipitation product, e.g. E-OBS or GPCCV.2018, leads to the better performance of that respective product."

In the results section, a more detailed interpretation of the resulting graphs need to be made. I think it would be very nice here to show a graph with your NSE for all catchments (map with the values where your catchments are). Maybe then you can also group the results into good, medium and poor performance.

A12: We thank the reviewer for pointing this out and have added Figure S1 illustrating the NSE values obtained from streamflow observations and simulated runoff time series (line 96). Basically, the results are yielded over catchments with good performance, yet we have done the analyses over catchments with NSE>=0.5 which confirms our findings (lines 142-148).

"Further, we repeat the uncertainty propagation analysis using … (iii) using an NSE limit of 0.5 instead of 0.36 to select catchments where the SWBM is applicable (Figure S6). We find that Figures S4-S6 show similar patterns as in Figure 4, which confirms that our findings are robust with respect to the methodological approach, … the applied NSE threshold to determine the applicability of the model (see also Section 2.3)."

P3L101 you say there is a strong relationship between precipitation and runoff but the R2 is only 0.39. Does this show a strong relationship?

A13: We have toned down the respective paragraph:

- Corrected (lines 120-123):
"Runoff simulations are impacted by precipitation uncertainty while the ET simulations are much less influenced by precipitation uncertainty, as indicated by the regression slope. The clear relationship between runoff and precipitation is in line with previous studies (e.g. Beck et al., 2017a,b; Sun et al., 2018, Blöschl et al., 2019b)."

Reviewer #2

The study setup is nice and well tailored, maybe beside the missing of sub-monthly evaluations of the streamflow. Outcomes are interesting, but not surprize with respect to general expectations.

B1: We thank the reviewer for encouraging comments and detailed suggestions. We have included daily analyses, which also confirm the clear dependency of runoff simulations on the existing uncertainty within the input precipitation dataset and the difference in the uncertainty propagation to runoff and ET simulations across climate regimes. The results are displayed in Figures S3 and S7.

- Results and discussion (lines 140-142):
"In addition to the previous analyses using monthly averaged data, we re-compute Figure 4 using daily data. The results are shown in Figure S3. The similarity between Figures 4 and S3 suggests that our findings on the climate-dependent propagation of precipitation uncertainty are valid across daily and monthly time scales."

- Results and discussion (lines 173-174):
"Repeating the evaluation from Figure 5 with daily data (Figure S7) we find similar results. This suggests that the relative quality of the considered precipitation is comparable across daily and monthly time scales."

I am quite disappointed by the missing information on the calibration and validation of the model. Did I miss a link to previous work with your model?

B2: We thank the reviewer for raising this point. More details on the model calibration/validation are included in (lines 89-94):
"The simple water balance model employed in this study includes six adjustable parameters: water-holding capacity, inverse streamflow recession time scale, runoff ratio exponent, ET ratio exponent, maximum evaporative fraction, and a snow melting parameter (as in Orth and Seneviratne 2015, see also Table S1). For model calibration, 500 parameter sets are tested which are randomly sampled from the entire parameter space using Latin Hypercube Sampling (LHS; McKay et al., 1979). The ranges for each parameter within this parameter space are obtained from O et al., 2020 (see also Table S1). This way, we performed 500 corresponding simulations for each catchment over the entire considered time period 1984-2007."

- Data and methodology (lines 69-73):
"We use here the model version introduced by Orth and Seneviratne 2015 which is adapted to the daily time scale by addition of a streamflow recession parameter and an implicit form of the water balance equation. Note that the basic concept and the governing equations of runoff and ET formation used here are well established and employed in many similar conceptual models, such as HBV (Bergström 1995; Orth and Seneviratne, 2015)."
- Data and methodology (lines 101-103):
"Note that we perform only calibration of the model, and no validation. This is because we focus on the influence of the precipitation forcing on the modelled runoff performance, and not on the simulation capacity of the model outside training conditions which has been shown in previous studies (e.g. Orth et al. 2015)."

See all comments in the attached PDF.

Please also note the supplement to this comment:

https://www.hydrol-earth-syst-sci-discuss.net/hess-2019-660/hess-2019-660-RC2-

supplement.pdf

B3: Many thanks for the detailed comments. We have updated the manuscript following the reviewer's suggestion. Clarifications and additions inserted in response to your comments in the pdf have been highlighted in yellow for better traceability. Further, we particularly thank the reviewer for suggesting the inclusion of the SM2RAIN dataset into our analyses. As an independent and novel dataset, this would have been a valuable addition to our analyses. However, we decided not to use it as it does not cover the investigated time period 1984-2007, and the data gaps constitute a problem for application in hydrological modelling requiring gap-free data, while developing a suitable gap-filling approach was beyond the scope of this analysis.

Climate-dependent propagation of precipitation uncertainty into the water cycle

Commented [WU1]: Please note these highlighted phrases have been adapted to account for comments of reviewer #2 in the pdf.

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Abstract. Precipitation is a crucial variable for hydro-meteorological applications. Unfortunately, rain gauge measurements are sparse and unevenly distributed, which substantially hampers the use of in-situ precipitation data in many regions of the world. The increasing availability of high-resolution gridded precipitation products presents a valuable alternative, especially over poorly gauged~~gauge-sparse~~ regions. ~~Nevertheless, uncertainties and corresponding differences across products can limit the applicability of these data.~~ This study examines the usefulness of current state-of-the-art precipitation datasets in hydrological modelling. For this purpose, we force a conceptual hydrological model with multiple precipitation datasets in >200 European catchments to obtain runoff and evapotranspiration. We consider a wide range of precipitation products, which are generated via (1) interpolation of gauge measurements (E-OBS and GPCC V.2018), (2) data assimilation into reanalysis models (ERA-Interim, ERA5, and CFSR), and (3) combination of multiple sources (MSWEP V2)~~, and (3) data assimilation into reanalysis models (ERA-Interim, ERA5, and CFSR) and (4) precipitation ensemble averaged over these products. For each catchment, runoff and evapotranspiration (Forcing should be mentioned here, eventually!?) simulations are obtained by forcing the model with the various precipitation products.~~ Evaluation is done at the daily and monthly ~~and sub-monthly~~ time scales during the period of 1984-2007. We find that simulated runoff values are highly dependent on the accuracy of precipitation inputs, ~~and thus show significant differences between the simulations (obvious!?).~~ b~~B~~y contrast, simulated evapotranspiration is generally much less influenced in our comparatively wet study region ~~(why? Also obvious)~~. ~~The results are further analysed with respect to different hydro-climatic regimes.~~ We also find that the impact of precipitation uncertainty on simulated runoff increases towards wetter regions, while the opposite is observed in the case of evapotranspiration. Finally, we perform an indirect performance evaluation of the precipitation datasets by comparing the runoff simulations with streamflow observations. Thereby, ~~besides the outperformed ensemble,~~ E-OBS yields the ~~best~~particularly strong agreement, while furthermore ERA5, GPCC V.2018 and MSWEP V2 show good performance. We further reveal climate-dependent performance variations of the considered datasets, which can be used to guide their future development. The overall best agreement is achieved when using an ensemble mean generated from all the individual products. In summary, our findings highlight a climate-dependent propagation of precipitation uncertainty through the water cycle; while runoff is strongly impacted in comparatively wet regions such as Central Europe, there are increasing implications on evapotranspiration towards drier regions ~~(no real surprise!?)~~.

