

Response to Interactive discussion: SC 1

Hydrology and Earth System Sciences (HESS)

Title: Assessment of Precipitation Error Propagation in Multi-Model Global Water Resources Reanalysis

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Md Abul Ehsan Bhuiyan, Efthymios. I. Nikolopoulos, Emmanouil. N. Anagnostou, Jan Polcher, Clement Albergel, Emanuel Dutra, Gabriel Fink, Alberto Martínez-de la Torre, and Simon Munier

10 We are glad that our work provided material for educational purposes and we hope that it triggered an interesting discussion in the class. We would like to thank the Professor and his/her students for reading our manuscript and for providing insightful discussion and constructive suggestions. Below we provide a point-by-point response to these comments. Comments are in red and our responses in black font.

15 The main objective of the article is the assessment of both uncertainty in precipitation forcing and in the structure of several land-surface models by simulating hydrological variables. Methodology proceeds by studying the relative differences of three simulated hydrological variables by running five state-of-the-art models each forced by six precipitation datasets of various source. I think there is a strong need of capturing the relative influence of uncertainty from as well the datasets as the model structure to increase efficiency in hydrological predictions for water resources and to explore the possible usefulness of multi-model/multi-forcing ensembles. Therefore, the assessment of integrated structural errors would be an addition to the scientific literature on this topic and would definitely be a topic of interest for HESS audience. The paper is generally well-written in an understandable way, and the use of English is good. However, in my view the manuscript in its current state is yet ready for publication and needs revision before it can be accepted. I hope the authors are willing to modify their manuscript, also taking into account the comments provided here. I feel the paper might benefit from a thorough restructuring to assure the manuscript meets the expected quality for HESS publications. Specific comments of three

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Major recommendations

30 The introduction starts very clear and leads correctly to a certain problem statement. Although, the research question and aim of the paper which are following, are very broad and besides I do not get a clear view of the specific objective of the authors. The integration between precipitation error and model structure error is important and should be assessed, but the question raised in this paper needs a more precise aim. Momentarily, the aim of this paper leads to general results and a broad discussion and conclusion. For example, the conclusion partly states that the interaction between precipitation characteristics and different modelling schemes is very complex and the uncertainties in model simulations are due to precipitation and modelling structure errors. This conclusion is not a contribution to the scientific literature of this topic (Haddeland et al. 2011), while this subject has the competence to

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deliver a valuable product. To be more precise, in the introduction a problem is sketched which needs attention but the following query is too broad. In my opinion, the paper should focus on a smaller and more specific subject to deliver an enhanced final product. The decision for coming to an alternative/specific aim is completely in hands of the original authors. Several suggestions to narrow this subject:

- Decreasing the number of precipitation forcings to one. As a consequence, more detailed results will be provided and a quantification of how the precipitation uncertainties behave or affect the different model-structures of the land-surface models. Via this way, the integration of the precipitation and model structure uncertainty will remain the main subject of the paper, but it will limit the scope.
- The other way around is also possible. By decreasing the number of land-surface models to one, the paper will show how the different precipitation forcings will influence the model structure uncertainty (in terms of hydrological variables).
- If, according to the authors, the essence of the article is damaged by reducing the number of forcings or models, the relative same procedure as before can be used. The disadvantage of this method is the huge amount of workload, because the results require a distinct end product, like quantifications of uncertainties, distinguished per model or per forcing

The second concern is the main methodology of simulation. Although the selection of the several diverse precipitation products and the five state-of-the-art models is proper, I do not understand why the one hydrological model is calibrated, but the four landsurface models are not. From my point of view, the outcomes of the simulations are only useful (in terms of considering model structure errors) when the models function in the same way, excluding the relative differences caused by alternative parameterization. This is also confirmed by Yin (2018), indicating that calibration of the models is necessary to use the same parameters while only the meteorological data is unique. To eliminate the effect of different parameterization, I expected the models to be calibrated to expose the uncertainties in model structures. Despite the fact that I am not considering myself an expert in the field of model calibration or validation, the main point here is the fact that this essential part of the methodology is rather unclear and additional information will be needed. Thus, if the authors are able to verify that the current parameterization does not affect the results of the exposure of model structure error, the explanation of this issue is very important to include in the paper. If the results are possibly affected and the land-surface models do contain incomparable parameters, the assessment of model structure uncertainty may be inaccurate and therefore cannot be identified as a certified result. Then I would recommend to perform model calibration and consequently present the improved results. For inspiration of model calibration, I found very intriguing papers, such as the paper of Beven and Binley (1992) about the GLUE framework, and the paper of Clark (2008) about the modular framework FUSE,

focused on models structure. The last issue is the presentation of the results. Although the approach of the results is very clear, the display of the graphs is quite cluttered and the amount is way too much. This issue relates to the first point of the review, providing the paper a more distinct aim. If the results would be presented more specific, the exact objective will be targeted much more efficient. At this
5 moment, one does not know where to look for between 16 different graphs on one page and it gives the impression the reader needs to search for the results himself.

I would recommend to show only results that are specifically relevant to answer the research question, to prevent clustering of graphs and figures. Just use in the result section no more than one or two graphs of each sort of visual representation to support the corresponding findings. This recommendation does
10 not even revolve around

the possible change of the research question; even if the research question does not change, the authors should think of other ways of presenting their results.

References

Beven, K. Binley, A. (1992). “The Future of Distributed Models: Model Calibration and
15 uncertainty Prediction”. *Hydrological Processes*, 6, 279-298.

Clark, M. (2008), “Framework for Understanding Structural Errors (FUSE): A modular
framework to diagnose differences between hydrological models”. *Water Resources
Research*, 44(12).

Haddeland, I. (2011). “Multimodel Estimate of the Global Terrestrial Water Balance: Setup and First
20 Results”. *Journal of Hydrometeorology*, 12(5), 869-884.

Yin, Z. et al. (2018). “Comparing the Hydrological Responses of Conceptual and Process-Based
Models with Varying Rain Gauge Density and Distribution”. *Sustainability*,10(9).

Thank you for your comments. Few studies have been dedicated on the analysis of the integrated impact
25 of both forcing and model uncertainty on hydrologic simulations and from the existing ones most of them were focused on a single hydrologic variable such as streamflow/evapotranspiration. So, this paper uses the multi-forcing/multi-model experiment to address the following research questions:

1. How does the precipitation uncertainty propagate through the multi-model hydrologic simulations?

2. What is the relative importance of precipitation vs. modeling uncertainty on the simulation of key water cycle variables (surface/subsurface runoff and ET)?
3. What is the spread of the precipitation uncertainty in simulation of hydrological variables and how this depends on model type?
- 5 As mentioned above, this paper presents a unique precipitation-to-hydrologic simulations error analysis based on different hydrologic variables, multiple models and multiple precipitation datasets, to evaluate the role of uncertainty in precipitation forcing relative to modeling error. For this purpose, we considered multiple precipitation datasets and a number of global and land surface hydrologic models, which led to a comprehensive error propagation investigation. At the same time in our revised version we significantly
10 expanded the model description, which will clarify the rationale of using both calibrated and uncalibrated hydrologic models. Moreover, the conceptual surface runoff generation process in WaterGAP3 was calibrated with measured river discharge because one of its initial purposes was to reproduce and assess current and past water resources – primarily in rivers. For the other models the focus was/is on the accurate reproduction of processes such as energy and mass fluxes at the surface, etc. For these physically well-
15 defined processes, calibration is not necessary.

According to one of our research questions, how precipitation uncertainty propagates to the multi-model hydrologic simulations to assess hydrologic uncertainty in more than a single variable that will allow to make hydrologic predictions more accurate for water resources applications. These investigations provide quantification of the predictive uncertainty of multi-model/multi-forcing scenarios. Therefore, we would
20 like to keep all these precipitation forcings and models to present relative performances of hydrologic variables for the different multi-model/multi-forcing.

General comments

25 One of the keywords of this paper is “model structure” and its respective uncertainty. However, the definition of this keyword is not thoroughly described and therefore different interpretations are allowed. In addition, there is a fine line between the concept of model structure and their corresponding parametrization. Thus, I would recommend to sharply define this keyword and so delineate its meaning for this paper. I would recommend to add a line to the section concerning the study area why this area has been chosen. This is especially needed because in the discussion section (line 1-4) the authors
30 insinuate that one of the hydrologic variables (evapotranspiration) is not the best measure of sensitivity for this study area. This is quite logical, because the study area is semi-arid and the amount of evapotranspiration is water-limited instead of energy-limited. Although the location of the study area is not damaging the research, in my opinion it would help to support the choice in this case.

Thank you for your suggestion. In the revised manuscript, we substantially elaborated each model description which is related to model structure, additional data used, model parametrization etc. The reason behind choosing the study area is discussed in the introduction part: “The study area for this investigation is the Iberian Peninsula, which has precipitation and climate variability due to complex orography influenced by both Atlantic and Mediterranean climates (Rodríguez-Puebla et al., 2001; de Luis et al., 2010; Herrera et al., 2010)”.

Further small remarks

Page 4, line 20: Change “hydrologic variable” to “hydrologic variables”.

Thank you. It is corrected in the revised manuscript.

10 Page 5, line 15: Change “semiarid” to “semi-arid” (for consistency, because at page 18, line 2, also “semi-arid” is used)

Thank you. It is corrected in the revised manuscript.

Page 6, line 4: remove the capital letter of ‘Land surface model’

Thank you. It is corrected in the revised manuscript.

15 Page 7, line 11: Change “3hourly” to “3-hourly”.

Thank you. It is corrected in the revised manuscript.

Page 8, line 15: Add comma after “column”.

Thank you. It is corrected in the revised manuscript.

20 Page 12, line 13: Change “NCRMSE (variables)” to “NCRMSE (hydrologic variables)” or “NCRMSE (simulated variables)”.

Thank you. “NCRMSE (variables)” is replaced by “NCRMSE (simulated variables)” in the revised version of the manuscript.

Page 17, line 23: Change “result” to “results”.

Thank you. It is corrected in the revised manuscript.

25 Page 18, line 18: Change “ORCHIDDE” to “ORCHIDEE”.

Thank you. It is corrected in the revised manuscript.

Page 32: Please add the full description for the graph, as on page 31.

Thank you. It is updated in the revised manuscript.

Page 33: Please add the full description for the graph, as on page 31.

5 Thank you. It is updated in the revised manuscript.

Page 37: Description of the Taylor diagram of SURFEX: change “maen sqaure” to “mean square”

Thank you. It is corrected in the revised manuscript.

Response to Interactive discussion: Reviewer 2

Hydrology and Earth System Sciences (HESS)

Title: Assessment of Precipitation Error Propagation in Multi-Model Global Water Resources Reanalysis

5

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10 We would like to thank the Reviewer for his insightful discussion and constructive suggestions. Below we provide a point-by-point response to his comments. Reviewer's comments are in red and our responses in black font.

General Comment:

15 This paper compares outputs of four land surface models (LSMs) and a global hydrologic model (GHM) in the Iberian Peninsula forced by different precipitation (P) products for a period of 11 years. Precipitation products include satellite, reanalysis, and combined (stochastically generated) products. The SAFRAN precipitation products, which merge reanalysis and gauge observations, and the hydrologic simulations obtained with these precipitation inputs are assumed as reference. The authors perform a set of analyses to evaluate how the uncertainties due to precipitation products and model structure affect three hydrologic variables, including surface runoff, subsurface runoff, ET.

20 The topics of the paper are interesting for the audience of HESS. The paper is, for the most part, well written. Thus, I am supportive of its publication. However, in my opinion, there are a few unclear parts in the text and analyses that require to be addressed first.

Major concerns:

25 1. It is not clear how the metrics used in the analyses are applied in terms of space and time aggregation. This should be clearly specified for each metric in the methodology section. For example, what is/are the time step/s of RD? How is this metric used in figure 5? Is figure 5 presenting the distribution of the RD's in all pixels (i.e., how is space considered)? Similar questions arise for the boxplots, the Taylor diagrams, and the CV. Please, clarify.

30 RD of annual average estimates of the precipitation forcing and different hydrological variables are calculated using daily datasets at the spatial resolution of 0.25° . Moreover, cumulative probability of estimated annual average relative differences among precipitation forcings and the simulated hydrological variables are calculated using same spatial resolutions 0.25° . Similarly, the normalized Taylor diagrams summarized model results for two different temporal scales (3-hourly and daily) at the spatial resolution

of 0.25⁰. CV and CVr are determined using all precipitation forcing and variables examined at 0.25⁰/daily resolution. In the revised manuscript, we included detailed information on the application of each metric and the associated spatio-temporal scales.

2. The time resolution of the satellite-based P products is 3 hours. How about the other two products?
5 This, in combination with the resolution of the hydrologic simulations, affects the interpretation of the ability to simulate the hydrologic processes (notably, surface runoff).

The time resolution of all precipitation products (satellite, reanalysis and the combined products) is 3 hours. In the revised manuscript, we included table 1 which specifies the time resolution of each precipitation dataset, which will clarify the confusion.

- 10 3. The authors should provide in the Methodology section three details on the hydrologic simulations and their evaluation:

(i) What is the time resolution adopted for each model?

(ii) Was the model calibrated (I guess only one was) and, if not, which set of parameters was used?

- (iii) State that: (i) simulations are evaluated for long-term averages of annual, daily and, in some cases,
15 3-hour variables (see comment 1); and (ii) no seasonal analysis is performed.

In the revised manuscript, we significantly reworked section 3.1, Hydrological Simulations, providing the information requested by the reviewer, which should clarify the confusion.

- Specifically, the time resolution for each model is included in Table 2. Section 3.1 is updated by additional information with calibration information, parameters setting etc. The models were already evaluated at
20 all time scales from daily to multi-annual.

4. The first result that I was expecting to see is the comparison of the bias between SAFRAN and the other P products (a figure like figure 2 but for P). This would give immediately an idea of what to expect for runoff and other hydrologic variables.

- Thank you for the suggestion. In the revised paper, we added figure 2 to show the comparison of the bias
25 between SAFRAN and the other P products.

5. Related to the previous point: In my opinion, time series (at monthly resolution?) of spatially averaged P, Qs, Qsb and E would be quite useful to have an idea of how the models vary among each other, across years, and within each year.

Thank you for the comment. We would like to show you the figures that provide those time series comparisons. In this response document, the monthly spatially averaged precipitation time series for different forcing are shown in Figure 1. Overall, individual satellite products overestimated precipitation, while the combined product and atmospheric reanalysis precipitation were more consistent relative to the reference precipitation. Similarly, the variability in the performance of different hydrologic simulated variables for different models and their inconsistencies relative to the reference are presented in Figure 2-4. Overall, there is no significant change in evapotranspiration within years. But, the monthly Qs shows overestimation for satellite precipitation forcing during the period of 2000-2010. Specifically, 3B42 (V7) based simulated Qs overestimated during the study period, which indicated poor performance compared to other forcing.

In our paper, to show the relative importance of precipitation and modeling uncertainty on the simulation of different variables, we focused our analysis mostly on two temporal scale (3-hourly and daily). Therefore, to maintain the consistency of the paper, we would like to exclude the monthly time series analysis results from the paper, although these results have great insight to get the idea of variability of precipitation forcing and hydrologic variables.

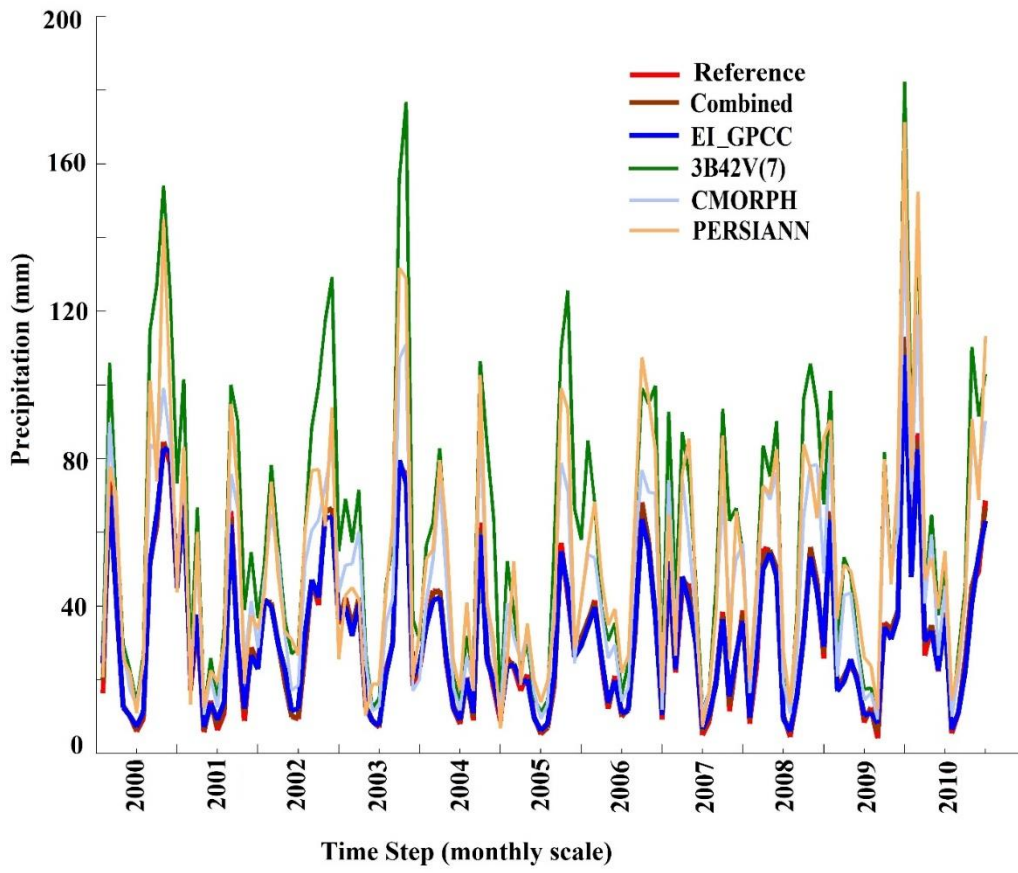
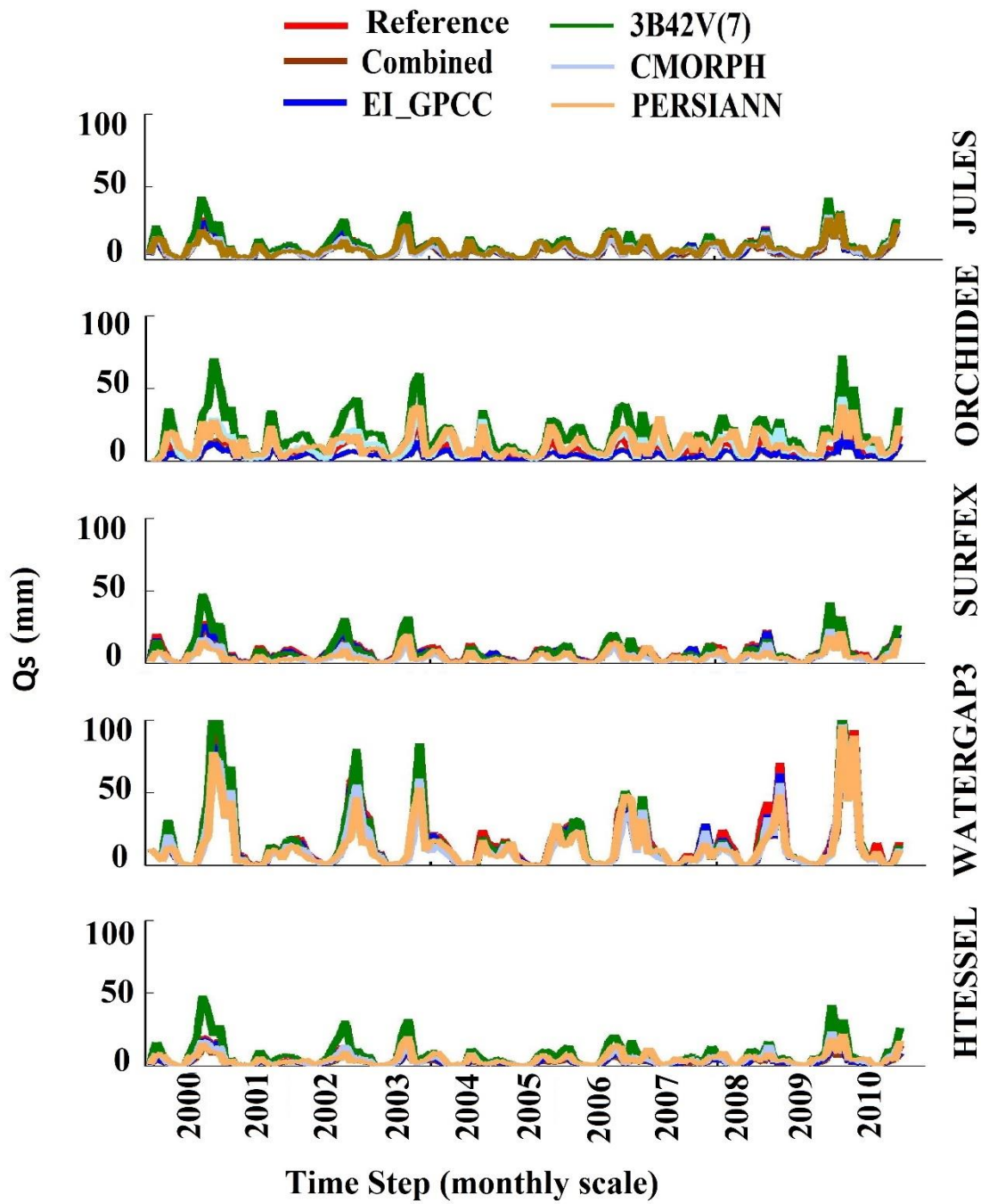


Figure 1: Time series of spatially averaged precipitation at monthly scale.