1. Introduction

Precipitation is a key quantity in the water cycle since it controls water availability including both blue and green water resources (Falkenmark and Rockström, 2006; Orth and Destouni, 2018). This way, changes in precipitation translate into changes in water resources which could have severe impacts on ecosystems, and consequently economy and society (Oki and Kanae, 2006; Kirtman et al., 2013; Abbott et al., 2019). Changes in precipitation can be induced or intensified by climate change and consequently lead to amplified impacts (Blöschl et al., 2017; Blöschl et al., 2019b). Thus, accurate precipitation information is essential for monitoring water resources and managing related impacts.

Despite the necessity of accurate precipitation datasets, in most regions, reliable gauge measurements are not widely available. Further, these measurements need to be corrected for potential errors such as wind-induced inaccuracies or precipitation undercatch, especially in higher altitudes (Sevruk et al., 2009; Mekonnen et al., 2015)~~)~~. Next to gauge measurements, precipitation information can be inferred from satellite observations and/or model simulations. Based on these sources, a variety of global gridded precipitation datasets have emerged. While some of these datasets make direct use of gauge measurements to interpolate them in time and space, others make indirect use of the gauge information to calibrate satellite retrieval algorithms or models, enabling them to estimate gridded large-scale precipitation.

Across these datasets, there are ample discrepancies in space and time, highlighting the need for comparative assessments (e.g. Koutsouris et al., 2016; Alijanian et al., 2017, 2019; Balsamo et al., 2018; Sun et al., 2018; Massari et al., 2019; Brocca et al., 2019; Sharifi et al., 2019; Caroletti et al., 2019; Levizzani and Cattani, 2019; Roca et al., 2019; Fallah et al., 2020~~19~~; Satgé et al., 2020; Contractor et al., 2020; Xu et al., 2020). In particular, indirect evaluation of the datasets through application in hydrological modelling is a valuable alternative in this context~~,~~ as precipitation is translated into variables with more ~~(~~reliable ~~) large-scale~~ observations such as runoff, ~~given their relatively low variability across scales~~as long as this is measured in catchments with near-natural dynamics ~~-~~(Thiemig et al., 2013; Nerini et al., 2015; Beck et al., 2017a,b,2019a,b; Arheimer et al., 2019; Fereidoon et al., 2019; Bhuiyan et al., 2019; Mazzoleni et al., 2019). However, while this approach relies on the propagation of precipitation uncertainty into runoff it is largely underexplored when and where this propagation pathway is active. Vice versa, it is unclear in which regions or conditions, gridded datasets of runoff (Gudmundsson and Seneviratne, 2016) or evapotranspiration (e.g. Martens et al., 2017; Jung et al., 2019) are impacted by the existing precipitation uncertainties.

In this study, we investigate the uncertainty across six widely used gridded precipitation datasets, including its propagation into the hydrological cycle, i.e. runoff and evapotranspiration (ET). Thereby, we consider gauge-interpolated (E-OBS v17.0, GPCC V.2018)~~, multi-source (MSWEP V2), and~~ reanalyses (ERA-Interim, ERA5, CFSR), multi-source (MSWEP V2) datasets ~~and eventually the mean ensemble~~. With each of them, and with an ensemble mean computed from all of them, we force a conceptual land surface model and compare the respectively simulated runoff and ET. This is done separately for different hydro-climatological regimes. In addition, validating the runoff simulations against respective observations we can indirectly infer the performance of the precipitation datasets. This further allows us to obtain guidelines with respect to the usefulness of the different types of precipitation products in the considered regimes.

Section 2 introduces the reference, forcing datasets and model calibration used in the study, and Section 3 illustrates results and discussion. Finally, in Section 4 the conclusions of this study are presented.

2. Data and methodology

2.1. Forcing data

Runoff and ET are modelled with a conceptual hydrological model, the Simple Water Balance Model (SWBM). The underlying framework was initially presented by Koster and Mahanama 2012 where runoff (normalised by precipitation) and ET (normalised by net radiation) are assumed to be polynomial functions of soil moisture (Whan et al., 2015). We use here the model version introduced by Orth and Seneviratne 2015~~3~~ which is adapted to the daily time scale by addition of a~~, and a new~~ streamflow recession parameter and an implicit form of the water balance equation ~~have been implemented~~. Note that the basic concept and the governing equations of runoff and ET formation used here are well established and employed in many similar conceptual models, such as HBV ~~model families~~ (Bergström 1995; Orth and Seneviratne, 2015~~3~~). ~~.~~ As inputs, the model uses temperature, net radiation, and precipitation. For each catchment, temperature and net radiation are used from the respective grid cells from the E-OBS (~~Haylock et al., 2008~~Cornes et al., 2018) and ERA-Interim (Dee et al., 2011) datasets, respectively. Corresponding grid cell-based precipitation data is used from various datasets derived from different sources: gauge-based (E-OBS, GPCC V.2018), ~~multi-source (MSWEP V2),~~ ~~and~~ reanalysis ~~datasets~~ (ERA-Interim, ERA5, CFSR), and multi-source datasets (MSWEP V2)~~, and eventually the mean ensemble~~. A summary of all precipitation datasets and their respective characteristics is shown in Table 1.

Before using the precipitation datasets to force the SWBM, they are re-gridded to a common 0.5° spatial resolution, if necessary. This was done through conservative remapping which preserves the water mass (Jones, 1999) using climate data operators (Schulzweida, 2019). The SWBM simulations are performed with a daily time step, and the analysis thereof is done at daily and monthly time scales.~~While theIn addition to SWBM simulations are performed with a daily time step, we focus on monthly averaged data throughout the analyses in this study to mitigate the influence of synoptic weather variability. However, tThe results at the daily scale are provided in Supplementary.~~

2.2. Reference data

Modelled runoff is evaluated against ~~monthly mean and daily~~ streamflow observations obtained from 41~~2~~6 catchments distributed across Europe (Stahl et al., 2010). The streamflow data were collected from the European water archive, national ministries and meteorological agencies and from the WATCH project. These daily data are available ~~at a daily scale~~ for the period 1984-2007. There is no~~-~~ or little human influence on the streamflow in these catchments, which are mostly between 10-100 km^2 in size. More details on the data and catchments can be found from Stahl et al., 2010.~~.~~

2.3. Model calibration

~~In a first step, the best possible model performance was determined in each catchment to test the respective applicability of the model. For this purpose, the model is calibrated against streamflow observations over the entire time period (1984-2007) in each catchment. There is no validation period with independent data as this calibration process aims to examine the general suitability of model parameters and input-ouput data (need refs?). . The >400 catchments are distributed across Europe, and across different hydro-climatological regions (Fig. 1).~~

The simple water balance model employed in this study includes six adjustable parameters: water-holding capacity, inverse streamflow recession time scale, runoff ratio exponent, ET ratio exponent, maximum evaporative fraction, and a snow melting parameter (as in Orth and Seneviratne 2015, see also Table S1). For model calibration, 500 parameter sets~~s~~ are tested which are randomly sampled from the entire parameter space using Latin Hypercube Sampling (LHS; McKay et al., 1979). ~~, to sample the entire parameter space while t~~The ranges for each parameter within this parameter space ~~is~~ are obtained from O~~rth and Seneviratne 2015, and derived from observation-based model calibration~~ et al., 2020 (see also Table S1). This way, we~~and performed~~ performed 500 corresponding simulations for each catchment over the ~~24-yrs~~entire considered time period 1984-2007. For each simulation, we computed the resulting ~~T~~Nash-Sutcliffe efficiency (NSE, Nash and Sutcliffe, 1970) between observed and simulated runoff to determine the best-performing parameter set. The results are shown in Figure S1. In addition, any catchments with NSE<0.36 even with in the case of the best parameter set were disregarded from the further analyses (Motovilov et al., 1999; Moriasi, 2007). The model was deemed not applicable there due to e.g. human influence on the local runoff dynamics, or model shortcomings. This way, out of the original >400 catchments, 264 are retained for the actual analyses, which are well distributed across the European continent and its climate regimes.

Note that we perform only calibration of the model, and no validation. This is because we focus on the influence of the precipitation forcing on the modelled runoff performance, and not on the simulation capacity of the model outside training conditions which has been shown in previous studies (e.g. Orth et al., 2015).

~~was determined by NSE between observed and simulated runoff, and the catchments showing NSE >=0.36 with any parameter set are selected for the further analysis. All six model parameters include water-holding capacity, inverse streamflow recession time scale, runoff ratio exponent, ET ratio exponent, Max ET ratio (Orth et al., 2013) and a snow melting parameter.~~

~~Calibration should be explained here!!!!! Please move the sentences below here (later, you mentioned “the above-mentioned calibration using E-OBS precioitation)~~

~~The agreement between modelled and observed runoff is determined by computing the Nash-Sutcliffe efficiency (NSE, Nash and Sutcliffe, 1970).~~; ~~the resuls are shown in Fig. S1. using monthly data during 1984-2007. Only catchments where NSE>=0.36 (Motovilov et al., 1999; Moriasi, 2007) are retained for the further analyses, which leaves 26443 catchments out of >400 that are well distributed across the continent. Figure S1 illustrates NSE values in each catchment computed by runoff daacross Europe, and across different hydro-climatological regions (Fig. 1). Also, NSE values are shown in Fig. S1 (Supplementary material).~~

As shown in Fig. 1, the hydro-climatological regime is characterised through long-term average temperature and aridity (Budyko, 1974). Thereby, for each catchment, the temperature is taken~~derived~~ from the E-OBS dataset, and aridity is computed as the ratio of mean annual net radiation to mean annual precipitation calculated from ERA-Interim and E-OBS, respectively.

In each of the 264~~43~~ catchments, the SWBM is forced with temperature, net radiation and the different precipitation datasets, respectively, as illustrated in Figure 2 ~~(Fig. 2)~~. This way, six simulations with the six different precipitation datasets are performed for each catchment, leaving the temperature and net radiation data unchanged. The model parameters are thereby obtained from the above-mentioned calibration using E-OBS precipitation. As this can potentially introduce biases into our results, we additionally calibrated the model ~~We also obtained new sets of parameters~~ using GPCC V.2018 precipitation data to derive alternative parameters with which we ~~and~~ re-computed the main analyses. ~~(see Supplementary). Our main results and conclusions remain almost the same regardlessedd of t he either parameters used. while these parameters are also re-computed based on GPCC V.2018 precipitation data.~~ .

All analyses are performed during the warm season (May-September) ~~because ET is of minor relevance during cold months and~~ to ~~exclude~~ minimise the impact of snow and ice even though snow melting can locally affect streamflow even in the warm season (Jenicek et al., 2016). ~~although snowmelt affects discharge long after the end of the melt season, in some regions (Jenicek et al., 2016ref). , and because ET is of minor relevance during cold months.~~

3. Results and discussion

3.1. Impact of precipitation uncertainty on runoff and ET

Figure 3 illustrates the propagation of precipitation uncertainty into simulated runoff and ET at the monthly scale. Each point denotes the standard deviation across the six simulations obtained with the different precipitation datasets and represents a particular month (May-Sep) in a specific catchment. Runoff simulations are ~~strongly influenced~~impacted by precipitation uncertainty while the ET simulations are much less influenced by precipitation uncertainty, as indicated by the regression slope. The clear ~~The strong~~ relationship between runoff and precipitation is in line with previous studies (e.g. Beck et al., 2017a,b; Sun et al., 2018, Blöschl et al., 2019b). It is related to the fact that most of the considered catchments are located in relatively wet climate (aridity<1) such that soils are often saturated, triggering a rather direct runoff response to precipitation (Ghajarnia et al., 2020). Also, in these climate regimes ET is typically energy-controlled rather than water-controlled (Koster et al., 2004, Pan et al., 2019; Zheng et al., 2019; Denissen et al., 2020), leading to the observed low sensitivity of ~~ ~~ET to precipitation (uncertainty).

3.2. Climate-dependent propagation of precipitation uncertainty

~~regimes~~In addition to examining the role of precipitation uncertainty for runoff and ET across all considered catchments, we analyse this uncertainty propagation within individual hydro-climatological regimes (Fig. 4). For this purpose, we compute the median of the standard deviations from catchments within each regime, considering all respective warm season months~~.). Move the FigS2 sentences here!~~. Figure S2 shows the number of catchments located within each regime. Only regimes with >5 catchments are considered in the analysis. The uneven distribution of catchments across the regimes induces higher uncertainties in the results obtained for the wettest and driest regimes. ~~For this purpose, we compute the median of the standard deviations from catchments within each regime, considering all respective warm season months.~~ As shown in Fig. 4a, the precipitation ~~uncertainty~~variability across the considered products is higher in comparatively cold and wet regions. This could be related to especially sparse gauge networks and more intense rainfall in these regions which are known to increase precipitation uncertainty (Dinku et al., 2008; Hu et al., 2016; Beck et al., 2017b; O and Kristetter, 2018).

Similarly, Figs. 4b and 4c illustrate the fraction of precipitation uncertainty propagating into runoff and ET, respectively. Interestingly, we find systematic variations in this uncertainty propagation with respect to climate. In wet and cold regions, precipitation uncertainty almost exclusively affects runoff whereas ET remains unchanged. ~~(no suprize!?);~~ Towards drier and warmer climate the uncertainty propagation shifts, affecting runoff less and increasingly influencing ET.