Figure

2: Time series of spatially averaged surface runoff at monthly scale.

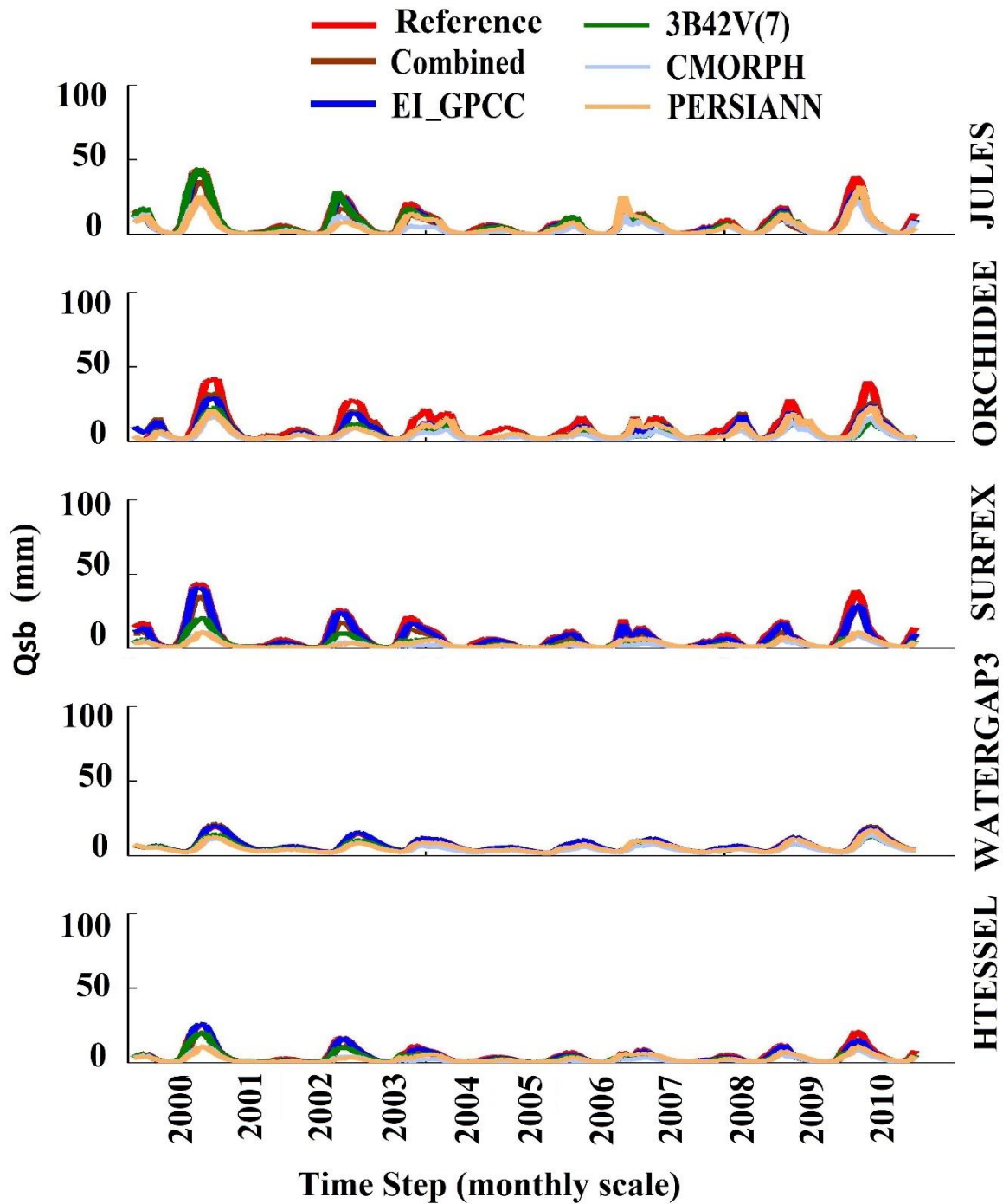
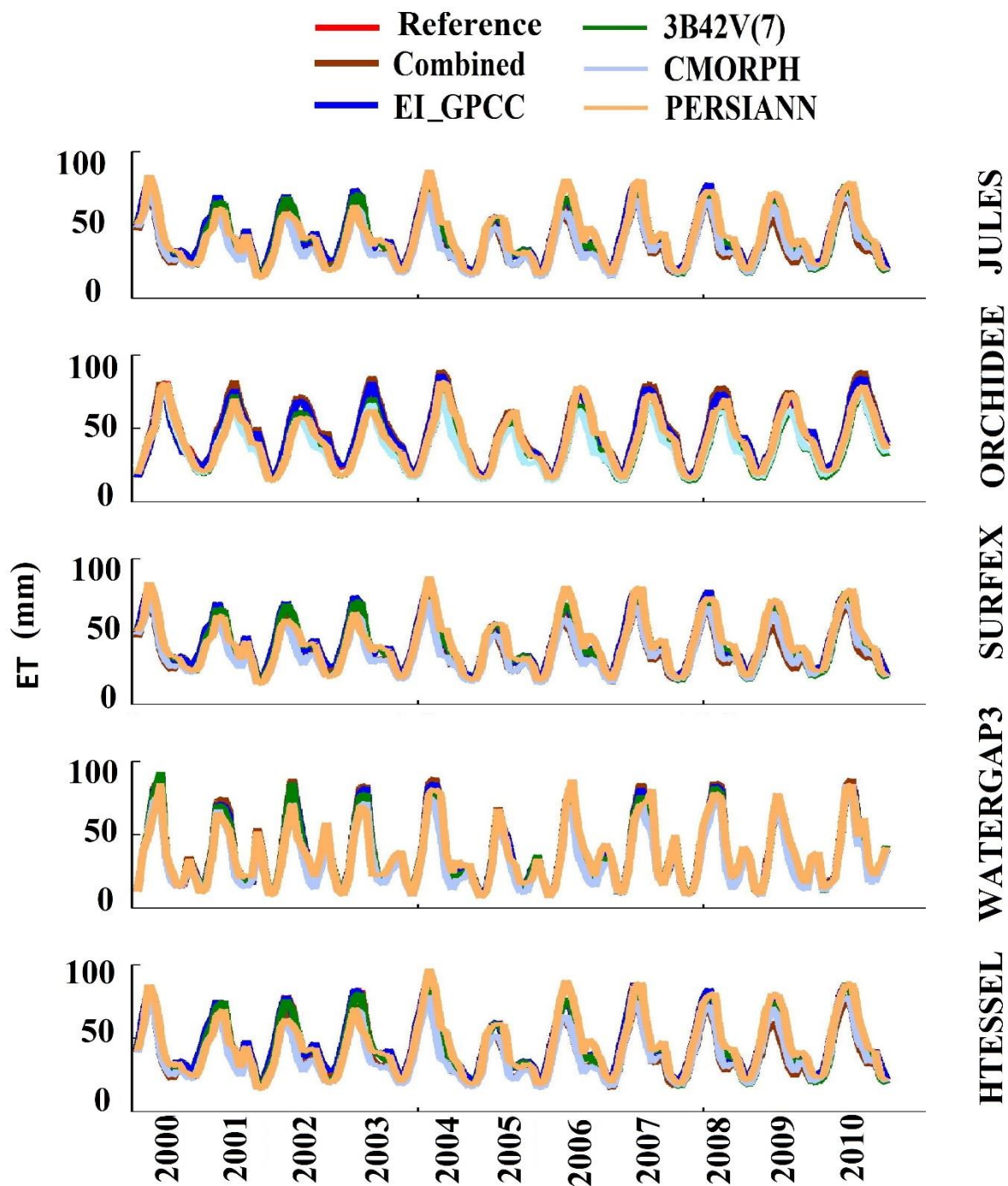


Figure3: Time series of spatially averaged subsurface runoff at monthly scale.



Figure

4: Time series of spatially averaged evapotranspiration at monthly scale.

6. The analyses of the ensemble spread is not properly introduced in Section 3.4. What are the ensemble members referring to? Also, the definition of the metrics and associated symbols is not clear. Things become a bit clearer in section 4.4. However, I think that Sections 3.4, 4.4 and Figure 13 should be eliminated, since, as it stands, this analysis is superficial and does not add much to the message of the paper.

In the revised manuscript, we reworked the analysis of the ensemble spread. Note that, the combined product is an ensemble based precipitation product; for the evaluations presented in this paper we use ensemble-mean as forcing. For the analysis and propagation of the precipitation ensemble spread to hydrologic simulations, we used 20 ensemble members, which are generated stochastically by the quantile regression forests (QRF) tree-based regression model (Meinshausen, 2006). We would like to keep these sections because they describe how variability in precipitation ensembles translates to variability of the various simulated hydrological variables and thus provides quantification of the predictive uncertainty of the combined product-based simulations. Information on this predictive uncertainty and insight on its dependence on model structure and hydrologic variable is novel and informative for the potential use of approaches related to the combined product for probabilistic prediction of hydrologic variables.

7. The interpretation on page 8, lines 21-23 is counterintuitive or I did not have enough information to understand it (see comment 3). To me, if an LSM is run at 3-hour resolution with a P product that has the resolution of 3 hours, there are higher chances that infiltration-excess runoff will be generated. This is because P products should be able to capture storms localized in time. In contrast, if an LSM is run at 3-hour resolution with a P product that has the original resolution of 24 hours and a uniform P intensity is assumed to create inputs at 3-hour resolutions, then the chances are lower.

On the other hand, if an LSM runs at 24-hour resolution and it has not been calibrated with P products at 3-hour resolution, then we can have unexpected effects on the generated runoff. In this case, I am not able to say a-priori what we should expect. Thus, the biases that the authors have found may be an effect of the calibrated parameters, rather than the model structure. I suggest the authors to clarify this part and elaborate more.

Thank you for this comment. We indeed considered a time disaggregation of the rainfall from 3h to 15 minutes (as well as for other variables). But for rainfall it is much more difficult. We have chosen to spread the entire 3hourly rainfall over 1.5hours in these simulations because of sensitivity of modelled runoff. In the revised manuscript, the ORCHIDEE model description is elaborated with this aspect.

Minor concerns:

P 4, lines 12-16. This sentence seems too long.

Thank you. This sentence is modified in the revised paper.

5 P 5, lines 14-17: Please revise the sentences on climate and “topography in the Pyrenees”. It doesn’t make sense to me.

Thank you. It is updated in the revised paper.

Section 2.1: Can the authors provide some quantitative information on the SAFRAN performances against rain gauges?

Thank you. It is updated in the revised paper.

10 P6, line 4: consider using the acronym LSM for land surface model. Otherwise, don’t capitalize “L”.

Thank you. It is updated in the revised paper.

P 15, line 22: I could not verify in the figure that $NCRMSE > 0.75$ for surface runoff simulated with 3B42 in all (or most) cases. Can the authors check this again and explain?

15 In the revised paper, we updated by proper information to clarify this issue. As shown in Figure 10, the points for the 3B42 (V7) were always the furthest from the reference ($NCRMSE > 0.75$) with low correlation coefficient (0.4-0.55) except SURFEX, which means 3B42 (V7) was always associated with the worst performance for all other models.

P. 16, lines 8-10: What are the implications of this? Is it expected? I could not figure this out by myself without knowing for which time scale the CV was computed.

20 From the boxplots of CV from reference-based simulations, the distributions of ET showed low variability ($CV < 1$), while the variability for all the other hydrological variables was high ($CV > 1$). Variability of ET is much lower than the other variables examined and it is well captured in all simulations scenarios. This is expected for ET, because, it is primarily controlled by atmospheric demand, plant and soil hydraulic constraints, and solar radiation (Wallace et al., 2010). When sufficient energy is available for
25 rainfall to evaporate directly without contributing to surface/subsurface runoff, simulation of ET is not only affected by precipitation uncertainty, but also other atmospheric constrains. CV was computed in daily scale.

P. 16, lines 10-13: I could not verify this interpretation in the figure. The median of the boxplots for SURFEX are for the most part larger than 1. Please, clarify.

In the revised paper, we explained precisely to clarify this issue. In terms of CV_r, the SURFEX model performed very well by producing medians close to 1 (CV_r=1, means equivalent degree of variability captured by the model) for all the precipitation forcing datasets but CMORPH.

Section 4.2: I suggest moving the sentence on page 16, lines 14-20 after line 8, as I believe that the comment on precipitation should be provided first.

Thank you. It is updated in the revised paper according to your suggestion.

Figure 7 should be improved. There are labels in the y axes only in some panels.

10 Thank you. It is corrected in the revised paper.

Response to Interactive discussion: Reviewer 3

Hydrology and Earth System Sciences (HESS)

Title: Assessment of Precipitation Error Propagation in Multi-Model Global Water Resources Reanalysis

5

Md Abul Ehsan Bhuiyan, Efthymios. I. Nikolopoulos, Emmanouil. N. Anagnostou, Jan Polcher, Clement Albergel, Emanuel Dutra, Gabriel Fink, Alberto Martínez-de la Torre, and Simon Munier

10 We would like to thank Reviewer for his insightful discussion and constructive suggestions. Below we provide a point-by-point response to his comments. Reviewer's comments are in red and our responses in black font.

15 The manuscript examines propagation of uncertainties in precipitation forcing (from satellite and reanalysis) and in land surface models into simulation of hydrological variables, specifically, surface runoff, subsurface runoff, and evapotranspiration. The study was conducted in the Iberian Peninsula. The importance of this " study is in presenting the large uncertainties exist in both precipitation and models, which induce substantial uncertainties in hydrological simulation. In accordance to previous studies, it is shown in this work that precipitation uncertainties have the largest role in prediction uncertainties, but the authors also show that there is a substantial uncertainties originate from the model itself. This finding is important to be emphasized and to take into account in hydrological simulations.

20

I have few suggestions for improvement:

1) I suggest adding a table comparing the different precipitation and reanalysis products, as was done for the land surface models. Such a table should include information about the resolution, and what data sets were used.

25 In the revised manuscript, we provided Table 1 describing the different precipitation products with necessary related information such as resolution, references etc.

30 2) Sensitivity to product resolution: the different forcing products have different resolution, which one could expect to affect the simulation results. It would be good to separate between the uncertainty related to the product itself and the one related to its resolution, which may too coarse for example for representing a given process. I suggest the authors to refer to this aspect.

We would like to note that all precipitation forcing data used were aggregated at 0.25° spatial resolution and 3-hourly temporal resolution. Therefore, uncertainty related to precipitation forcing relates to the estimation uncertainty of each product and not with the space/time resolution.

- 3) There is almost no discussion of the role of the specific conditions in the Iberian Peninsula and their relations with the findings. For example, it can be expected that surface runoff sensitivity to precipitation uncertainties would be different in arid/semi-arid region compared to more humid areas.
- 5 Since the study area includes a gradient of conditions, it would be good to compare the different indexes among regions and possibly discuss this issue in Section 5.

We would like to thank the reviewer for this comment. We have revised the manuscript according to the following text to further discuss the spatial pattern of results.

- 10 “By examining the spatial pattern of relative differences (Figs 2-5) one can recognize that there is no consistent spatial pattern among the different model/forcing combinations. There are cases where the pattern of the differences is dominated by the pattern of precipitation differences, as for example the case of PERSIANN where the maximum of differences are concentrated in the central and eastern part of the peninsula. While there are other cases where the pattern is dominated by the sensitivity of the model (see for example results for ORCHIDEE/3B42 for surface runoff). “

15

4) What are the sources for additional data required for the models such as soil types, groundwater table, others?

In the revised paper, we included details about additional data required for the models in the model description section.

- 20 **Technical comments (typo errors and other):**

P. 6 L. 4: “land” and “Land”

Thank you. It is corrected in the revised manuscript.

P. 6 L. 10: “from” instead of “form”

Thank you. It is corrected in the revised manuscript.

- 25 P. 7 L. 11: “3-hourly”

Thank you. It is corrected in the revised manuscript.

P. 8 L. 11-12: “. . . the water flux reaching the surface exceeds the maximum infiltration rate of the soil”. I believe the authors mean here the “final” infiltration, which is actually a minimum, but not the maximal infiltration.

Thank you. This section is significantly modified in the revised manuscript to clarify this issue.

5 P. 9 L. 11: Please explain “Dunne runoff”

In the revised paper, Dunne runoff is precisely defined that would clarify this issue.

P. 10 L. 6: “a” is missing P. 13 Eq. 7: index i seems to be missing; why representing range by max – min and not std? why not using “y” for reference?

Thank you. In the revised manuscript, Eq. 7 is updated based on reviewer’s suggestion.

10 The maximum and minimum of ensemble values at each time step, indicate a comprehensive measurement (full coverage) of the expected prediction intervals relative to the reference value. Therefore, we chose ensemble range ($X_{\max} - X_{\min}$), instead of standard deviation.

P. 13 L. 10: please check, it is not clear

In the revised manuscript the issue is completely modified.

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Assessment of Precipitation Error Propagation in Multi-Model Global Water Resources Reanalysis

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Abstract

This study focuses on the Iberian Peninsula and investigates the propagation of precipitation uncertainty, and its interaction with hydrologic modelling, in global water resources reanalysis. Analysis is based on ensemble hydrologic simulations for a period spanning 11 years (2000–2010). To simulate the hydrological variables of surface runoff, subsurface runoff, and evapotranspiration, we used four land surface models—JULES (Joint UK Land Environment Simulator), ORCHIDEE (Organizing Carbon and Hydrology in Dynamic Ecosystems), SURFEX (Surface Externalisée), and HTESSEL (Hydrology-Tiled ECMWF Scheme for Surface Exchange over Land)—and one global hydrological model, WaterGAP3 (Water–Global Assessment and Prognosis). Simulations were carried out for five precipitation products—CMORPH, PERSIANN, 3B42 (V7), ECMWF reanalysis, and a machine learning-based blended product. As reference, we used a ground-based observation-driven precipitation dataset, named SAFRAN, available at 5 km/1 h resolution. We present relative performances of hydrologic variables for the different multi-model/multi-forcing scenarios. Overall, results reveal the complexity of the interaction between precipitation characteristics and different modelling schemes and show that uncertainties in the model simulations are attributed to both uncertainty in precipitation forcing and the model structure. Surface runoff is strongly sensitive to precipitation uncertainty and the degree of sensitivity depends significantly on the runoff generation scheme of each model examined. Evapotranspiration fluxes are comparatively less sensitive for this study region. Finally, our results suggest that there is no single model/forcing combination that can outperform all others consistently for all variables examined and thus reinforce the fact that there are significant benefits in exploring different model structures as part of the overall modelling approaches used for water resources applications.

1. Introduction

Improved estimation of global precipitation is important to the analysis of continental water resources and dynamics. Over the past few decades, several studies have described the use of different precipitation algorithms to develop precipitation products (<http://ipwg.isac.cnr.it/algorithms.html> and <http://reanalyses.org>) at high spatial and temporal resolution on a quasi-global scale and for different hydrological applications, such as flood early warning and control, and drought monitoring (Hong et al., 2010; Wu et al., 2012; and Vernimmen et al., 2011 amongst others). Precipitation estimates suffer, however, from various sources of error that consequently impact hydrologic investigations (Mei et al., 2015; Mei et al., 2016; Seyyedi et al., 2014, 2015; Bhuiyan et al., 2017, Nikolopoulos et al., 2013).

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Over the last decade, an increasing number of studies have contributed to the development of global precipitation estimation (Pan et al., 2010; Beck et al., 2017a; Kirstetter et al., 2014; Carr et al., 2015; Dee et al., 2011) aiming at the overall improvement of the hydrological applications and global water resource reanalysis. Numerous models of varying complexity can be used to generate an array of hydrological products from precipitation forcing datasets (Vivoni et al., 2007; Ogden et al., 1994; Carpenter et al., 2001; Borga, 2002; Schellekens et al., 2017). Different hydrological models have different applications depending on the spatial and temporal scales of interest, as well as the simulated variables of interest, such as subsurface runoff, surface runoff, and evapotranspiration. Past studies (Fekete et al., 2004; Biemans et al., 2009) have revealed that the uncertainty in simulated hydrological variables mainly depends on the uncertainty in precipitation and model parametrisation, and suggested subsequent exploration of different model structures as part of the overall modelling approach.

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So far there are several studies that have analysed uncertainty in precipitation forcing and its impact on hydrologic simulations by usually evaluating hydrologic simulations based on multiple forcing applied on a single model (Falck et al., 2015; Bitew et al., 2012; Behrangi et al., 2011; Mei et al. 2016; Bhuiyan et al., 2018; Gelati et al., 2018 among others). On the other hand, there are also past studies that have evaluated the model structural uncertainty and its impact on hydrologic simulations, usually by analysing the simulation outputs from multiple models and a single forcing dataset (Breuer et al., 2009; Haddeland

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et al. 2011; Gudmundsson et al., 2012; Smith et al. 2013; Huang et al. 2017; Beck et al., 2017b). However, fewer studies have been dedicated on the analysis of the integrated impact of both forcing and model uncertainty on hydrologic simulations and from the existing ones most of them were focused on a single hydrologic variable such as streamflow (see for example Qi et al. 2016), evapotranspiration (Vinukollu et al., 2011) or a given hydrologic index such as drought index (Prudhomme et al., 2014; Samaniego et al. 2017). Findings from these past investigations have demonstrated that both forcing and model structure uncertainty have a great impact on hydrologic predictions and therefore highlight that using multi-model/multi-forcing ensemble is a more appropriate path forward for advancing the use of hydrologic model outputs. This conclusion raises at the same time the need for better understanding, characterizing and quantifying the uncertainty associated to multi-model/multi-forcing hydrologic ensembles. Thus, a better understanding of the ensemble spread of precipitation and simulated hydrological variables is necessary to improve water resource management and planning. **This additionally means that there is also a need to assess hydrologic uncertainty in more than a single variable to be able to have a better and more integrative view on the interaction between forcing uncertainty, model uncertainty and hydrologic variable of interest. It will allow to make hydrologic predictions more effective for water resources applications at large scale.**

This study builds upon a unique numerical experiment that was carried out, as part of the activities of the Earth2Observe project (Schellekens et al. 2017), to investigate the impact of precipitation uncertainty propagation and its dependence on model structure and hydrologic variables. In this investigation, we used different precipitation forcing datasets based on (i) reanalysis, (ii) satellite estimates, as well as (iii) a “combined” stochastic precipitation dataset (Bhuiyan et al., 2018). To consider model structure and parameters, we examined simulations from five state-of-the-art global-scale hydrological and Land Surface Models (LSMs). With regard to water cycle variables, we evaluated precipitation uncertainty propagation to surface runoff, subsurface runoff, and evapotranspiration fluxes. The study area for this investigation is the Iberian Peninsula, which has precipitation and climate variability due to complex orography influenced by both Atlantic and Mediterranean climates (Rodríguez-Puebla et al., 2001; de Luis et al., 2010; Herrera et al., 2010). The analysis comprised two main parts: (1) performance and

sensitivity evaluation of the different model/forcing scenarios and (2) precipitation uncertainty propagation to the hydrological variables. We analysed hydrological simulation with a comparative assessment of the hydrological products and provided a detailed analysis of uncertainty in hydrological simulations for the different global hydrological and land surface models used in the multi-model global water resources reanalysis. Finally, we examined the performance of precipitation products in hydrological applications and potential uncertainty attributed to precipitation error propagations.

The paper is structured as follows: section 2 presents the different types of forcing datasets used for the study and section 3 details the methodology we used for our model development and hydrological model analysis. Section 4 summarizes the hydrological results, section 5 discusses the results and section 6 draws conclusions from the research conducted.

2. Study area and forcing data

This study is focused on the Iberian Peninsula (Figure 1). The climate of the peninsula is primarily Mediterranean, with mostly oceanic at northern and semi-arid at southern parts. The topography varies from almost zero elevation to altitudes of 3500 m in the Pyrenees. Table 1 summarizes information and references of meteorological forcing datasets and a short description is provided below.

2.1. Reference Precipitation (SAFRAN)

The reference precipitation dataset, hereafter referred to as SAFRAN (Système d'analyse fournissant des renseignements atmosphériques à la neige), was recently created by Quintana-Seguí et al. (2016, 2017) using the SAFRAN meteorological analysis system (Durand et al., 1993). Spatially, SAFRAN precipitation data are presented at hourly time scale on a regular grid of 5 km resolution, spanning 35 years and covering mainland Spain, Portugal and the Balearic Islands (Quintana-Seguí et al, 2016). SAFRAN used an optimal interpolation algorithm (Gandin, 1966) to produce a quality controlled gridded dataset of precipitation which combines ground observations and outputs of a meteorological model (Quintana-Seguí et al, 2017). Quintana-Seguí et al, 2017 also compared the different precipitation analyses with rain gauge data and successfully evaluated their temporal and spatial similarities to the

observations by obtaining higher correlation (>0.75) than other precipitation products. The validation of SAFRAN with independent ground observations proved that SAFRAN is a robust product. On the other hand, several factors—including rainfall intermittency, discrete temporal sampling, and censoring of reference values for required quality—reduce the number of comparison samples for reference and satellite estimates. Therefore, the quality controlled SAFRAN dataset which is designed to force land surface model is chosen as reference dataset for the study area (Quintana-Seguí et al, 2017).

2.2. Satellite-Based Precipitation

Satellite-based simulations were based on three quasi-global satellite precipitation products. Among them CMORPH (Climate Prediction Center Morphing technique of the National Oceanic and Atmospheric Administration, or NOAA) is developed from passive microwave (PMW) satellite precipitation fields which is generated from motion vectors derived from Infrared (IR) data (Joyce et al., 2004). A neural network technique is used in PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) where IR observations are connected to PMW rainfall estimates (Sorooshian et al., 2000). Merged IR and PMW precipitation product from NASA are gauge adjusted for TMPA (Tropical Rainfall Measuring Mission Multisatellite Precipitation Analysis), or 3B42 (V7), which is available in near-real time and post-real time (Huffman et al., 2010). The satellite precipitation products have spatial resolution is $0.25^0 \times 0.25^0$ and time resolution of 3-hourly.

2.3. Atmospheric Reanalysis

The reanalysis product (EL_GPCC) is based on original ERA-Interim 3-hourly data, after rescaling based on GPCC (Global Precipitation Climatology Center) data. Note that total precipitation has been rescaled at monthly scale with a multiplicative factor to match GPCCv7 for the period 1979–2013 and GPCC monitoring for 2013–15. Data are further downscaled to $0.25^0 \times 0.25^0$ grid resolution by distributing the coarse grid precipitation according to CHPclim (Climate Hazards Group's Precipitation Climatology) high-resolution information for each calendar month. A similar approach was performed in the generation of ERA-Interim/Land (Balsamo et al., 2015), but using GPCP (Global Precipitation Climatology Project). In this study we used GPCC due to its higher spatial resolution when compared with GPCP.

2.4. Combined Product

The combined product is based on the application of a nonparametric statistical technique for blending multiple satellite and reanalysis precipitation datasets. Specifically, a machine learning technique, Quantile Regression Forests (QRF) (Meinshausen, 2006), was used to generate stochastically an improved precipitation **ensemble at the spatial/temporal resolution of 0.25°/3h**. The technique optimally merged global precipitation datasets and characterized the uncertainty of the combined product. Details on the methodology and data used to develop the combined product are presented in Bhuiyan et al. (2018).

2.5 Other atmospheric variables

Apart from precipitation forcing, the rest of atmospheric forcing variables required for the hydrologic simulations were derived from the original ERA-Interim 3-hourly data as used in ERA-Interim/Land (Balsamo et al. 2015) bilinearly interpolated to 0.25°. It includes a topographic adjustment to temperature, humidity and pressure using a spatially-temporally varying environmental lapse rate (ELR) computed similarly to Gao et al (2012). The correction is the following: (i) relative humidity is computed from the uncorrected forcing; (ii) air temperature is corrected using the ELR and altitude differences (ERA-Interim topography versus 0.25 topography); (iii) surface pressure is corrected assuming the altitude difference and updated temperature; and (iv) specific humidity is computed using the new surface pressure and temperature assuming no changes in relative humidity.

3. Methodology

3.1 Hydrological Simulations

The hydrological simulations for this study were carried out by different collaborators within the framework of Earth2Observe, a European Union (EU) funded project using a number of global scale land surface/hydrological models. In this study, simulations from four land surface models—JULES (Joint UK Land Environment Simulator), ORCHIDEE (Organizing Carbon and Hydrology in Dynamic Ecosystems), SURFEX (Surface Externalisée), and HTESSEL (Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land)—and one global hydrological model, the distributed global hydrological model of the WaterGAP3 (Water–Global Assessment and Prognosis) modeling framework (hereinafter

referred to as WaterGAP3) were considered. The models were already evaluated at all time scales from daily to multi-annual. The time-scale of the evaluation is mostly driven by the data availability. All the land surface models in the study are global models, built originally to work in coupled mode with atmospheric models. The “regionalization” or calibration of hydrological parameters at particular catchments or regions of these models, is an exercise that the different modelling groups/communities are certainly performing but was out of the scope of this study. All models were forced with the various precipitation datasets described in the previous section for an 11-year period (March 2000–December 2010). A summary of some basic characteristics of the models structure is presented in Table 1 and a short description is provided below. For more details on the modelling systems, the interested reader is referred to Schellekens et al. (2017) and references therein.

3.1.1 JULES

JULES (Best et al., 2011; Clark et al., 2011) is a physically-based land surface model. JULES uses an exponential rainfall intensity distribution to calculate throughfall through the canopy first (altered by interception), then the water reaching the surface is divided into infiltration into the soil and surface runoff. Surface runoff is generated either through infiltration excess or saturation excess. Infiltration excess runoff will be generated by JULES if the water flux reaching the surface exceeds the maximum infiltration rate of the soil (based on the saturated hydraulic conductivity). If the water flux reaching the surface over a time step (either rainfall, throughfall or snow melt) reaches a maximal infiltration rate, then infiltration excess runoff will be generated. This maximal infiltration rate in JULES is the saturated hydraulic conductivity multiplied by a vegetation dependent parameter (4 for trees and 2 for grasses). Saturation excess runoff is based on subgrid soil moisture variability, as a fraction of the grid is saturated and water flux over this fraction is converted to surface runoff (Probability Distribution Model; Blyth, 2002). Once infiltrated into the soil, water flows through the column, resolved using Darcy's Law and the Richards' equation. Subsurface runoff is calculated using the free drainage approach, with water flowing at the bottom of the resolved soil column at a rate determined by the soil hydraulic conductivity. There is no groundwater table in this version of JULES. The condition at the bottom of the resolved soil layers (3m) was assumed free drainage. The soil hydraulic characteristics were calculated applying pedotransfer functions to the soil texture data from the Harmonized World Soil Database (HWSD;

FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012). The vegetation cover data used by the JULES runs was derived from the International Geosphere-Biosphere Programme: <http://www.igbp.net/>. Further details on hydrology processes in JULES can be found in Best et al. (2011) and Blyth et al. (2018).

3.1.2 ORCHIDEE

5 ORCHIDEE (Krinner et al., 2005) is a complex land surface scheme that consists of a hydrological module, a routing (Ngo-Duc et al., 2007) and floodplain module (d'Orgeval et al., 2008). It also describes the vegetation dynamics and biological cycles but these features were not activated for the present study. The most relevant parametrisation of ORCHIDEE for the sensitivity of the model to rainfall is the one for partitioning between infiltration and surface runoff. In order to represent correctly the fast progression of
10 the moisture front during a rainfall event when the time step is above 15 minutes, a time-splitting procedure is used (d'Orgeval 2006). The parametrisation also takes into account re-infiltration in case of slopes below 0.5% or dense vegetation. We have chosen to spread the entire 3 hourly rainfall over 1.5 hours in these simulations. In terms of ancillary data, vegetation map (IGBP, Olson classification) and the soil types (FAO, 2003) are used for these simulations. Furthermore, as ORCHIDEE represents sub-
15 grid soil moisture by simulating separately the soil moisture column below bare soil, low and high vegetation, the infiltration process will display different sensitivities in each column.

3.1.3 SURFEX

The SURFEX modeling system of Météo-France (SURFace Externalisée, Masson et al., 2013) includes the ISBA LSM (Interactions between Soil, Biosphere, and Atmosphere, Noilhan and Mahfouf, 1996) that
20 can be fully coupled to the CNRM (Centre National de Recherches Météorologiques) version of the Total Runoff Integrating Pathways (TRIP, Oki et al., 1998) continental hydrological system (Decharme et al., 2010). This study uses ISBA multi-layer soil diffusion scheme (ISBA-Dif) as well as its 12-layers explicit snow scheme (Boon et al., 2001, Decharme et al., 2016). ISBA total runoff is contributed by both the surface runoff and a free drainage as bottom boundary condition soil layer. The soil evaporation is
25 proportional to its relative humidity. Parameters of the ISBA LSM are defined for 12 generic land surface patches: nine plant functional types (namely: needle leaf trees, evergreen broadleaf trees, deciduous broadleaf trees, C3 crops, C4 crops, C4 irrigated crops, herbaceous, tropical herbaceous, and wetlands) as well as bare soil, rocks, and permanent snow and ice surfaces. They are derived from ECOCLIMAP-

II, the land cover map used in SURFEX (Faroux et al.2013). Furthermore, the Dunne runoff (i.e. when no further soil moisture storage is available) and lateral subsurface flow are computed using a topographic subgrid distribution.

3.1.4 WATERGAP3

5 The modelling framework WaterGAP3 is a tool to assess the global fresh water resources on 30-minutes spatial resolution. It combines a spatially distributed rainfall-runoff model with a large-scale water quality model as well as models for five sectorial water uses (Flörke et al., 2013; Döll et al., 2009). Effective precipitation – calculated as superposed effects of snow accumulation, snow melt and interception – is split into (i) a fraction that fills up a single-layer soil moisture storage and (ii) a fraction that comprises
10 surface runoff and groundwater recharge. Groundwater recharge is the input of a single linear groundwater reservoir that is drained by base flow. Water for evapotranspiration, estimated with the Priestley-Taylor approach, is abstracted from the soil storage. **The WaterGAP3 setting used in this study is calibrated and validated against measured river discharge from 2446 stations of the Global Runoff data Center data repository (Weedon et al., 2014).** Thereby, calibration only concerns the separation of
15 effective precipitation into runoff and soil moisture filling. **For a detailed model description with additional data required for the model such as soil types, groundwater table, see Eisner (2015).**

3.1.5 HTESSEL

The land surface model (LSM) HTESSEL is part of the European Centre for Medium Range Weather Forecasts (ECMWF) numerical weather prediction model. The model represents the temporal evolution
20 of the snowpack, soil moisture and temperature and vegetation water content, as well as the turbulent exchanges of water and energy with the atmosphere. **HTESSEL considered soil texture, vegetation type and cover and mean annual climatology of leaf area index and albedo (12 maps for each calendar year) for the simulations (FAO, 2003).** The soil column is discretized in four layers (7, 21, 72 and 189 cm thickness), and the unsaturated vertical movement of water follows Richards's equation and Darcy's law.
25 The van Genuchten formulation is used to derive the diffusivity and hydraulic conductivity using 6 predefined soil textures. In case of partially or fully frozen soil, the water movement in the soil column is limited by reducing the diffusivity and hydraulic conductivity. The model assumes free drainage as bottom boundary condition (sub-surface runoff) while the top boundary condition considers precipitation

minus surface runoff and bare ground evaporation. Evapotranspiration is removed from the different soil layers following a prescribed root distribution (dependent on the vegetation type). Surface runoff generation is estimated as a function of the local orography variability, soil moisture state and rainfall intensity. Soil saturation state and rainfall intensity define the maximum infiltration rate which is modulated by a variable infiltration rate related to orography variability (Balsamo et al 2009).