~~Figure S1 shows the number of catchments located within each hydro-climatological regime. Only boxes with >5 catchments are considered in the analysis. The uneven distribution of catchments across the regimes induces higher uncertainties in the results obtained for the wettest and driest regimes.~~

In addition to the previous analyses using monthly averaged data, we re-compute Figure 4 using daily data. The results are shown in Figure S3. The similarity between Figures 4 and S3 suggests that our findings on the climate-dependent propagation of precipitation uncertainty are valid across daily and monthly time scales. ~~As the calibration of the SWBM using E-OBS precipitation data (see Section 2.3) (Declared but not shown!?) can induce biases in our analyses, we re-compute Figure 4 using model parameters obtained from calibration with GPCC V.2018 precipitation forcing, the results are shown in Fig.ure S32. The clear similarity between Figures 4 and S23 suggests minor relevance of the precipitation dataset used in the SWBM calibration.~~ Further, we repeat the uncertainty propagation analysis using (i) model parameters obtained from calibration with GPCC V.2018 precipitation forcing instead of E-OBS precipitation (Figure S4), (ii) using all months instead of focusing on the warm season (Figure S5), and (iii) using an NSE limit of 0.5 instead of 0.36 to select catchments where the SWBM is applicable (Figure S6). ~~,~~

We find that Figures S4-S6 show similar patterns as in Figure 4, which confirms that our findings are robust with respect to the methodological approach, particularly in terms of the precipitation dataset employed for model calibration, the considered season, and the applied NSE threshold to determine the applicability of the model (see also Section 2.3).~~also showing rather similar results (Fig.ure S43). In addition, the results are obtained based on NSE limit >=0.5 instead of >=0.36 (Fig. S5), which indicates the independence of findings with the catchments filtering. Moreover, re-computing the analysis based on daily time scale, as shown in Fig. S6, confirms the observed patterns in the propagation of precipitation uncertainty into runoff and ET simulations.~~

3.3. Indirect validation of precipitation dataset qualities

Given the preferential propagation of precipitation uncertainty to runoff in the considered European catchments, we focus in the following on runoff only. ~~In other words, in our region, due to weak or missing relationship between ET and precipitation input quality, the evaluation based on ET products seems inadequate (See Fig. 3).~~ In this context, we use streamflow measurements from the catchments to validate the modelled runoff, which allows us to draw conclusions also on the usefulness of the employed precipitation forcing datasets, and of a mean ensemble thereof. This is, however, not possible in the case of ET due to the lacking relationship between ET and the precipitation forcing in our study region (Figure 3). For the runoff validation, we consider the correlation of monthly anomalies in each catchment and the absolute bias. To obtain anomalies, we remove the mean seasonal cycle from the observed and modelled runoff time series of each catchment. The six runoff simulations derived with the individual precipitation products alongside the runoff simulation obtained with the mean ensemble~~, accompanied by the ensemble, in each catchment~~ are then ranked in each catchment with respect to (i) correlation and (ii) bias. ~~, and t~~The sum of these 2 ranks is used to obtain an overall ranking of runoff simulations and corresponding precipitation forcing datasets in each catchment ~~(Individual scores are shown in Supplementary)~~. ~~.~~

Figure 5 shows the number of catchments in which each precipitation product yields the best-ranked runoff simulation. Our findings show that overall the performance of modelled runoff is clearly dependent on the employed precipitation product. This is expected given the considerable disagreement between precipitation products, and the preferential propagation of this uncertainty to runoff (Fig. 4). Generally, among the individual products, the runoff computed with ~~the mean ensemble and then~~ E-OBS precipitation agrees best with observations. Also, ERA5, MSWEP V2, and GPCC V.2018 yield comparatively good runoff estimates. In contrast, runoff simulations obtained with ERA-Interim and CFSR agree less well with observations. ~~—~~The precipitation ensemble outperforms all individual products, highlighting the usefulness of multi-source and multi-product approaches in the derivation of suitable precipitation datasets for hydrological modelling. Furthermore, we compute runoff performance assessments separately for anomaly correlation and absolute bias (Fig. S10). This reveals that the performance of the precipitation datasets is rather similar in terms of resulting runoff biases. Only ERA5 seems to lead to reduced biases compared with the other products, probably as it does not suffer from a gauge-based precipitation undercatch. In contrast, there are considerable differences in terms of the runoff anomaly correlation performance across the products. This indicates that the differences across products shown in Fig. 5 are mostly resulting from contrasting performance with respect to runoff anomaly correlation.

Repeating ~~this~~the evaluation from Figure 5 with daily data (Figure S7~~x~~) we find similar results. This suggests that the relative quality of the considered precipitation is comparable across daily and monthly time scales. In addition, we re-compute Figure 5 using all months of the year (Fig. S8~~4~~), and GPCC-derived SWBM parameters (Fig. S9~~5~~), which both ~~and daily time series (Fig. S9)~~largely confirm~~s~~ the described results~~.~~. Note that, not surprisingly, model calibration with a particular precipitation product, e.g. E-OBS or GPCCV.2018, leads to the better performance of ~~the~~that respective product. ~~It should be noted that the yielded results based on daily time series highlight the promising performance of MSWEP V2 compared to GPCC V.2018 in daily analyses.~~

~~Furthermore, we compute runoff performance assessments separately for anomaly correlation and absolute bias (Fig. S106). This reveals that the performance of the precipitation datasets is rather similar in terms of resulting runoff biases. Only ERA5 seems to lead to reduced biases compared with the other products, probably as it does not suffer from gauge-based precipitation undercatch. In contrast, there are considerable differences in terms of the runoff anomaly correlation performance across the products. This reveals that the differences across products shown in Fig. 5 are mostly resulting from contrasting performance with respect to runoff anomaly correlation.~~

Figure 6 shows the runoff performance resulting from the various precipitation products for the previously considered hydro-climatological regimes. Interestingly, ~~W~~we find remarkable performance differences across the regimes, suggesting differential usefulness of precipitation products for hydrological modelling across different climate zones. ~~-~~Also, we can identify regimes where the precipitation products perform particularly well or not. For example, MSWEP V2 leads to strong agreement between modelled and observed runoff mostly in comparatively cold and wet climate and less so in warmer and drier regimes. This might be related to problems of the products incorporated in MSWEP in capturing convective rainfall in warm and dry regions while this is less problematic in colder regions (Ebert et al., 2007; Beck et al., 2017a,b; Massari et al., 2017; Fallah et al., 2020~~19~~). The opposite performance pattern is observed for GPCC V.2018. The weaker~~lower~~ performance in cold climate, which is also present in the case of E-OBS, might be related to smaller gauge network density, and more complex topography in colder areas (Beck et al., 2017b; Ziese et al., 2018). For the other products such as CFSR and ERA-Interim, the performance is less dependent on the hydro-climatological regime.

4. Conclusions

In this study, we investigate how the remarkable discrepancy across state-of-the-art gridded precipitation datasets propagates through the water cycle. This is essential for hydrological modelling and the applicability of resulting simulations of water balance components such as runoff or ET. Our findings reveal that the uncertainty across precipitation datasets propagates mainly into runoff rather than ET simulations in Europe. In addition, the partitioning of precipitation uncertainty between runoff and ET is climate-dependent. In comparatively cold and wet regions such as Europe runoff is more impacted, whereas in drier and warmer regions the uncertainty partitioning shifts towards ET. This applies across daily and monthly time scales.