3.2. Evaluation metrics

To examine the magnitude and variability of differences among hydrological variables, we used relative difference (RD) defined as:

$$RD = \left(\frac{\hat{y}_i - y_i}{y_i} \right), \quad (1)$$

where y_i denotes reference variables (SAFRAN-driven simulations) and \hat{y}_i denotes simulated variables (based on the other forcing data considered) for each time step i . RD indicates the magnitude and direction of error with positive (negative) value indicating overestimation (underestimation). *RD of annual average estimates of the precipitation forcing and different hydrological variables are calculated using daily datasets at the spatial resolution of 0.25°. Moreover, cumulative probability of estimated annual average relative differences among precipitation forcings and the simulated hydrological variables are calculated using same spatial resolutions 0.25°.*

To collectively assess the performance of various precipitation forcing datasets, models and simulated hydrological variables, we used a normalized version of the Taylor diagram (Taylor, 2001). Specifically, we normalized the values of the centered root mean square error (CRMSE) and the standard deviation with the standard deviation of the reference. Therefore, the reference (that is, the target point to which the model outputs should be closest) corresponds to the point on the graph with the normalized CRMSE equal to zero, while both the correlation coefficient and normalized standard deviation equal one. *The*

normalized Taylor diagrams summarized model results for two different temporal scales (3-hourly and daily) at the spatial resolution of 0.25° .

To evaluate the degree of variation of various precipitation datasets and simulated hydrological variables, we used coefficient of variation (CV) and coefficient of variation ratio (CVr). CV and CVr are determined using all precipitation forcing and variables examined at 0.25° /daily resolution. CV is a measure of variability defined as the ratio of the standard deviation to the mean. To compare the degree of variation from one data series to another, we used CV where we considered distributions with $CV < 1$ as low variance, while we considered those with $CV > 1$ as high variance. We defined CVr as the ratio of the CV of model to the CV of reference. The defined parameters are expressed as follows:

$$CVm = \frac{\sigma_m}{\bar{m}} \quad (2)$$

$$CVo = \frac{\sigma_o}{\bar{o}} \quad (3)$$

$$CVr = \frac{CVm}{CVo} \quad (4)$$

CVm and CVo indicate coefficient of variation of model and coefficient of variation of reference, with the means \bar{m} and \bar{o} and standard deviations σ_m and σ_o , respectively. The CVr includes two components: the ratio of the means and ratio of the standard deviation. Details on the statistical metrics, including name
 5 conventions and mathematical formulas, are provided in the Appendix.

3.3. Metrics of uncertainty propagation

The random error component was based on the normalized centered root mean square error (NCRMSE). To demonstrate how error in precipitation forcing translates to error in the simulated hydrological variables—surface runoff (Qs), subsurface runoff (Qsb), and evapotranspiration (ET)—we used the
 10 NCRMSE error metric ratio as follows:

$$NCRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n \left[\hat{y}_i - y_i - \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) \right]^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2}}, \quad (5)$$

$$\alpha_{NCRMSE} = \frac{NCRMSE_{(simulated\ variables)}}{NCRMSE_{(precipitation)}}, \quad (6)$$

where $NCRMSE$ is normalized centered root mean square error and α_{NCRMSE} is NCRMSE error metric ratio at multiple temporal (3-hourly and daily) and spatial (0.25^0) resolutions. The α_{NCRMSE} metric
 15 quantifies the changes in the random error from precipitation to simulated hydrological variables (Qs, Qsb, and ET) and can thus be used to assess magnification ($\alpha_{NCRMSE} > 1$) or damping ($\alpha_{NCRMSE} < 1$).

3.4. Analysis of Ensemble Spread

To assess how variability in precipitation ensemble translates to variability of the various hydrological simulations (Qs, Qsb, and ET) for the different modeling systems, we performed an analysis of ensemble spread (Δ) formulated as

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$$\Delta = \frac{\sum_{i=1}^n (X_{max} - X_{min})}{\sum_{i=1}^n Y}, \quad (7)$$

in which X_{max} and X_{min} represent, respectively, the maximum and minimum of ensemble values at each time step, while Y is the corresponding value of the reference. Here, the members of ensemble constitute a sequence for each time step (X_1, X_2, \dots, X_{20}). The ensemble spread (Δ) is calculated at monthly scale for combined product and simulated hydrologic variables. Note that, the combined product is an ensemble based precipitation product; for the evaluations presented in this study we use ensemble-mean as forcing. For the analysis and propagation of the precipitation ensemble spread to hydrologic simulations, we used 20 ensemble members, which are generated stochastically by the quantile regression forests (QRF) tree-based regression model (Meinshausen, 2006). Δ provides a measurement of the expected prediction intervals relative to the reference value. Δ value of 1 indicates the maximum possible uncertainty of the prediction interval. To achieve accurate and successful prediction, comparatively small prediction intervals are expected.

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4. Results

4.1 Variability of Multiple Hydrological Model Simulations

To examine the magnitude and variability of the differences among both models and forcing datasets, we analysed the multi-model simulation results for three hydrological variables including surface runoff (Qs), subsurface runoff (Qsb), and evapotranspiration (ET). Throughout this analysis, we used the SAFRAN-based simulation as the reference for comparison. Figures 2 to 5 present spatial maps of annual average values for each model, along with the relative differences of annual average estimates of precipitation

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forcing and the different hydrological variables for all the precipitation forcing datasets and models. The relative differences in precipitation forcing (Figure 2) exhibit considerable spatial variability for satellite precipitation forcing (relative difference >20%) and relatively lower for EI_GPCC and combined product.

Examination of SAFRAN-based annual average values of surface runoff show that WaterGAP3, estimates considerably higher surface runoff than the rest of the models particularly in the north and north-western part of the study area (Figure 3). Consequently, subsurface runoff (Figure 4) and evapotranspiration (Figure 5) from WaterGAP3 were lower in that part of the study area. All these results display substantial differences in the spatial pattern of relative differences, which suggests that simulations are sensitive to both precipitation forcing and model uncertainty. Certain models seem to be more sensitive for given variables. For example, HTESSSEL and ORCHIDEE are the models with the largest relative difference of Q_s and both models exhibited different behaviour, relative to the other models, when forced by the satellite precipitation. This suggests a distinct structural difference on the way precipitation is partitioned into surface/subsurface runoff between the two groups.

Looking at the variability of results for combined and reanalysis (EI_GPCC) forcing datasets, no substantial differences occurred between reference and simulated surface runoff (Q_s). However for the satellite-based simulations, there were significant deviations. Specifically, the CMORPH-based simulation showed significant overestimation for ORCHIDEE and HTESSSEL, but this pattern was reversed for JULES, SURFEX, and WaterGAP3, an outcome that highlights the impact of model structure on precipitation error propagation.

For subsurface runoff, similar spatial patterns (with respect to Q_s) were exhibited for the reference and the rest of simulations (Figure 4), which were also affected substantially by precipitation uncertainty. For example, looking at the different model simulations we can see that WaterGAP3 results reveal the lowest relative differences of Q_s for almost all the precipitation forcings. In addition, CMORPH-based simulation underestimated substantially for all the models. Figure 5 presents the spatial pattern of the results for evapotranspiration. For the combined product and EI_GPCC, results were consistent with low relative difference (<25%). On the other hand, CMORPH-based simulation showed an overall

underestimation and deviated considerably from the results of the other precipitation products. By examining the spatial pattern of relative differences (Figs 2-5) one can recognize that there is no consistent spatial pattern among the different model/forcing combinations. There are cases where the pattern of the differences is dominated by the pattern of precipitation differences, as for example the case of PERSIANN where the maximum of differences are concentrated in the central and eastern part of the peninsula. While there are other cases where the pattern is dominated by the sensitivity of the model (see for example results for ORCHIDEE/3B42 for surface runoff).

We also present a comparison of cumulative probability of the relative differences among precipitation forcings (Figure 6) and the simulated hydrological variables (Figure 7). The distribution of relative differences, both in terms of type (denoted by the shape of the Cumulative Density Function-CDF) and magnitude, differed as a function of precipitation forcing, model, and the variable considered. The CDF of precipitation relative differences shows that CMORPH deviated significantly from the other precipitation products (Figure 5). The surface runoff based on ORCHIDEE/HTESSSEL displayed a clear separation of the CDF for combined product/EI_GPCC and satellite-based precipitation forcing (Figure 7). Specifically, it is interesting to note how 3B42 (V7) responds very differently from other precipitation forcing datasets for ORCHIDEE, highlighting again the sensitivity of runoff response to precipitation structure (space/time variability) and its dependence on the rainfall-runoff generation mechanism.

Boxplots of the relative difference of different hydrological variables for the various forcing datasets/models at daily scale are shown in Figure 8. Note the inclusion of the relative difference of precipitation forcing to allow the comparison between relative differences in precipitation with that in the other hydrological variables. For each model, the boxplot shows a lower interquartile range (IQR), marking lower variability for Qsb and ET compared to Qs. Results for combined product/EI_GPCC-based simulations showed less variability than the satellite based simulations. The SURFEX and WaterGAP3 exhibited the lowest variability compared to the other models. Overall, with the exception of few cases (e.g. 3B42(V7) for ORCHIDEE/HTESSSEL and CMORPH for ORCHIDEE), uncertainty reduces progressively from precipitation to surface runoff, subsurface runoff and finally ET.

4.2 Performance of Multi-model Simulations

The normalized Taylor diagrams summarize the results for two different temporal scales. Figure 9 shows the results for the 3-hourly scale only for the two models with output available at that resolution (JULES and SURFEX), while Figure 10 presents results at daily scale for all five models. We aggregated the 3-hourly results from JULES and SURFEX to daily to compare them with the nominal daily output of ORCHIDEE, WaterGAP3 and HTESSSEL. Results improved with the temporal aggregation in reducing random error for JULES and SURFEX. As shown in Figure 10, the points for the 3B42 (V7) were always the furthest from the reference (NCRMSE>0.75) with low correlation coefficient (0.4-0.55) except SURFEX, which means 3B42 (V7) was always associated with the worst performance for all other models. Simulations based on combined product/EI_GPCC were always consistent with significantly reduced NCRMSE values in the range of 0.25-0.8 for all the hydrological models. Results for simulated ET are more consistent among the various precipitation forcing datasets exhibiting normalised standard deviations in the range of 0.8-1.2. NCRMSE reduced significantly (<0.35) for each forcing dataset; accordingly, the correlation coefficient (CC) also raised considerably (>0.9) showing a very high degree of agreement with reference-based simulations. For surface/subsurface runoff, SURFEX and WaterGAP3 models performed comparatively better than other models by reducing NCRMSE values especially for the combined product and EI_GPCC.

To illustrate the relative variability between precipitation and individual hydrological variables, we calculated the coefficient of variation (CV) and the coefficient of variation ratio (CVr) for all the hydrological models. To provide an understanding of the impact of precipitation uncertainty in hydrological simulations, we produced boxplots of CV and CVr for precipitation forcing datasets and individual hydrological variables for all the models, as shown in Figure 11. A precipitation-forcing-wise comparison indicates that, the combined product/reanalysis underestimated precipitation variability more than other precipitation forcings, which affected the corresponding variability in Qs, for all the models except ORCHIDEE. Although there were no significant differences in terms of variability for combined product and reanalysis based simulations for the four models (JULES, SURFEX, WaterGAP3, and HTESSSEL), substantial differences in variability between precipitation and Qs were observed for ORCHIDEE model. Satellite products overestimated precipitation variability, leading to overestimation

of the variability of surface and subsurface runoff. The variability of ET was much lower than that of the other variables examined and well captured in all the simulation scenarios. From the boxplots of CV from reference-based simulations, the distributions of ET showed low variability ($CV < 1$), while the variability for all the other hydrological variables was high ($CV > 1$). In terms of CV_r , the SURFEX model performed very well by producing medians close to 1 ($CV_r=1$, means ideal consistency) for all the precipitation forcing datasets but CMORPH.

4.3 Assessment of Precipitation Error Propagation

To investigate the possible amplification, or dampening, of the precipitation error to the hydrologic variables examined, we quantified the NCRMSE error metric ratio (α_{NCRMSE}) and results are demonstrated in Figures 12 and 13. For all the scenarios (at 3-hourly and daily scales) and almost all models, α_{NCRMSE} values were less than 1, which highlighted the damping effect on the random error of precipitation in simulated variables. In general, the damping effect increases (i.e. α_{NCRMSE} reduces) moving from surface to subsurface runoff and ET, highlighting once again the interaction between the different runoff generating mechanisms as well as coupled water-energy balance processes and precipitation uncertainty. Interestingly, the relationship between error propagation among the different hydrologic variables varied greatly between models and precipitation forcing. Values of α_{NCRMSE} for surface and subsurface runoff are generally close for the SURFEX model but distinctly different for satellite-based results of ORCHIDEE and WaterGAP3.

4.4 Stochastic Precipitation Ensemble and Corresponding Simulated Hydrological Variables

20 Analysis Results

The following summarizes the results of our analysis of ensemble precipitation (20 members), generated stochastically according to the algorithm used for the “combined” product, and their corresponding hydrological simulations. To show the relationship between the precipitation ensemble and simulated hydrological variables (generated ensemble), we presented an analysis of ensemble spread. Figure 13 depicts density plots between ensemble spread of precipitation and the simulated hydrological variables (Qs, Qsb, and ET) at monthly scale. A strong correlation between ensemble spread of Qs and precipitation is found for almost all models. For the other variables (ET, Qsb), ensemble spread was significantly narrower and rather independent of the ensemble spread of precipitation, manifested as the horizontal

structure of contours in Figure 14. The ensemble spread of Q_s was higher (ORCHIDEE and HTESSEL) or lower (SURFEX, WaterGAP3) depending on the model, elucidating again the impact of modelling structure on the propagation of precipitation uncertainty.

5. Discussion

5 Precipitation from different satellite and reanalysis datasets exhibits considerable differences in pattern and magnitude, which results in significant differences in hydrologic simulations. Results presented in this paper demonstrated clearly that magnitude and dynamics of uncertainty in hydrologic simulations depend not only on the uncertainty of the forcing variable, but also on the model and examined hydrologic variable.

10

For example, surface runoff (Q_s) appears to be highly sensitive to precipitation differences, while ET was not for this semi-arid study region (Figures 3 to 5). Particularly, ET exhibited reduced sensitivity to precipitation forcing, which potentially suggests that the water volume available to be converted to ET did not deviate significantly among the precipitation scenarios. This is expected for ET, because, it is primarily controlled by atmospheric demand, plant and soil hydraulic constraints, and solar radiation (Wallace et al., 2010). When sufficient energy is available for rainfall to evaporate directly without contributing to surface/subsurface runoff, simulation of ET is not only affected by precipitation uncertainty, but also other atmospheric constrains.

Consequently, results (Figures 6 to 7) for ET were more consistent among the various model/precipitation forcing scenarios, indicating a smaller degree of uncertainty in ET (relative to Q_s and Q_{sb}). These results suggest that precipitation has a stronger influence on surface runoff, in particular precipitation intensity, i.e. the same amount of precipitation distributed over 3 hours or over 1 day will impact mostly surface runoff, and this is associated with the model representation of this fast process. Similarly, if we look at the distribution of precipitation relative difference, CMORPH tends to decrease in magnitude compared to other precipitation products. Therefore, for subsurface runoff, CMORPH-based simulations displayed a gross underestimation compared to other precipitation forcing.

25

Precipitation-to-surface runoff sensitivity is strongly controlled by the corresponding runoff generation scheme in each model. For example, in the case of HTESSEL and ORCHIDEE, precipitation intensity has a great effect on the generation of surface runoff. The satellite precipitation datasets have higher precipitation intensities (Figure 6), when compared to the remaining datasets, which explains the different behaviour of these two models. However, in the case of JULES, the infiltration excess mechanism is rarely invoked when the drivers are provided at a 3-hourly time step, as the maximum infiltration rate is not reached. Therefore, the significance of differences that HTESSEL and ORCHIDEE show with more intense rainfall are not shown by JULES due to distinct differences of their corresponding surface runoff generation modules.

10 Evaluation of the performance of the various simulations, relative to SAFRAN-based, emphasized the issues due to low correlation and increased random error from satellite products. On the other hand, the reanalysis (EI_GPCC) and combined product resulted in reduction of random error, suggesting that relying on gauge adjusted reanalysis or blended (satellite and reanalysis) products offers improvement relative to satellite-alone products.

15

Certain dynamics resolved from this analysis were generally consistent among different models such as the fact that uncertainty reduced systematically from precipitation to surface runoff to subsurface runoff and eventually to ET simulations. This is also in accordance to our expectations given that soil moisture (storage) integrates in time the precipitation variability. Surface runoff exhibits high correlation to precipitation while uncertainty in subsurface runoff is modulated by storage capacity of the soils. In addition ET is affected only if water availability deviates significantly from the water demand in terms of potential evapotranspiration. Our findings related to the surface runoff uncertainty (due to model structure and precipitation) suggest that the use of surface runoff (e.g. flash floods diagnostics) should be carefully considered in each application in view of each model formulation.

25 **6. Conclusions**

This study investigated the propagation of precipitation uncertainty in hydrological simulations and its interaction with hydrologic modelling, which was based on satellite and reanalysis precipitation forcing

of a number of global hydrological and land surface models for the Iberian Peninsula. The following are the major conclusions from this study.

Simulation of surface runoff was shown to be highly sensitive to precipitation forcing, but the direction (that is, overestimation/underestimation) and the magnitude of relative differences indicated strong dependence on the modeling system. Hydrological simulations based on reanalysis and combined product forcing datasets performed overall better than satellite precipitation-driven simulations. Moreover, simulation-results using CMORPH as forcing exhibit overall overestimation for ORCHIDEE/ HTESSEL which is totally opposite to the results from the other models (JULES, SURFEX and WaterGAP3). These types of differences highlight the complexity of the interaction between precipitation characteristics and different modelling schemes and should be used as a “reference for caution” for when generalizing findings produced from single model simulations.

Modeling uncertainty appeared to be much less important for evapotranspiration than for surface and subsurface runoff. The sensitivity of hydrological simulations to different precipitation forcing datasets was shown to depend on the hydrological variable use and model parameterization scheme. Finally, based on our evaluation of the performance of the different hydrological models and five precipitation products—CMORPH, PERSIANN, 3B42 (V7), reanalysis, and combined product—we could not identify a single model that consistently outperformed others i.e. certain models appeared more successful on the simulation of certain variables.

This study suggests important benefits may accrue from exploring different model structures as part of the modeling approach. This study assessed the multi-model performances regarding three different hydrologic variables (surface/subsurface runoff, evapotranspiration). Apart from precipitation forcing, other atmospheric forcing variables required for the hydrologic simulations are also essential to investigate the significance of hydrological model uncertainty. In addition, the only calibrated model in this study WaterGAP3 performs better in specific locations (e.g., hilly) for all the hydrologic variables than other models. Therefore, investigation should be performed in calibrating and regionalizing models

for different parameters. Nevertheless, a clear outcome of the current work is that uncertainty in hydrologic predictions is significant and should be assessed and quantified in order to foster the effective use of the outputs of global land surface/hydrologic models. Considering ensemble representation (e.g. multi-model/multi-forcing) of hydrologic variables provides an appropriate path to address this issue.

5

Advancing our understanding on precipitation/model uncertainty and their interaction will potentially also aid in the investigation of the impacts of climate change (and associated uncertainty) on hydrological cycle components and water resource systems. Finally, this research provides a fine platform to discuss advances in the applications of different precipitation algorithms, hydrology, and water resource
10 reanalysis.

Data availability.