The results in this study are obtained with a single model and are potentially dependent on the choice of that model. Even though this model has been validated thoroughly and applied in previous studies (~~Orth and Seneviratne, 2014;~~ Orth et al., 2015; Orth and Seneviratne, 2014, 2015; Schellekens et al., 2017;~~,~~ O et al., 2019), future research needs to explore precipitation error propagation with other models (as in Bhuiyan et al., 2019). This should particularly include distributed models adding to our use of a lumped scheme. However, we do obtain similar results with different calibrations of this model, while previous research indicated that differences across model calibrations can be similar to that across models (Tebaldi and Knutti, 2007).

The strong link between precipitation and runoff in Europe allowed us to perform an indirect validation of precipitation products through the performance of the respectively modelled runoff~~, while such an indirect evaluation, in Europe, does not seem plausible via ET reference datasets~~. Overall, the~~ mean ensemble and then~~ E-OBS precipitation dataset yields the most reliable streamflow simulations in Europe across the considered precipitation products. Weaker but still comparatively good agreement between modelled and observed streamflow is obtained with ERA5, GPCC V.2018 and MSWEP V2. Thereby the products differ mostly with respect to the temporal dynamics rather than the overall amount of precipitation (Sun et al., 2018; Fallah et al., 2020). The interpolated products overall outperform the satellite-derived products in Europe. This is probably due to the high density of gauge observations, as previous research found contrasting conclusions in regions with low gauge density (e.g. Thiemig et al., 2013 for Africa). We further find that the ensemble mean of the considered precipitation datasets outperforms the individual datasets, suggesting that such approaches are promising to obtain more reliable precipitation forcing for hydrological modelling as shortcomings in individual datasets seem to cancel out to some extent when used within an ensemble. Further, we study the performance of the considered precipitation products ~~performance~~ with respect to climate. We find systematic variations for datasets like MSWEP V2 and GPCC V.2018 whereas ERA5, ERA-Interim, and CFSR perform more similarly across climate regimes. ~~While reanalyses show large discrepancies with regard to their performance highlighting the necessity of more accurate modelling (Sun et al., 2018).~~ Revealing climate-dependent accuracies in some precipitation datasets supports focused development of these products. This way, innovative hydrological validation of precipitation data, in addition to direct validation against ground truth, can contribute to address the still considerable uncertainty across state-of-the-art gridded products in future efforts.

Further, these findings allow a more targeted combination of products to compensate for individual weaknesses and preserve respective strengths. The climate-dependent (propagation of) precipitation uncertainties illustrates that there is no best overall product but instead a careful regional, climate-based selection can support hydrological applications. Overall, these findings highlight the usefulness of streamflow measurements capturing truly large-scale hydrological dynamics which can ~~even~~then be used to make inference on the accuracy of precipitation datasets (Behrangi et al., 2011; Thiemig et al., 2013; Beck et al., 2017a, 2019a; Arheimer et al., 2019; Bhuiyan et al., 2019; Mazzoleni et al., 2019; Alnahit et al., 2020). ~~Moreover, in future efforts, a (more accurate) combination of precipitation datasets as an ensemble precipitation product may show some values leading to overall better performance.~~

Another important outcome of our analyses is that ET simulations are mostly insensitive to precipitation uncertainty in European climate, confirming previous studies (Bhuiyan et al., 2019; Zheng et al., 2019). However, in warmer and drier regions such as the Middle East, Central North America or Australia, the link between ET and precipitation should be stronger. Wherever available in these regions, ET measurements can and should be used for indirect evaluation of large-scale precipitation products to complement the results in this study where we focused more on comparatively wet regions.

Moreover, our findings suggest that, across Europe and regions with similar climate, gridded runoff datasets (e.g. Gudmundsson and Seneviratne, 2016) inevitably suffer from the existing uncertainty in state-of-the-art precipitation datasets, although this depends on the extent to which they rely on precipitation data. In contrast, gridded ET products (e.g. Martens et al., 2017, Jung et al., 2019) are not impacted by precipitation uncertainty in these regions. In warmer and drier regions, however, the gridded ET products are more challenged than the runoff products.

Overall, our findings highlight the important role of precipitation accuracy and the understanding of the propagation of existing inaccuracies through the water cycle. Revealing the climate-dependency of this propagation, this study contributes to improved modelling and monitoring of water resources which is of particular relevance in the case of extreme events such as floods and droughts (e.g. Golian et al., 2019), which might increase in a changing climate.

Competing interests. The authors declare no conflicts of interest.

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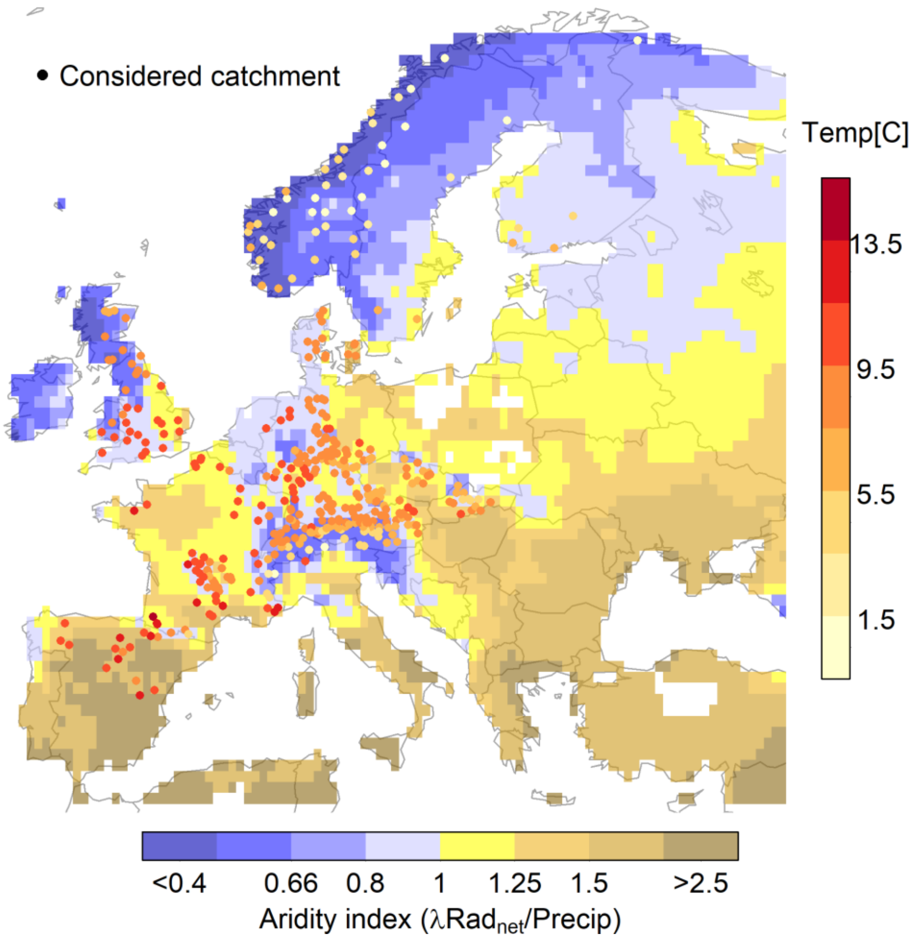
Table 1: Summary of the precipitation datasets evaluated in this study

Group	Dataset	Temporal coverage	Spatial coverage	Spatial resolution	Data sources	Reference
Interpolated	E-OBS	1950-2019~~8~~	Europe	0.25°	Gauge	~~Haylock et al., 2008~~Cornes et al., 2018
	GPCC V.2018	1901-2016	Global	1°	Gauge	Ziese et al., 2018
Multi-source	MSWEP V2	1979-2017~~NRT[1]~~	Global	0.1°	Satellite + Gauge + Reanalysis	Beck et al., 2019
	ERA-Interim	1979-2019	Global	0.5°	Reanalysis	Dee et al., 2011
Modelled	ERA5	1950-current~~NRT[2]~~	Global	~0.28°	Reanalysis	Copernicus Climate change Service, 2017
	CFSR	1979-current~~NRT[1]~~	Global	0.5°	Reanalysis	Saha et al., 2010, 2012

~~[1] Near Real-Time product available until the present with a delay of several hours.~~

~~[2] Available until the present with a delay of several months.~~



• Considered catchment
Temp[C]
13.5
9.5
5.5
1.5
<0.4
0.66
0.8
1
1.25
1.5
>2.5
Aridity index (λRadnet/Precip)

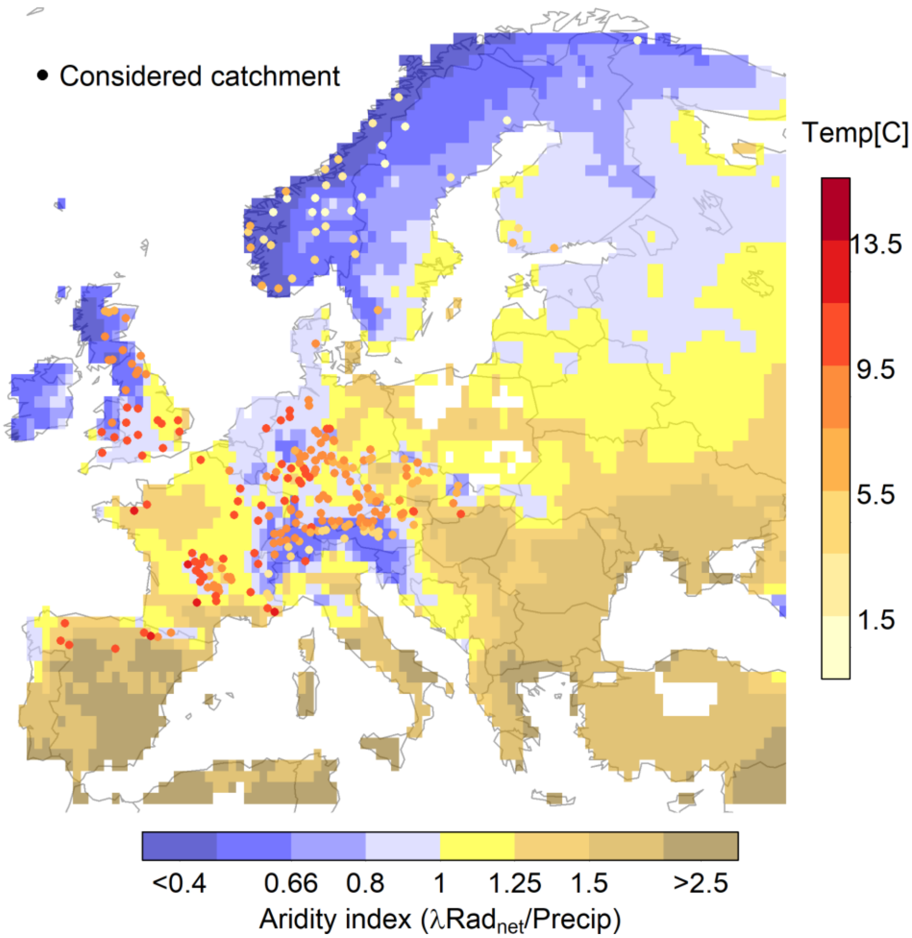


Figure 1: Map of the study area. Signs mark the position of the 264~~426~~ study catchments, with color indicating their annual average temperature. Map colors show the aridity index of regions as determined by a ratio of long-term average net radiation and precipitation (1984-2007).

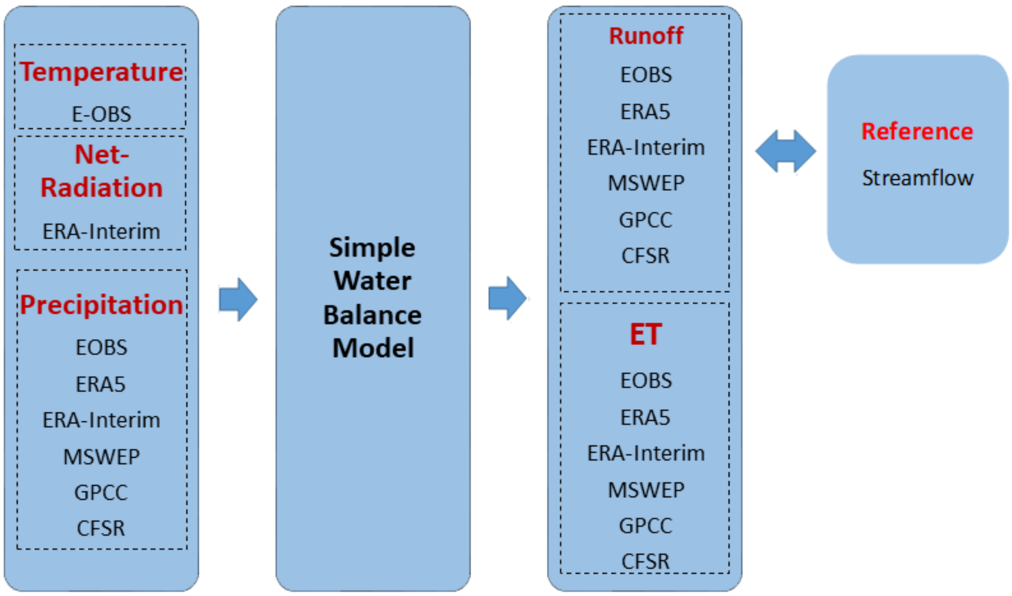
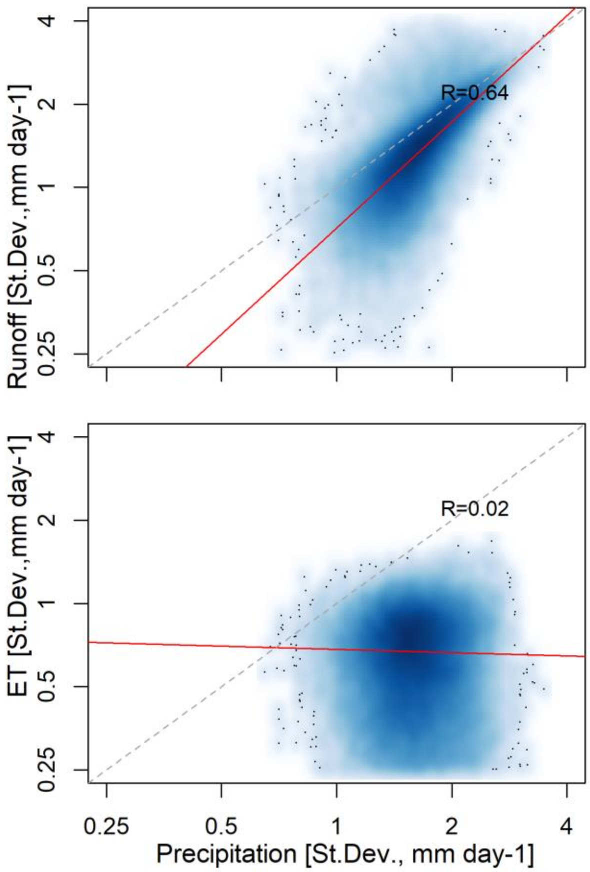