The datasets are available online for SAFRAN (<https://doi.org/10.14768/MISTRALS-HYMEX.1388>),
15 CMORPH (ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/RAW/0.25deg-3HLY/),
PERSIANN (http://fire.eng.uci.edu/PERSIANN/data/3hrly_adj_cact_tars/),
3B42 (V7) (<https://mirador.gsfc.nasa.gov>), atmospheric reanalysis dataset
(<https://wci.earth2observe.eu/portal/>), satellite-derived near-surface daily soil moisture data
(<http://www.esa-soilmoisture-cci.org/node/145/>) and
20 the combined product (<https://sites.google.com/uconn.edu/ehsanbhuiyan/research>).

25

Competing interests. The authors declare that they have no conflict of interest.

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References

Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Albert I J M van, Dijk, Weedon, G. P., Brocca, L.,
30 Pappenberger, F., Huffman, G.J., and Wood, E.F.: Global-scale evaluation of 22 precipitation datasets

- using gauge observations and hydrological modeling, *Hydrology and Earth System Sciences*, 21, 6201-6217. <http://dx.doi.org/10.5194/hess-21-6201-2017>, 2017a.
- Borga, M.: Accuracy of radar rainfall estimates for streamflow simulation, *J. Hydrol.*, 267, 26–39, 2002.
- Beck, H. E., van Dijk, A. I. J. M., de Roo, A., Dutra, E., Fink, G., Orth, R., and Schellekens, J.: Global
5 evaluation of runoff from 10 state-of-the-art hydrological models, *Hydrol. Earth Syst. Sci.*, 21, 2881-2903, <https://doi.org/10.5194/hess-21-2881-2017>, 2017b.
- Breuer, L., Huisman, J.A., Willems, P., Bormann, H., Bronstert, A., Croke, B.F., Frede, H.G., Gräff, T., Hubrechts, L., Jakeman, A.J, and Kite. G.: Assessing the impact of land use change on hydrology by ensemble modeling (LUCHEM). I: Model intercomparison with current land use, *Advances in Water
10 Resources*, 32,129-46, 2009.
- Boone, A. , and Etchevers, P.: An intercomparison of three snow schemes of varying complexity coupled to the same land-surface model: Local scale evaluation at an Alpine site, *J. Hydrometeor.*, 2, 374–394, 2001.
- Blyth, E.: Modelling soil moisture for a grassland and a woodland site in south-east England,*Hydrol.
15 Earth Syst. Sci.* 6, 39-48, doi:10.5194/hess-6-39-2002, 2002.
- Blyth, E. M., Martinez-de la Torre, A., and Robinson, E. L.: Trends in evapotranspiration and its drivers in Great Britain: 1961 to 2015, *Hydrol. Earth Syst. Sci. Discuss.*, <https://doi.org/10.5194/hess-2018-153>, in review, 2018.
- Bhuiyan, M. A. E., Nikolopoulos, E. I., Anagnostou, E. N., Quintana-Seguí, P., and Barella-Ortiz, A.: A
20 nonparametric statistical technique for combining global precipitation datasets: development and hydrological evaluation over the Iberian Peninsula, *Hydrol. Earth Syst. Sci.*, 22, 1371-1389, <https://doi.org/10.5194/hess-22-1371-2018>, 2018.
- Bhuiyan, M. A. E., Anagnostou, E. N., and Kirstetter, P. E.: A nonparametric statistical technique for modeling overland TMI (2A12) rainfall retrieval error, *IEEE Geosci. Remote S.*, 14, 1898–1902, 2017.
- 25 Bitew, M. M., Gebremichael, M., Ghebremichael, L. T., and Bayissa, Y. A.: Evaluation of high-resolution satellite rainfall products through streamflow simulation in a hydrological modeling of a small mountainous watershed in Ethiopia, *J. Hydrometeorol.*, 13, 338–350, 2012.

- Balsamo, G., Albergel, C., Beljaars, A., Boussetta, S., Brun, E., Cloke, H., Dee, D., Dutra, E., Muñoz-Sabater, J., Pappenberger, F., de Rosnay, P., Stockdale, T., and Vitart, F.: ERA-Interim/Land: a global land surface reanalysis data set, *Hydrol. Earth Syst. Sci.*, 19, 389-407, <https://doi.org/10.5194/hess-19-389-2015>, 2015.
- 5 Biemans, H., Hutjes, R.W.A., Kabat, P., Strengers, B., Gerten, D., and Rost, S.: Effects of precipitation uncertainty on discharge calculations for main river basins, *J. Hydrometeorol.* 10, 1011–1025. <http://dx.doi.org/10.1175/2008JHM1067.1>, 2009.
- Behrangi, A., Khakbaz, B., and Jaw, T.C., AghaKouchak, A., Hsu, K., Sorooshian, S.: Hydrologic evaluation of satellite precipitation products over a mid-size basin. *J. Hydrol.* 2011, 397, 225–237.
- 10 Balsamo, G., Beljaars, A., Scipal, K., Viterbo, P., van den Hurk, B., Hirschi, M., and Betts, A. K.: A revised hydrology for the ECMWF model: Verification from field site to terrestrial water storage and impact in the Integrated Forecast System, *J. Hydrometeorol.*, 10, 623–643, 2009.
- Best, M. J., Pryor, M., Clark, D. B., Rooney, G. G., Essery, R. L.H., Ménard, C. B., Edwards, J. M., Hendry, M. A., Porson, A., Gedney, N., Mercado, L. M., Sitch, S., Blyth, E., Boucher, O., Cox, P. M.,
- 15 Grimmond, C. S. B., and Harding, R. J.: The JointUK Land Environment Simulator (JULES), model description –Part 1: Energy and water fluxes, *Geosci. Model Dev.*, 4,677–699, <https://doi.org/10.5194/gmd-4-677-2011>, 2011.
- Carr, N., Kirstetter, P.E., Hong, Y., Gourley, J.J., Schwaller, M., Petersen, W., Wang, N.Y., Ferraro, R.R., and Xue, X.: The influence of surface and precipitation characteristics on TRMM Microwave Imager
- 20 rainfall retrieval uncertainty, *Journal of Hydrometeorology*, 16,1596-614, .2015.
- Clark, D. B., Mercado, L. M., Sitch, S., Jones, C. D., Gedney, N., Best, M. J., Pryor, M., Rooney, G. G., Essery, R. L. H., Blyth, E., Boucher, O., Harding, R. J., Huntingford, C., and Cox, P. M.: The Joint UK Land Environment Simulator (JULES), model description – Part 2: Carbon fluxes and vegetation dynamics, *Geosci. Model Dev.*, 4, 701–722, <https://doi.org/10.5194/gmd-4-701-2011>, 2011.
- 25 Carpenter, T. M., Georgakakos, K. P. and Sperflagea, J. A. : On the parametric and NEXRAD-radar sensitivities of a distributed hydrologic model suitable for operational use, *J. Hydrol.*, 253, 169–193, 2001.

- de Luis, M., Brunetti, M., Gozález-Hidalgo, J. C., Longares, L. A., and Martín-Vide, J. : Changes in seasonal precipitation in the Iberian Peninsula during 1946-2005, *Global and Planetary Change*, 74,2010.
- Döll, P., Fiedler, K., and Zhang, J.: Global-scale analysis of river flow alterations due to water withdrawals and reservoirs, *Hydrol. Earth Syst. Sci.*, 13, 2413-2432, doi:10.5194/hess-13-2413-2009, 5 2009.
- Decharme, B., Alkama, R., Douville, H., Becker, M., and Cazenave, A.: Global evaluation of the ISBA-TRIP continental hydrological system. Part II: Uncertainties in river routing simulation related to flow velocity and groundwater storage, *J. Hydrometeorol.*, 11, 601–617, <https://doi.org/10.1175/2010JHM1212.1>, 2010.
- 10 Decharme, B., Brun, E., Boone, A., Delire, C., Le Moigne, P., and Morin, S.: Impacts of snow and organic soils parameterization on northern Eurasian soil temperature profiles simulated by the ISBA land surface model, *The Cryosphere*, 10, 853–877,doi:10.5194/tc-10-853-2016, 2016.
- Dee, D.P, Uppala, S.M., Simmons, A.J., Berrisford ,P., Poli, P., Kobayashi, S., Andrae, U,, Balmaseda, M.A., Balsamo, G., Bauer, P., Bechtold, P.: The ERA-Interim reanalysis: Configuration and 15 performance of the data assimilation system, *Quarterly Journal of the royal meteorological society*, ,137, 553-97, 2011.
- Durand, Y., Brun, E., Merindol, L., Guyomarc'h, G., Lesaffre, B., and Martin, E.: A meteorological estimation of relevant parameters for snow models, *Ann. Glaciol.*, 18, 65–71, 1993.
- d'Orgeval, T., Polcher, J., and de Rosnay, P.: Sensitivity of the West African hydrological cycle in 20 ORCHIDEE to infiltration processes, *Hydrol. Earth Syst. Sci.*, 12, 1387-1401, doi: 10.5194/hess-12-1387-2008, 2008.
- d'Orgeval: Impact Du Changement Climatique Sur Le Cycle de L'eau En Afrique de l'Ouest: Modélisation et Incertitudes, PhD Thesis of Université Pierre, Marie Curie., 2006.
- Eisner, S.: Comprehensive evaluation of the WaterGAP3 model across climatic, physiographic, and 25 anthropogenic gradients, PhD Thesis of University of Kassel 2015.

- Falck, A. S., Maggioni, V., Tomasella, J., Vila, D. A., and Diniz, F. L. R.: Propagation of satellite precipitation uncertainties through a distributed hydrologic model: A case study in the Tocantins-Araguaia basin in Brazil, *J. Hydrol.*, 527, 943–957, <https://doi.org/10.1016/j.jhydrol.2015.05.042>, 2015.
- Flörke, M., Kynast, E., Bärlund, I., Eisner, S., Wimmer, F., and Alcamo, J.: Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: A global simulation study, *Global Environ. Change*, 23, 144–156, <https://doi.org/10.1016/j.gloenvcha.2012.10.018>, 2013.
- Fekete, B.M., Vörösmarty, C.J., Roads, J.O., and Willmott, C.J.: Uncertainties in precipitation and their impacts on runoff estimates. *J. Climate* 17, 294–304, 2004.
- FAO (2003). Digital soil map of the world (DSMW). Technical report, Food and Agriculture Organization of the United Nations, re-issued version.
- Faroux, S., Kaptué Tchuenté, A. T., Roujean, J.-L., Masson, V., Martin, E., and Le Moigne, P.: ECOCLIMAP-II/Europe: a twofold database of ecosystems and surface parameters at 1 km resolution based on satellite information for use in land surface, meteorological and climate models, *Geosci. Model Dev.*, 6, 563-582, <https://doi.org/10.5194/gmd-6-563-2013>, 2013.
- Gandin, L. S.: Objective analysis of meteorological fields. By L. S. Gandin. Translated from the Russian. Jerusalem (Israel Program for Scientific Translations), *Q. J. Roy. Meteorol. Soc.*, 92, 447–447, [doi:10.1002/qj.49709239320](https://doi.org/10.1002/qj.49709239320), 1966.
- Gao, L., Bernhardt, M., and Schulz, K.: Elevation correction of ERA-Interim temperature data in complex terrain, *Hydrol. Earth Syst. Sci.*, 16, 4661-4673, [10.5194/hess-16-4661-2012](https://doi.org/10.5194/hess-16-4661-2012), 2012.
- Gudmundsson, L., Tallaksen, L.M., Stahl, K., Clark, D.B., Dumont, E., Hagemann, S., Bertrand, N., Gerten, D., Heinke, J., Hanasaki, N. and Voss, F.: Comparing large-scale hydrological model simulations to observed runoff percentiles in Europe, *Journal of Hydrometeorology*, 13, 604-620, 2012.
- Gelati, E., Decharme, B., Calvet, J.C., Minvielle, M., Polcher, J., Fairbairn, D. and Weedon, G.P.: Hydrological assessment of atmospheric forcing uncertainty in the Euro-Mediterranean area using a land surface model, *Hydrology and Earth System Sciences*, 22, 2091, 2018.
- Hong, Y., Adler, R., and Huffman, G.: Applications of TRMM-based multi-satellite precipitation estimation for global runoff simulation: Prototyping a global flood monitoring system, In *Satellite*

- Rainfall Applications for Surface Hydrology, 1st ed.; Gebremichael, M., Hossain, F., Eds. Springer: Dordrecht, The Netherlands, 245–265, 2010.
- Herrera, S., Gutiérrez, J.M., Ancell, R., Pons, M.R., Frías, M.D. and Fernández, J.: Development and analysis of a 50-year high-resolution daily gridded precipitation dataset over Spain (Spain02).
5 International Journal of Climatology, 32, 74-85, 2012.
- Huffman, G. J., Adler, R. F., Bolvin, D. T., and Nelkin, E. J.: The TRMM multi-satellite precipitation analysis (TMPA), in: Satellite rainfall applications for surface hydrology, edited by: Gebremichael, M. and Hossain, F., Springer, Dordrecht, 3–22, 2010.
- Haddeland, I., Clark, D.B., Franssen, W., Ludwig, F., VOß, F.R.A.N.K., Arnell, N.W., Bertrand, N., Best,
10 M., Folwell, S., Gerten, D., and Gomes, S.: Multimodel estimate of the global terrestrial water balance: Setup and first results, Journal of Hydrometeorology, 12,869-884, 2011.
- Huang, S., Kumar, R., Flörke, M., Yang, T., Hundecha, Y., Kraft, P., Gao, C., Gelfan, A., Liersch, S., Lobanova, A. and Strauch, M.: Evaluation of an ensemble of regional hydrological models in 12 large-scale river basins worldwide, Climatic Change, 141,381-397, 2017.
- 15 Joyce, R. J., Janowiak, J. E., Arkin, P. A., and Xie, P.: CMORPH: a method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution, J. Hydrometeorol., 5, 487–503, 2004.
- Krinner, G., Viovy, N., N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, P., Stich, S., and Prentice, I. C.: A dynamic global vegetation model for studies of the coupled atmosphere-
20 biosphere system, Global Biogeochem. Cy, 19, 1, <https://doi.org/10.1029/2003GB002199>, 2005.
- Kirstetter, P.E., Hong, Y., Gourley, J.J., Cao, Q., Schwaller, M. and Petersen, W.: Research framework to bridge from the Global Precipitation Measurement Mission core satellite to the constellation sensors using ground-radar-based national mosaic QPE., Remote Sensing of the Terrestrial Water Cycle, .61-79, , <https://doi.org/10.1002/9781118872086.ch4>, 2014.
- 25 Masson, V., Le Moigne, P., Martin, E., Faroux, S., Alias, A., Alkama, R., Belamari, S., Barbu, A., Boone, A., Bouyssel, F., Brousseau, P., Brun, E., Calvet, J. C., Carrer, D., Decharme, B., Delire, C., Donier, S., Essaouini, K., Gibelin, A. L., Giordani, H., Habets, F., Jidane, M., Kerdraon, G., Kourzeneva, E., Lafaysse, M., Lafont, S., Lebeaupin Brossier, C., Lemonsu, A., Mahfouf, J. F., Marguinaud, P., Mokhtari,

- M., Morin, S., Pigeon, G., Salgado, R., Seity, Y., Taillefer, F., Tanguy, G., Tulet, P., Vincendon, B., Vionnet, V., and Voldoire, A.: The SURFEXv7.2 land and ocean surface platform for coupled or offline simulation of earth surface variables and fluxes, *Geosci. Model Dev.*, 6, 929-960, doi: 10.5194/gmd-6-929-2013, 2013.
- 5 Mei, Y., Anagnostou, E. N., Nikolopoulos, E. I., & Borga, M. : Error Analysis of Satellite Precipitation Products in Mountainous Basins, *J. Hydrometeor.*, 16, 1445-1446, doi:10.1175/JHM-D-15-0022.1, 2015.
- Mei, Y., Nikolopoulos, E.I., Anagnostou, E.N., Zoccatelli, D. and Borga, M.: Error analysis of satellite precipitation-driven modeling of flood events in complex alpine terrain. *Remote Sensing*, 8, 293, 2016.
- Meinshausen, N.: Quantile regression forests, *J. Mach. Learn. Res.*, 7, 983–999, 2006.
- 10 Ngo-Duc, T., Laval, K., Ramillien, G., Polcher, J., and Cazenave, A.: Validation of the land water storage simulated by Organising Carbon and Hydrology in Dynamic Ecosystems (ORCHIDEE) with Gravity Recovery and Climate Experiment (GRACE) data, *Water Resour. Res.*, 43,4, <https://doi.org/10.1029/2006WR004941>, 2007.
- Nikolopoulos, E. I., Anagnostou, E. N., and Borga, M. : Using High-resolution Satellite Rainfall Products to Simulate a Major Flash Flood Event in Northern Italy:, *J. Hydrometeor.*, 14, 171-185, doi:10.1175/JHM-D-12-09.1,2013.
- Noilhan, J., and Mahfouf, J.F.: The ISBA land surface parameterisation scheme. *Global and planetary Change*, 13, 145-159, 1996.
- Ogden, F. L., and Julien, P. Y.: Runoff model sensitivity to radar rainfall resolution, *J. Hydrol.*, 158, 1–
20 18, 1994.
- Oki, T., and Sud, Y. C.: Design of Total Runoff Integrating Pathways (TRIP)—A Global River Channel Network, *Earth Interactions*, 2, 1-37, doi: 10.1175/1087-3562(1998)002<0001:dotrip>2.3.co;2, 1998.
- Pan, M., Li, H., and Wood, E.: Assessing the skill of satellite-based precipitation estimates in hydrologic applications, *Water Resour. Res.*, 46, W09535, <https://doi.org/10.1029/2009WR008290>, 2010.
- 25 Prudhomme, C., Giuntoli, I., Robinson, E. L., Clark, D. B., Arnell, N. W., Dankers, R., Fekete, B. M., Franssen, W., Gerten, D., Gosling, S. N., Hagemann, S., Hannah, D. M., Kim, H., Masaki, Y., Satoh, Y., Stacke, T., Wada, Y., and Wisser, D.: Hydrological droughts in the 21st century, hotspots and

- uncertainties from a global multimodel ensemble experiment, *P. Natl. Acad. Sci. USA*, 111, 3262–3267, doi:10.1073/pnas.1222473110, 2014.
- Quintana-Seguí, P., Turco, M., Herrera, S., and Miguez-Macho, G.: Validation of a new SAFRAN-based gridded precipitation product for Spain and comparisons to Spain02 and ERA-Interim, *Hydrol. Earth Syst. Sci.*, 21, 2187–2201, <https://doi.org/10.5194/hess-21-2187-2017>, 2017.
- Quintana-Seguí, P., Peral, M. C., Turco, M., Llasat, M.-C., and Martin, E.: Meteorological analysis systems in North-East Spain: validation of SAFRAN and SPAN, *J. Environ. Inform.*, 27, 116–130, <https://doi.org/10.3808/jei.201600335>, 2016.
- Qi, W., Zhang, C., Fu, G., Sweetapple, C. and Zhou, H.: Evaluation of global fine-resolution precipitation products and their uncertainty quantification in ensemble discharge simulations. *Hydrology and Earth System Sciences*, 20,903-920, 2016.
- Richards, L. A.: Capillary conduction of liquids through porous mediums. *Journal of Applied Physics*, 1, 318-333, 1931.
- Rodríguez-Puebla, C., Encinas, A.H. and Sáenz, J.Y.: Winter precipitation over the Iberian Peninsula and its relationship to circulation indices, *Hydrology and Earth System Sciences Discussions*, 5,233-244, 2001.
- Schellekens J, Dutra E, Martínez-de la Torre A, Balsamo G, van Dijk A, Weiland FS, Minvielle M, Calvet JC, Decharme B, Eisner S, Fink G. A global water resources ensemble of hydrological models: the eartH2Observe Tier-1 dataset. *Earth System Science*, 9, 389-413, 2017.
- Sorooshian, S., Hsu, K. L., Gao, X., Gupta, H. V., Imam, B., and Braithwaite, D.: Evaluation of PERSIANN system satellite based estimates of tropical rainfall, *B. Am. Meteorol. Soc.*, 81, 2035–2046, 2000.
- Seyyedi, H., Anagnostou, E. N., Beighley, E., & McCollum, J.: Hydrologic Evaluation of Satellite and Reanalysis Precipitation Datasets over a Mid-Latitude Basin, *Atmos Res.*, 164, 37-48, doi:10.1016/j.atmosres.2015.03.019, 2015.
- Seyyedi, H., Anagnostou, E. N., Kirstetter, P. E., Maggioni, V., Hong, Y., and Gourley, J. J.: Incorporating surface soil moisture information in error modeling of TRMM passive Microwave rainfall, *IEEE T. Geosci. Remote*, 52, 6226–6240, 2014.