Figure 2: Overview of the modelling approach. The SWBM model is forced with consistent net radiation and temperature data, but six different precipitation datasets. The obtained runoff and evapotranspiration are assessed in terms of the variability between the simulations. The performance of the runoff simulations is determined against streamflow observations.



Runoff [St.Dev.,mm day-1]
R=0.64
ET [St.Dev.,mm day-1]
R=0.02
0.25
0.5
1
2
4
Precipitation [St.Dev., mm day-1]

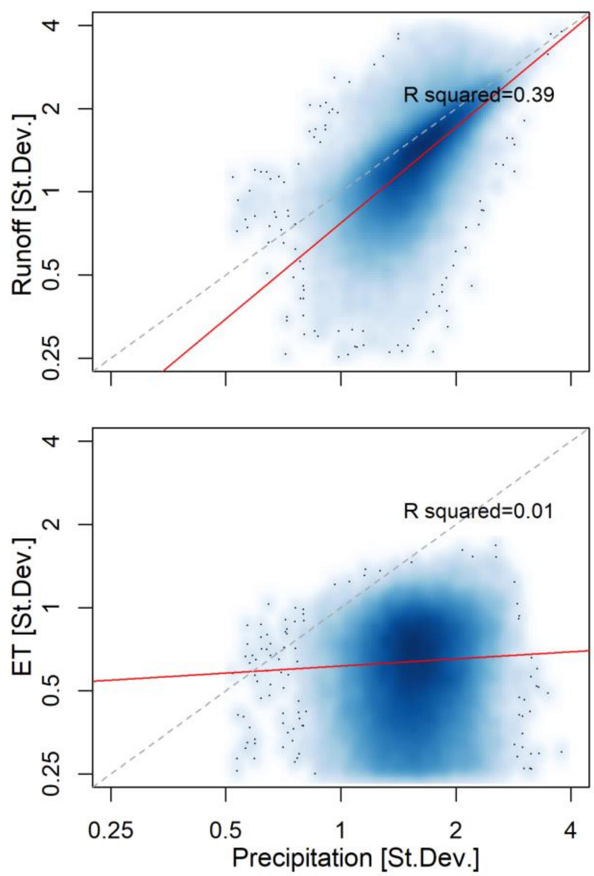
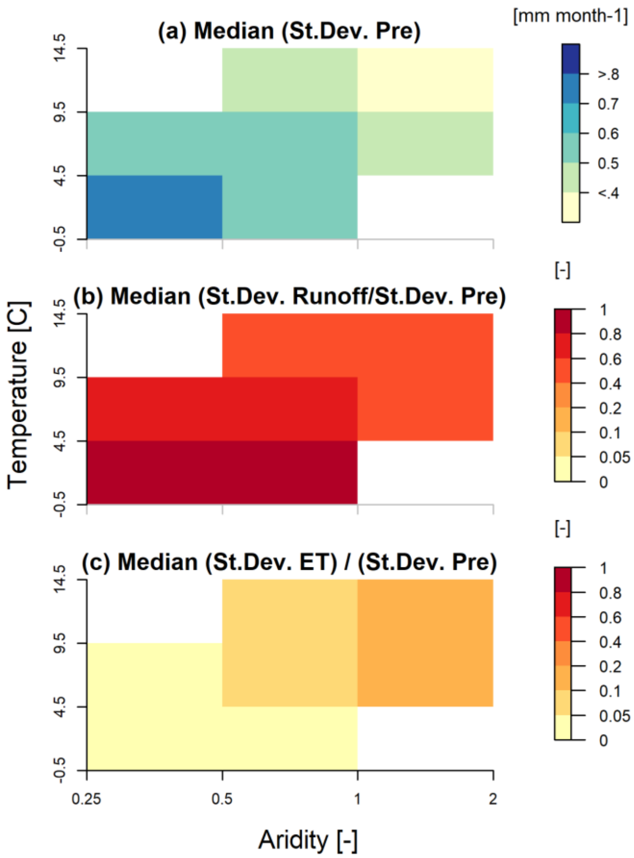


Figure 3: Propagation of precipitation uncertainty into the runoff and ET simulations. Standard deviations are computed across the precipitation estimates and resulting runoff and evapotranspiration values. This is done at every grid cell and every month between May and September. Red lines indicate linear regression lines. Note that a log-log scale is used.


(a) Median (St.Dev. Pre)
[mm month-1]
>.8
0.7
0.6
0.5
<.4
(b) Median (St.Dev. Runoff/St.Dev. Pre)
[-]
1
0.8
0.6
0.4
0.2
0.1
0.05
0
(c) Median (St.Dev. ET) / (St.Dev. Pre)
[-]
1
0.8
0.6
0.4
0.2
0.1
0.05
0
Temperature [C]
14.5
9.5
4.5
-0.5
0.25
0.5
1
2
Aridity [-]