- Samaniego, L., Kumar, R., Breuer, L., Chamorro, A., Flörke, M., Pechlivanidis, I.G., Schäfer, D., Shah, H., Vetter, T., Wortmann, M., and Zeng, X.: Propagation of forcing and model uncertainties on to hydrological drought characteristics in a multi-model century-long experiment in large river basins. *Climatic change*, 141,435-449, 2017.
- 5 Smith, M., Koren, V., Zhang, Z., Moreda, F., Cui, Z., Cosgrove, B., Mizukami, N., Kitzmiller, D., Ding, F., Reed, S., and Anderson, E.: The distributed model intercomparison project–Phase 2: Experiment design and summary results of the western basin experiments, *Journal of Hydrology*, 507,300-329, 2013.
- Taylor, K. E.: Summarizing multiple aspects of model performance in a single diagram, *Journal of Geophysical Research: Atmospheres*, 106, 7183-7192, doi:10.1029/2000jd900719,2001.
- 10 Vernimmen, R.R.E., Hooijer, A., Mamenun, and Aldrian, E.: Evaluation and bias correction of satellite rainfall data for drought monitoring in Indonesia, *Hydrol. Earth Syst. Sci.*, 8, 5969–5997, 2011.
- Vivoni, E.R., Entekhabi, D. and Hoffman, R.N.: Error propagation of radar rainfall nowcasting fields through a fully distributed flood forecasting model, *Journal of applied meteorology and climatology*, 46, 932-940, 2007.
- 15 Vinukollu, R.K., Meynadier, R., Sheffield, J. and Wood, E.F: Multi-model, multi-sensor estimates of global evapotranspiration: climatology, uncertainties and trends. *Hydrological Processes*, 25, 3993-4010, 2011.
- Wu, H., Adler, R.F., Hong, Y., Tian, Y., and Policelli, F.: Evaluation of global flood detection using satellite-based rainfall and a hydrologic model. *J. Hydrometeorol.*, 14, 1268–1284, 2012.
- 20 Wallace, J., McJannet, D.: Processes controlling transpiration in the rainforests of north Queensland, Australia. *J Hydrol* 384:107–117, 2010.

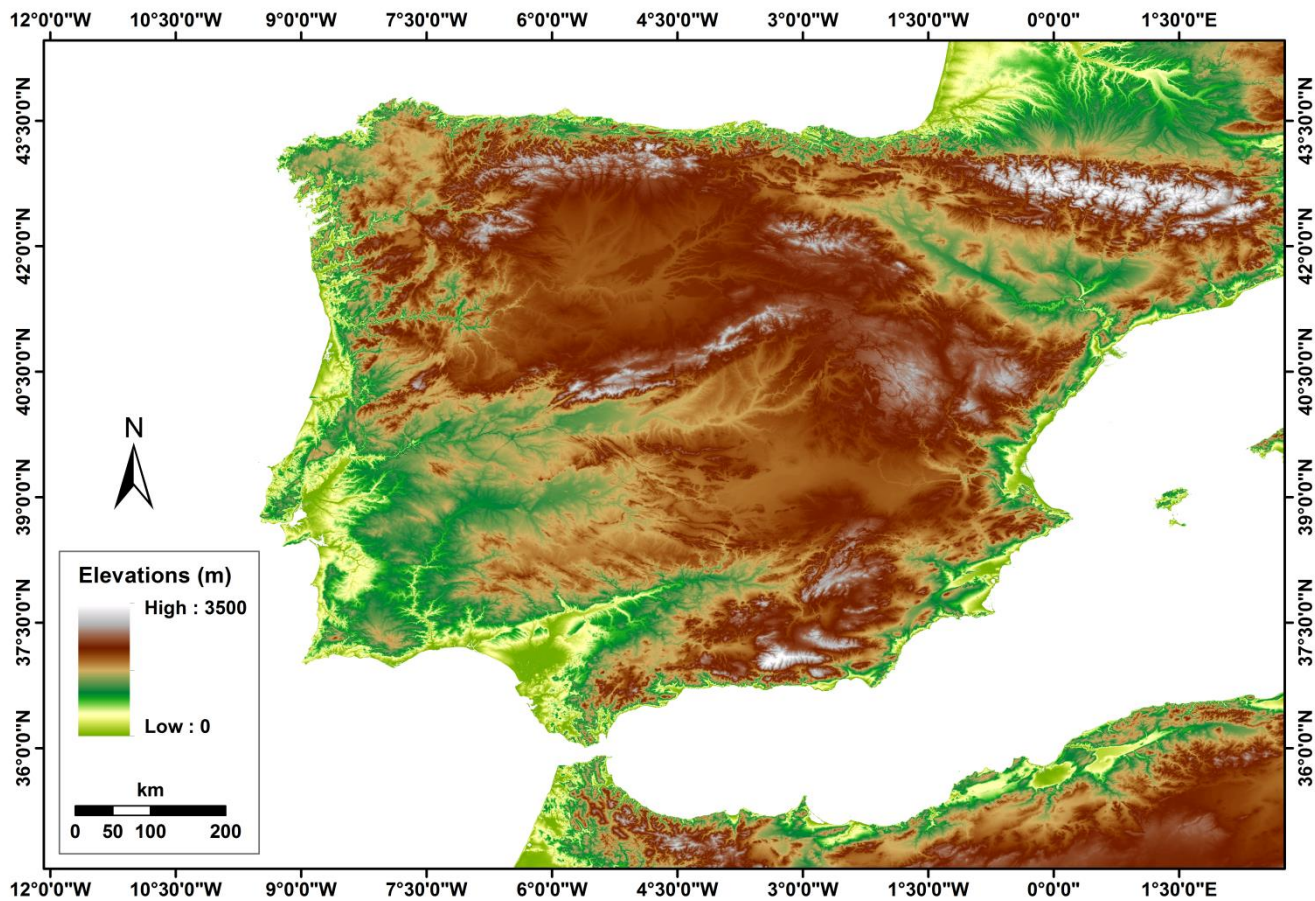


Figure 1. Map of Iberian Peninsula case study area.

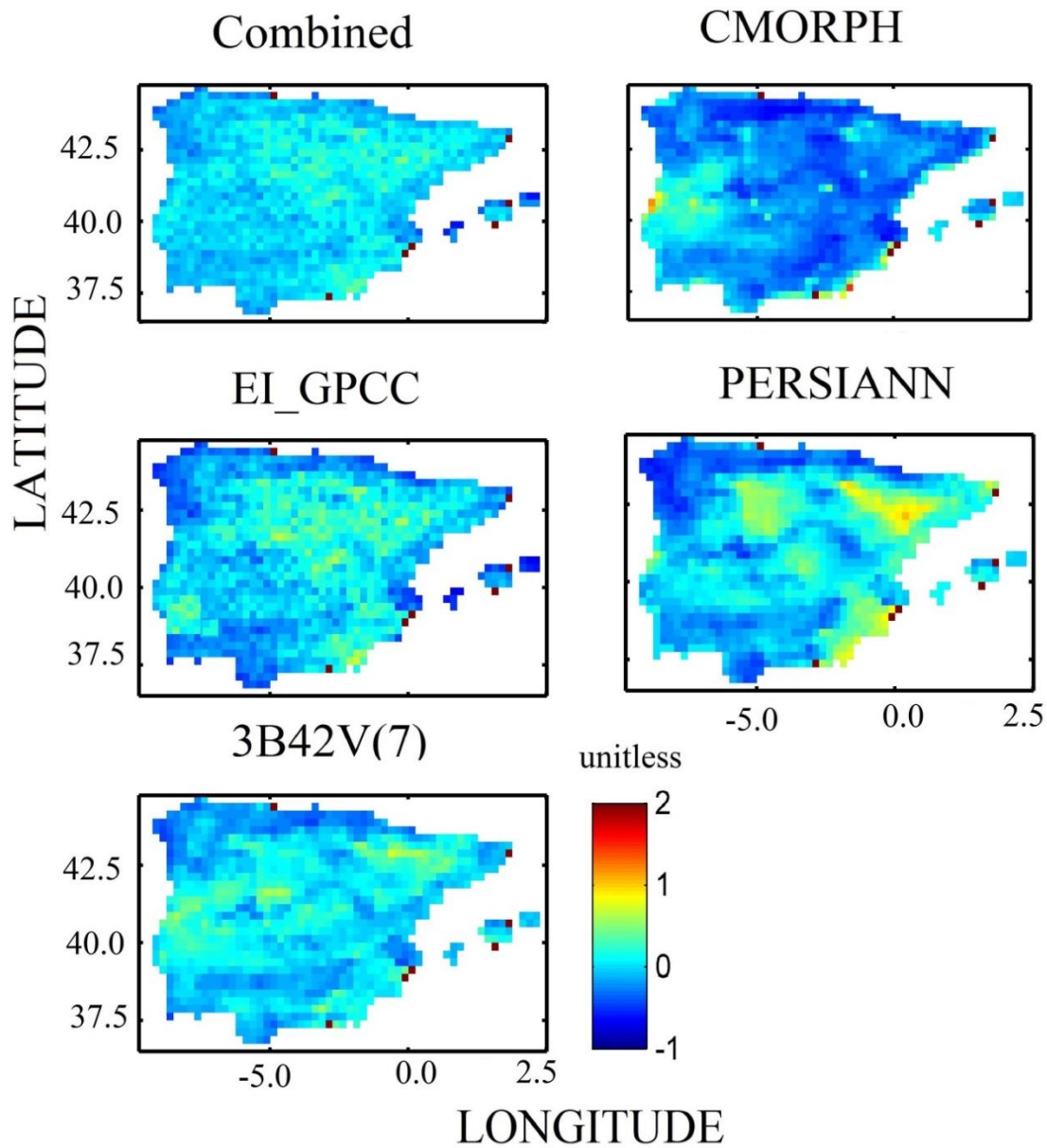


Figure 2: Map of the annual average relative difference (with respect to SAFRAN) for the different precipitation forcing dataset.

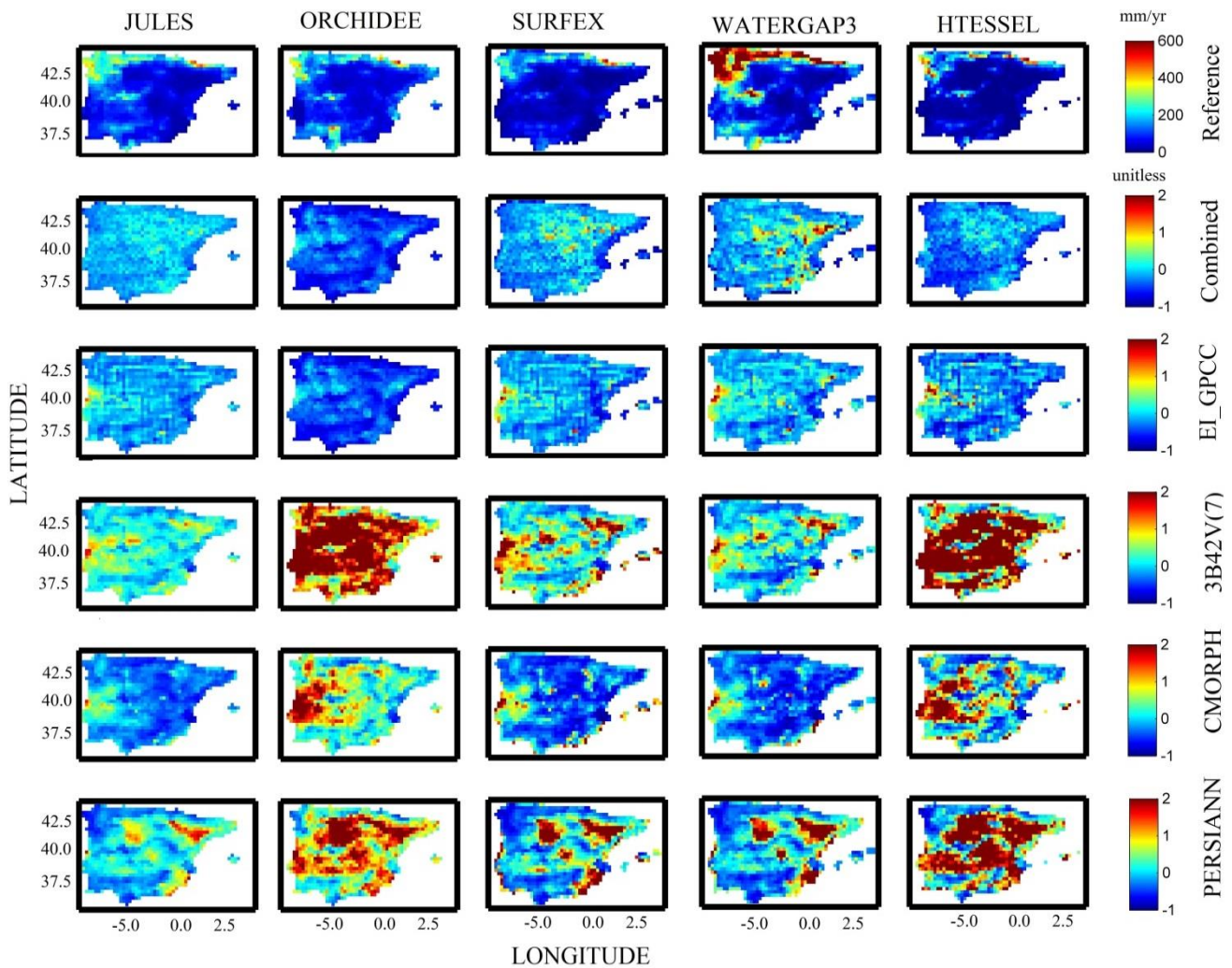


Figure 3: Map of SAFRAN-based simulations (Reference) of surface runoff (top row) and relative
5 difference for the various models (columns) and precipitation forcing (rows 2-5) analysed.

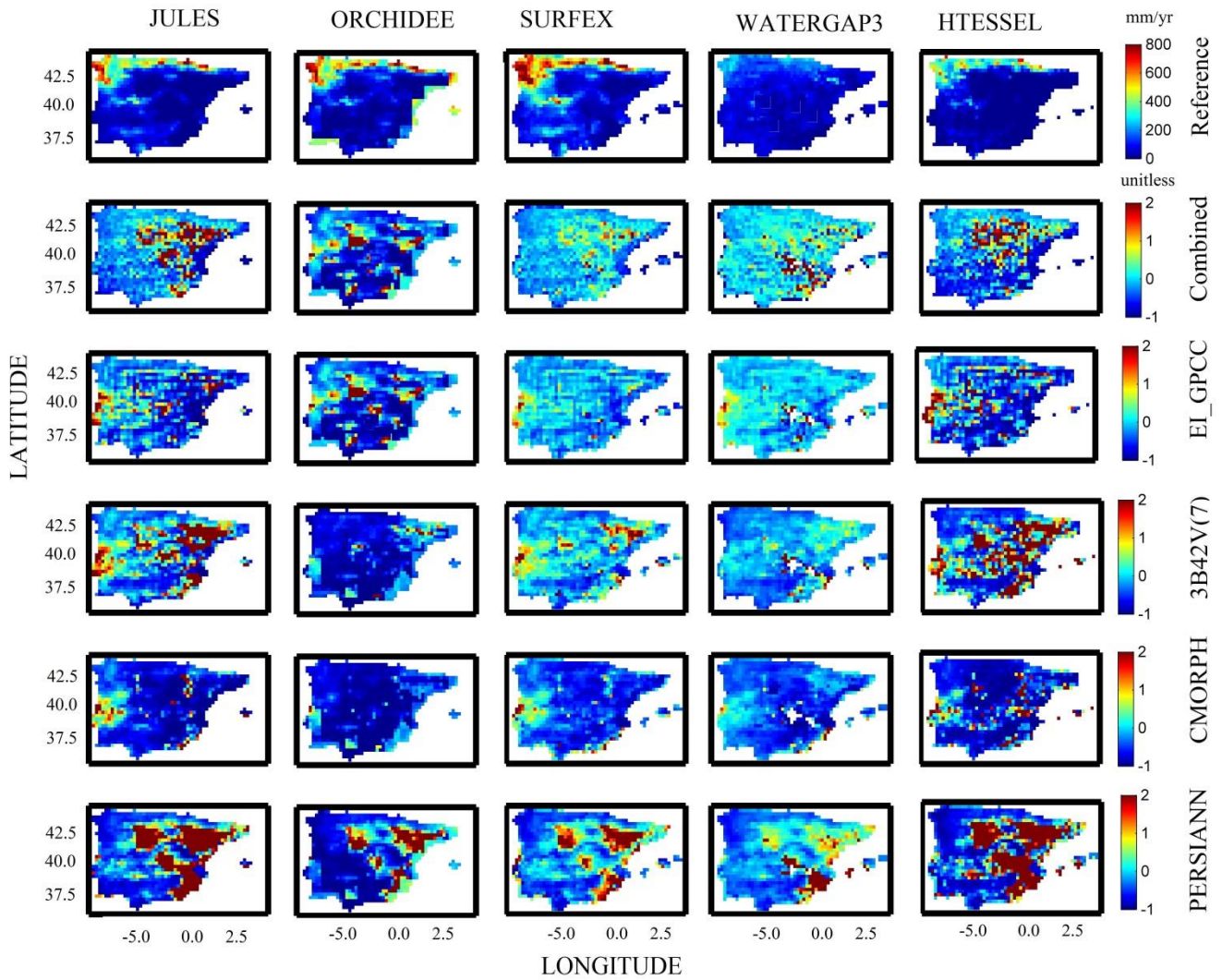


Figure 4: Map of SAFRAN-based simulations (Reference) of subsurface runoff (top row) and relative difference for the various models (columns) and precipitation forcing (rows 2-5) analysed.

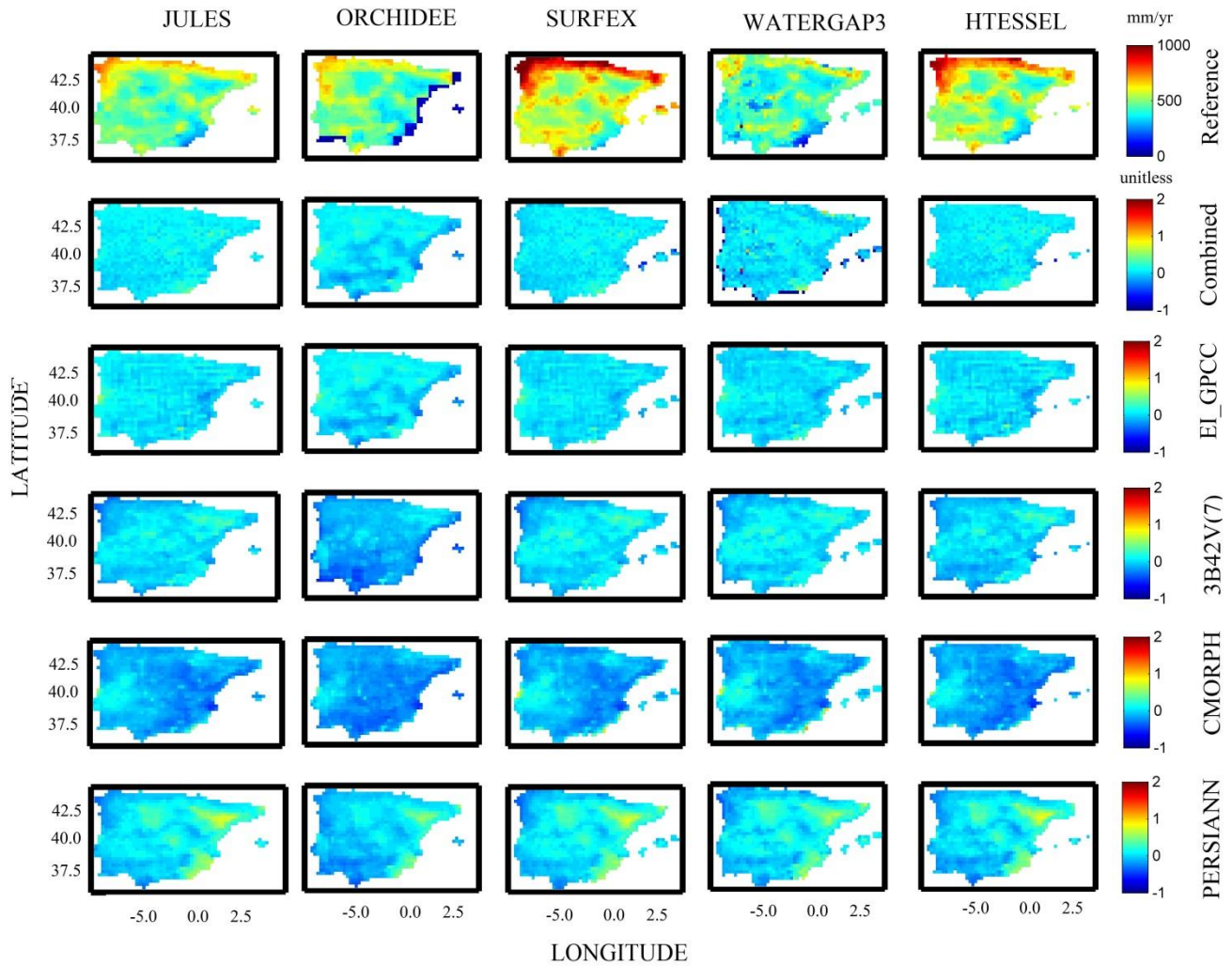


Figure 5: Map of SAFRAN-based simulations (Reference) of evapotranspiration (top row) and relative difference for the various models (columns) and precipitation forcing (rows 2-5) analysed.

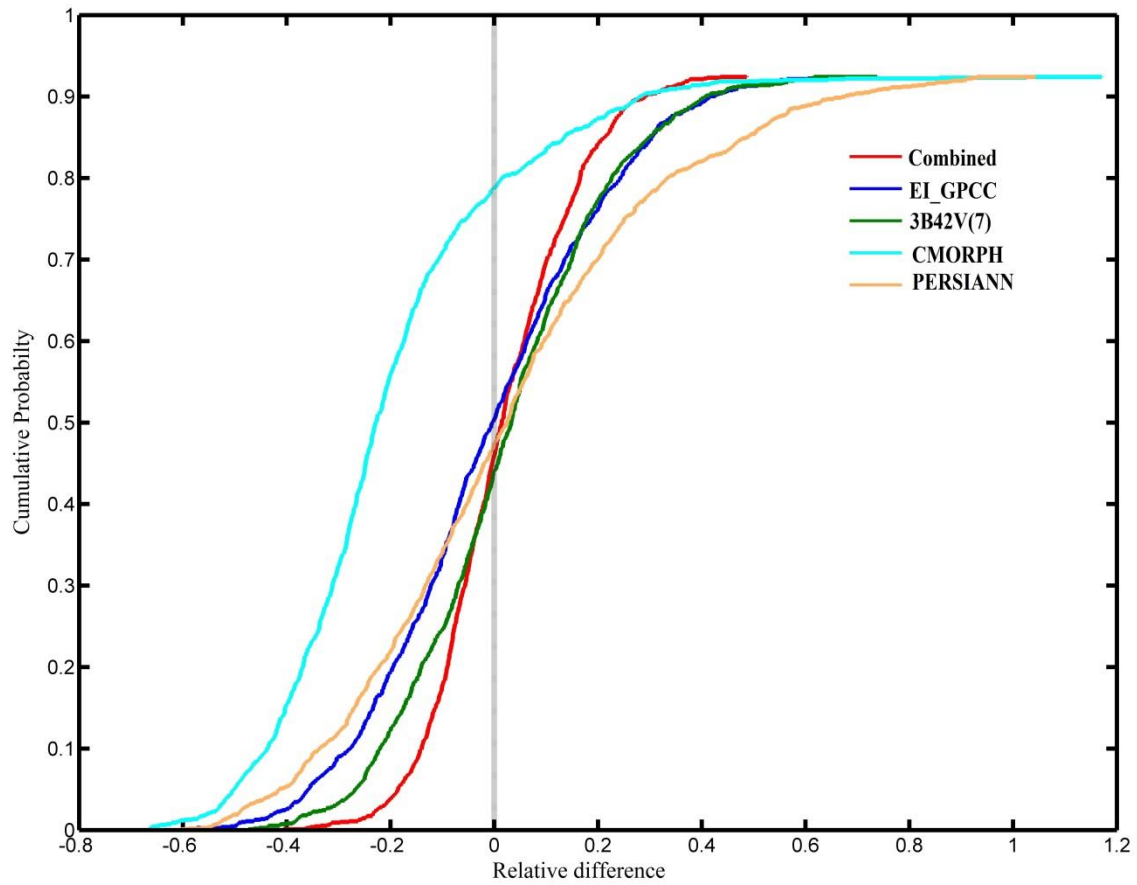


Figure 6: Cumulative probability for the precipitation forcing datasets.

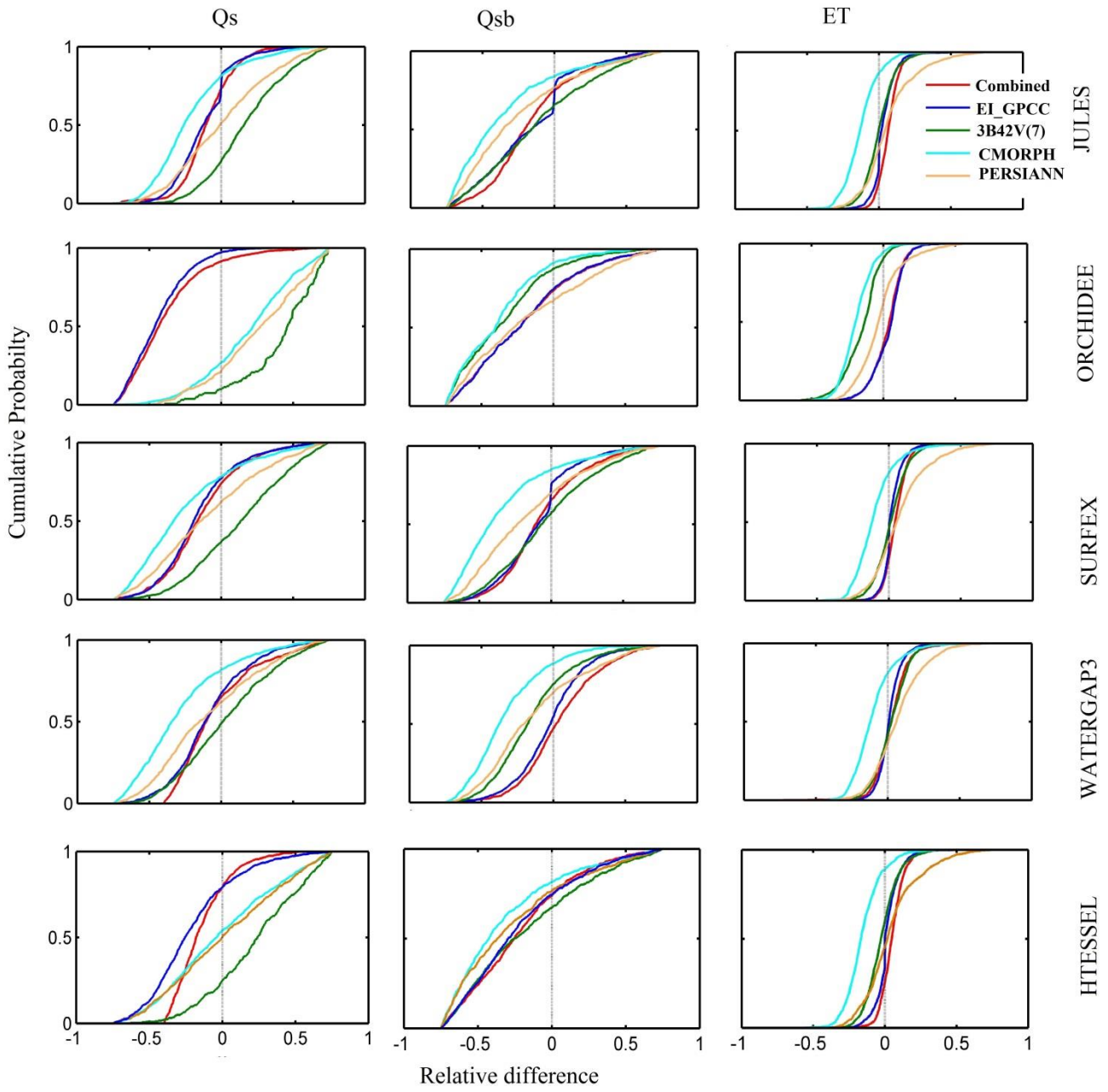


Figure 7: Cumulative probability for the multi-model, multi-forcing simulations for simulated hydrological variables.

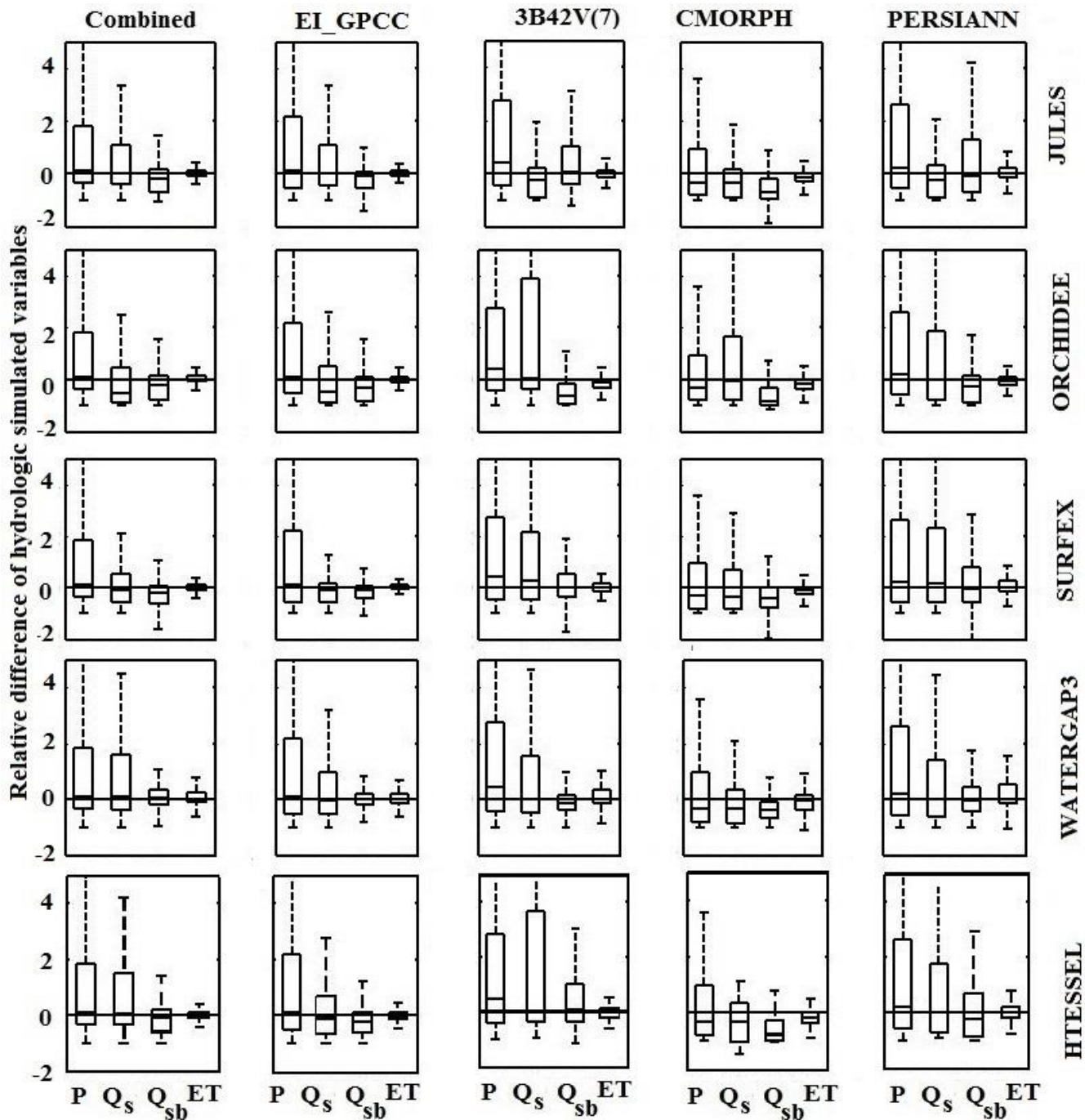


Figure 8: Relative difference presented for the various products and models at daily scale. In each box, the central mark is the median, and the edges are the first and third quartiles

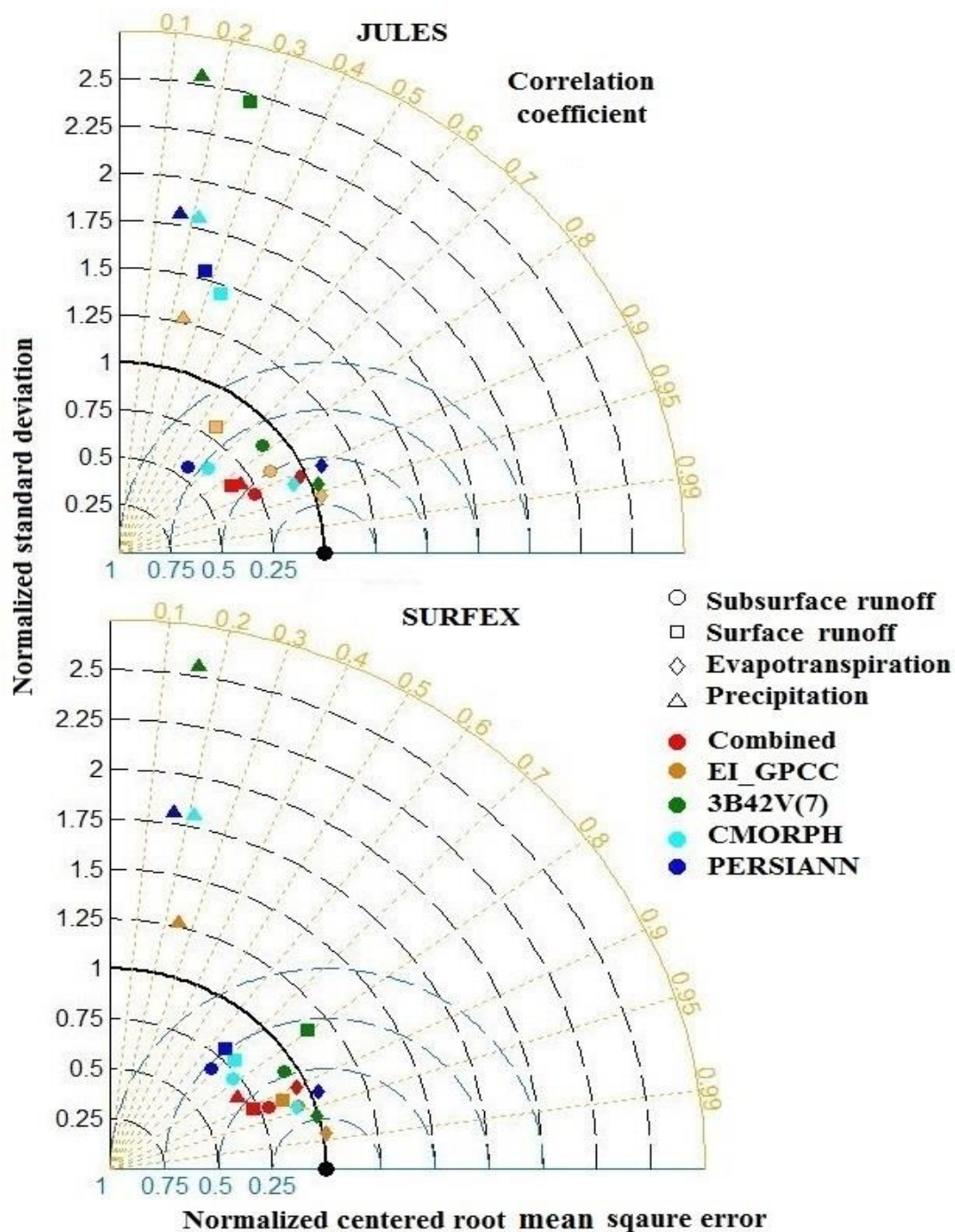


Figure 9: Normalized Taylor diagrams for 3-hourly precipitation and simulated hydrological variables based on SAFRAN and the satellite/reanalysis precipitation products used.