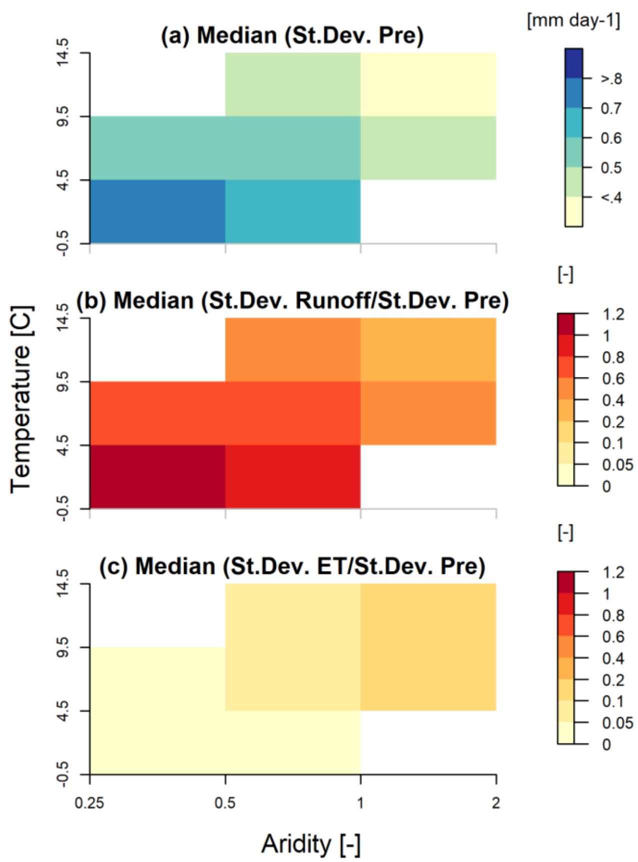
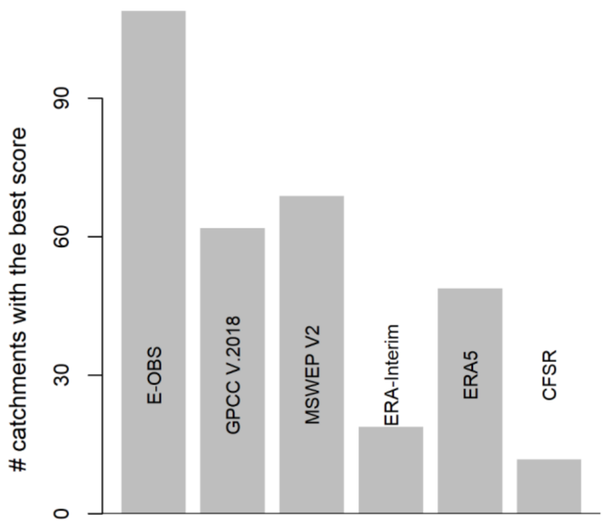


Figure 4: Climate-dependent propagation of precipitation uncertainty into runoff and ET. a) standard deviation across precipitation products, b) and c) relative standard deviation of resulting runoff and ET simulations with respect to that of precipitation, respectively.



catchments with the best score
0
30
60
90
E-OBS
GPCC V.2018
MSWEP V2
ERA-Interim
ERA5
CFSR

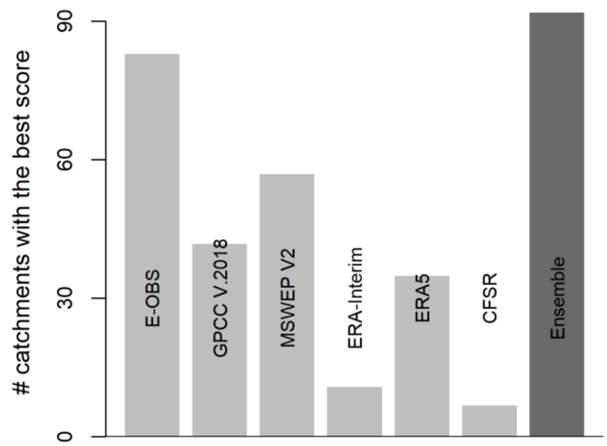
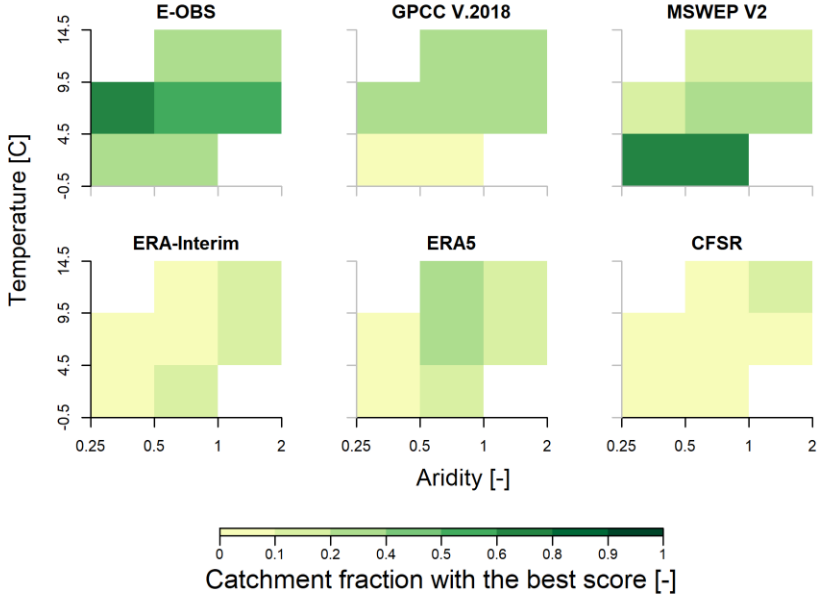


Figure 5: Number of catchments where each precipitation product yields the best agreement with runoff observations (May-September). Multiple data products can be best-performing at a catchment since they are ranked based on a merged score by combining anomaly correlation and absolute error.


E-OBS
GPCC V.2018
MSWEP V2
ERA-Interim
ERA5
CFSR
Temperature [C]
14.5
9.5
4.5
-0.5
0.25
0.5
1
2
Aridity [-]
0
0.1
0.2
0.4
0.5
0.6
0.8
0.9
1
Catchment fraction with the best score [-]

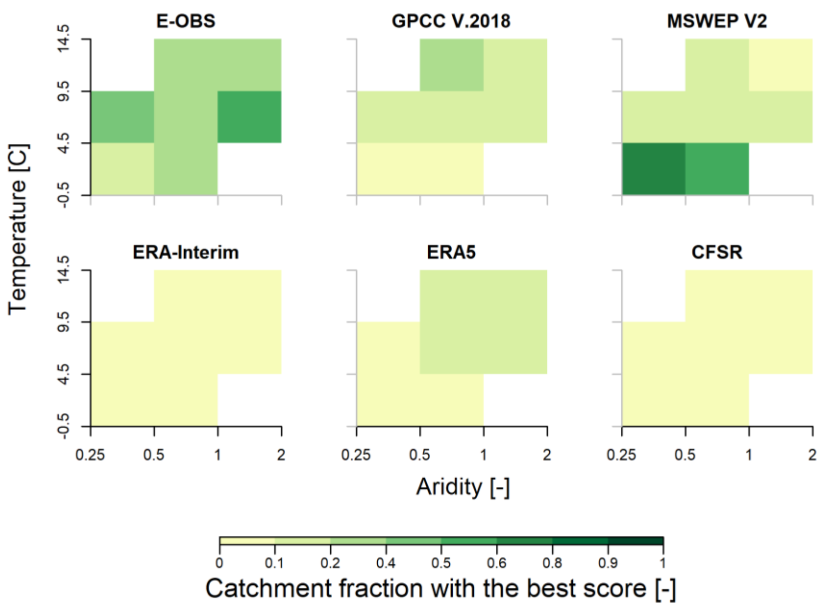

E-OBS
GPCC V.2018
MSWEP V2
ERA-Interim
ERA5
CFSR
Temperature [C]
14.5
9.5
4.5
-0.5
0.25
0.5
1
2
Aridity [-]
0
0.1
0.2
0.4
0.5
0.6
0.8
0.9
1
Catchment fraction with the best score [-]

Figure 6: Runoff-based performance of precipitation products across climate regimes. Colors refer to the percentage of catchments within each box recognized as the best performance based on anomaly correlation and absolute bias during May-September.