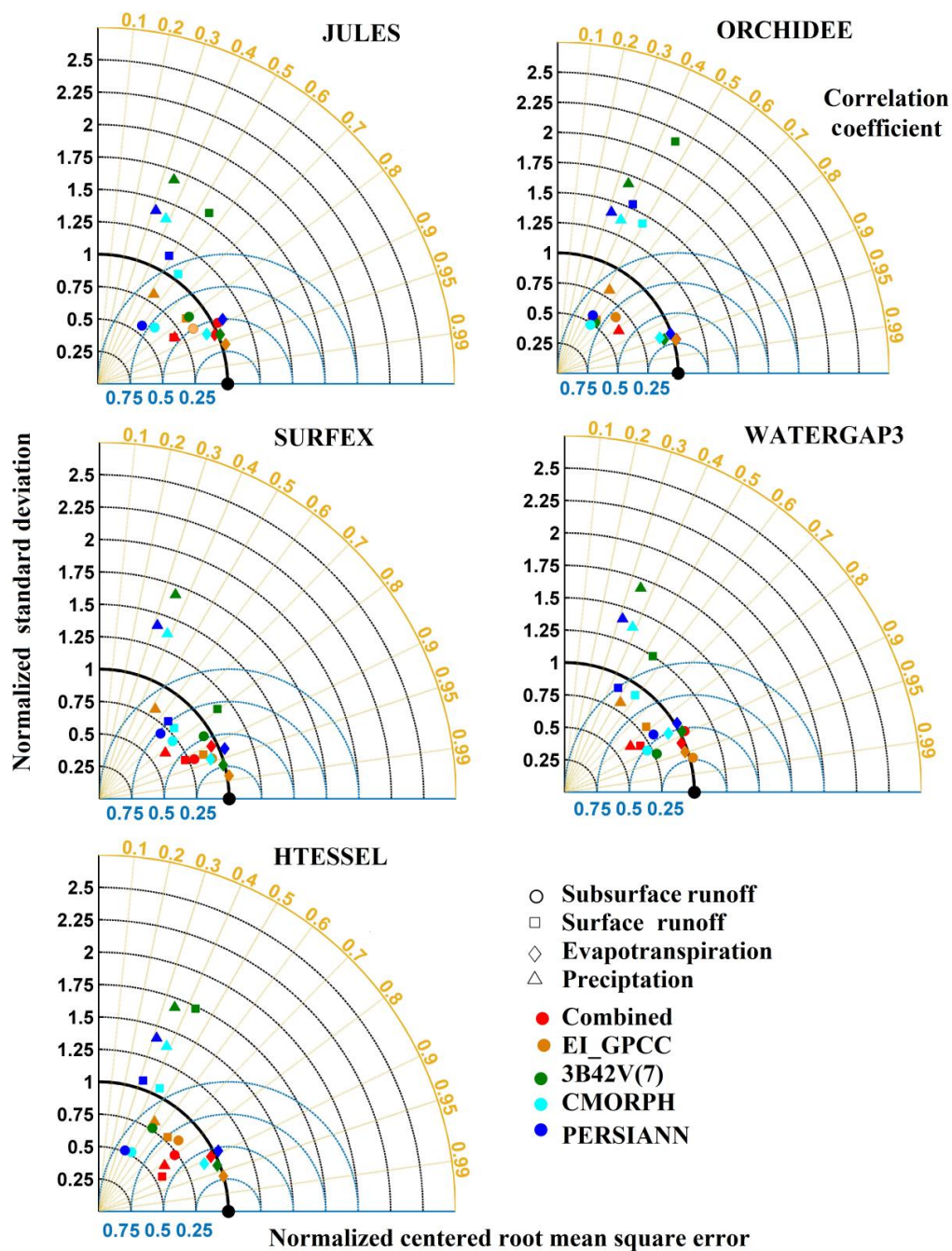


Figure 10: Normalized Taylor diagrams for daily simulated hydrological variables with SAFRAN and the satellite/reanalysis precipitation products used.

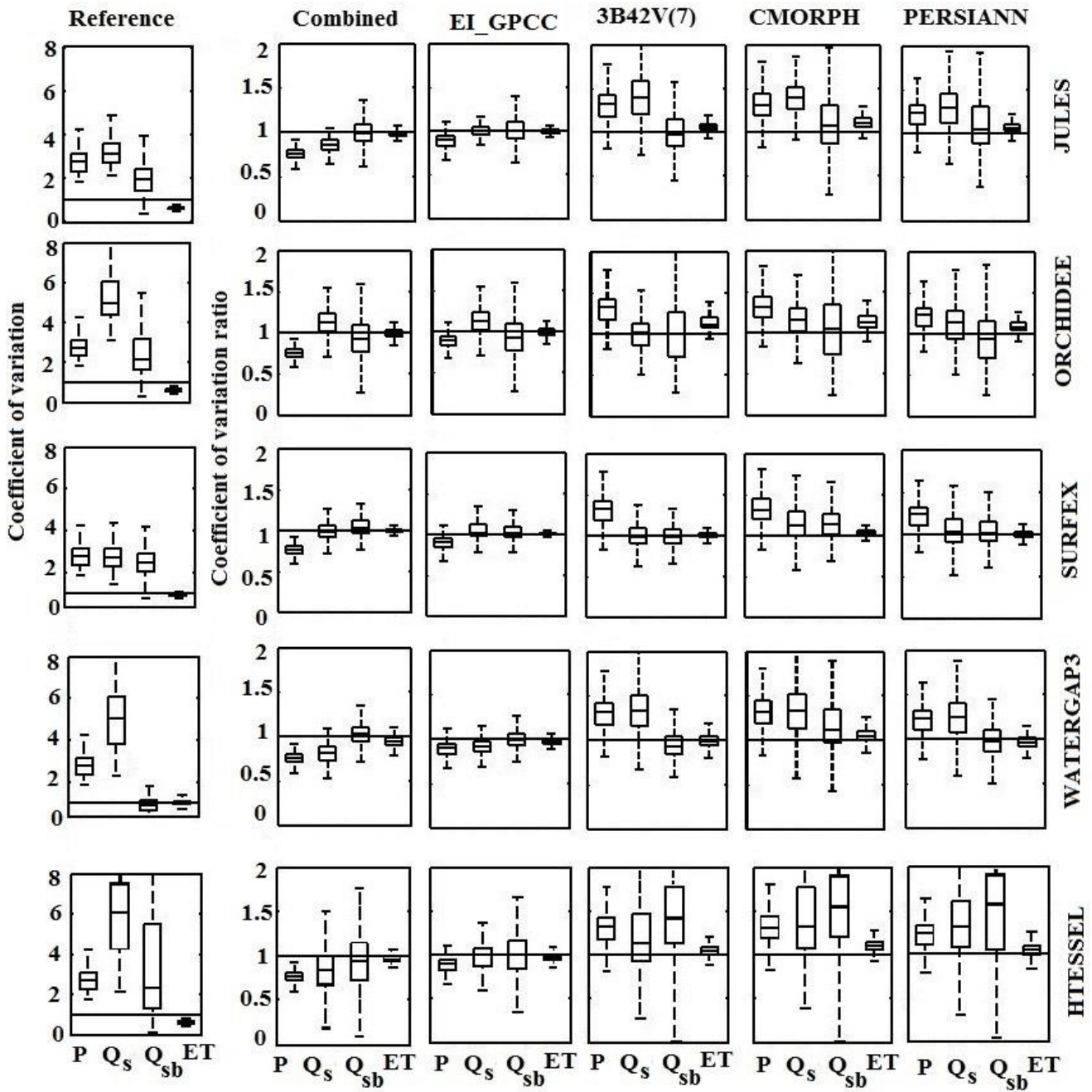


Figure 11: Relationship between coefficient of variation and coefficient of variation ratio of simulated hydrological variables and precipitation.

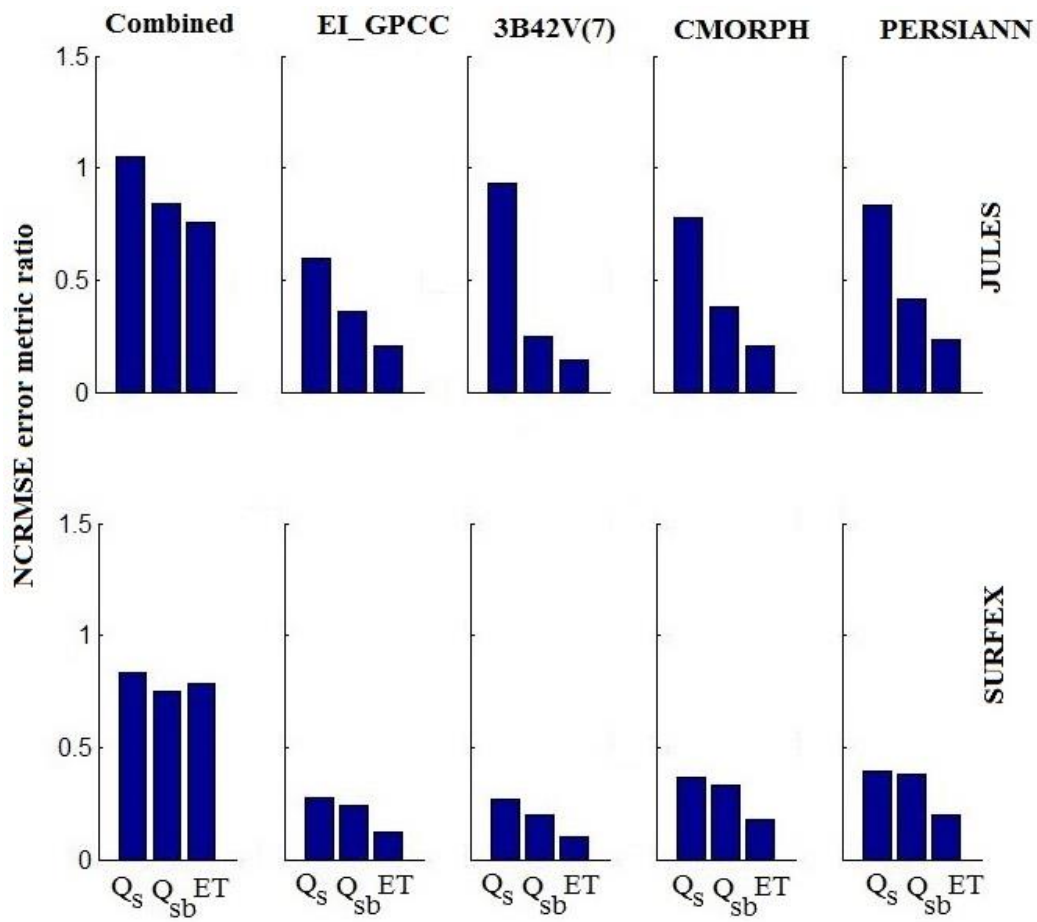


Figure 12: NCRMSE error metrics ratios presented for the various products and models at 3-hourly scale.

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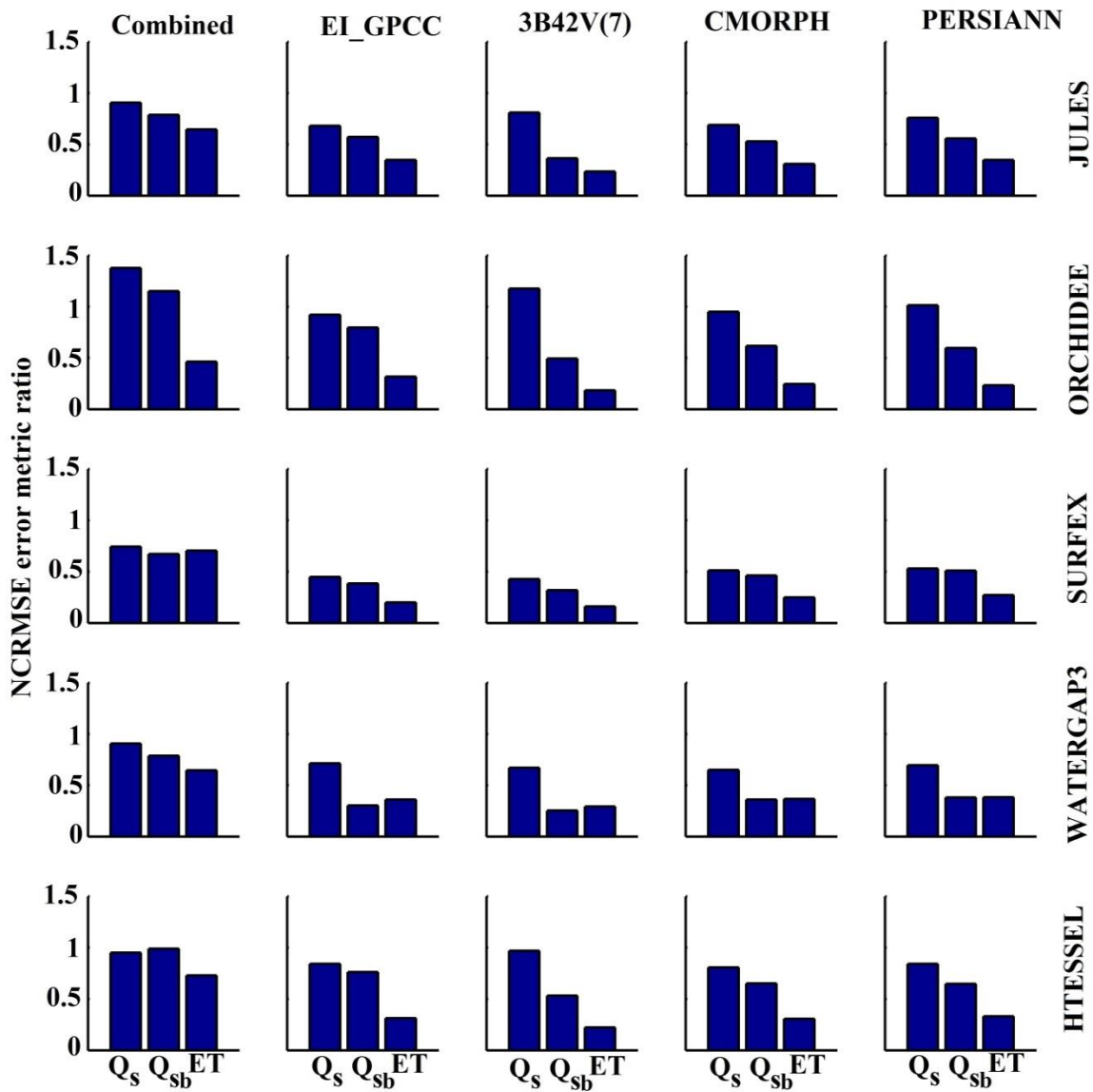


Figure 13: NCRMSE error metrics ratios presented for the various products and models at daily scale.

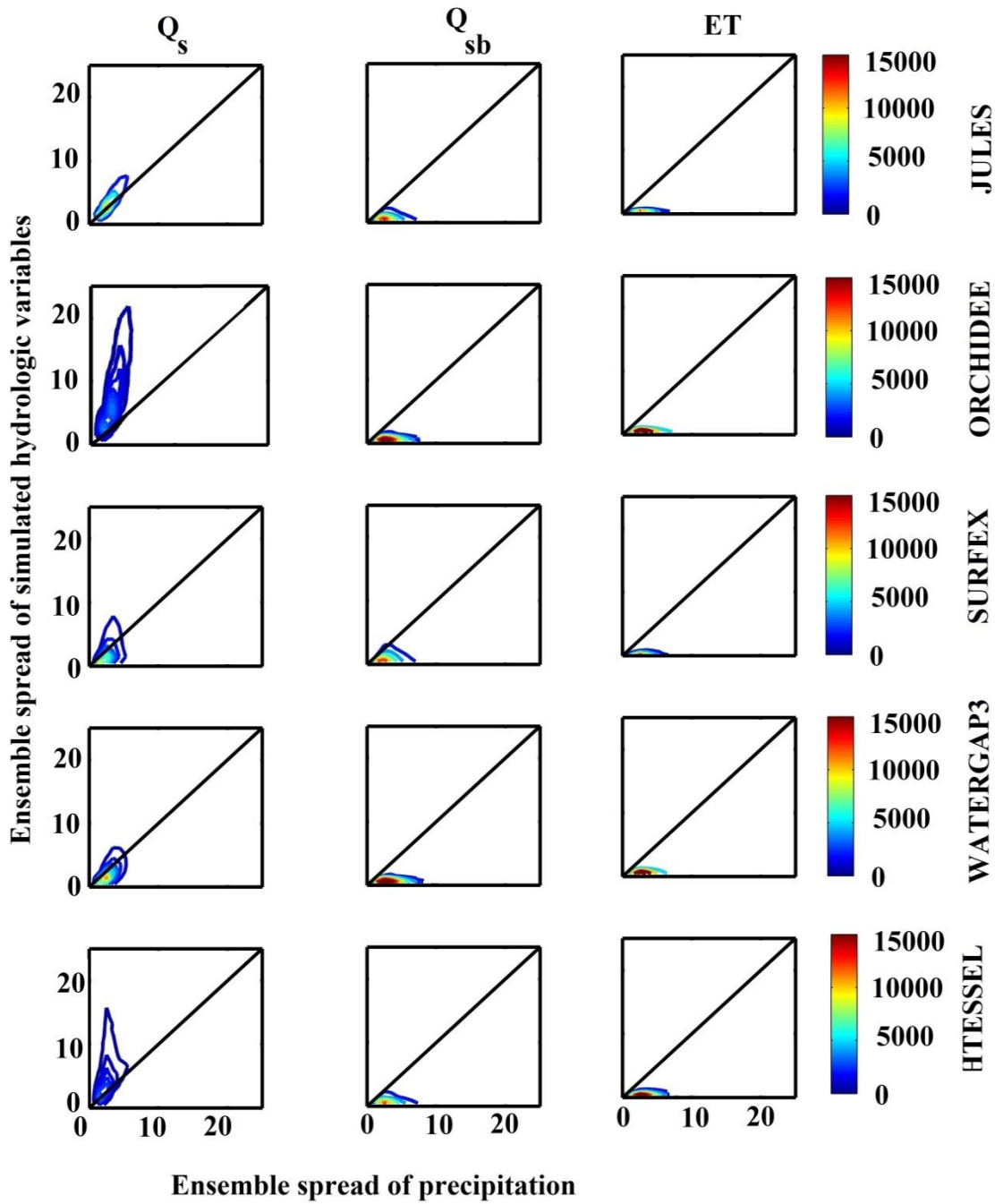


Figure 14: Density contour plot of the relationship between ensemble spread of simulated hydrological variables and precipitation at monthly scale. Color scale shows the frequency of occurrence. The black line is the 1:1 line.

Appendix:

The statistical metric, coefficient of variation ratio (*CVr*), used in the model evaluation analysis, was computed using following parameters:

$$\bar{o} = \frac{1}{N} \sum_{i=1}^N o_i \quad (8)$$

$$\bar{m} = \frac{1}{N} \sum_{i=1}^N m_i \quad (9)$$

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$$\sigma_o = \sqrt{\frac{1}{N} \sum_{i=1}^N (o_i - \bar{o})^2} \quad (10)$$

$$\sigma_m = \sqrt{\frac{1}{N} \sum_{i=1}^N (m_i - \bar{m})^2} \quad (11)$$

Here, o_i and $m_i (i = 1, \dots, N)$ are the observed and modeled time series of the product for times i , with the means \bar{o} and \bar{m} and standard deviations σ_o and σ_m , respectively; and N is the total number of
10 data points used in the calculations.

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Table 1: Information on precipitation products used.

5	Model	Original Spatial/Temporal Resolution	References
	SAFRAN	5 Km/1h	Quintana-Segui et al. (2016)
	Combined	0.25 ⁰ /3h	Bhuiyan et al. (2018)
10	EI_GPCC	0.25 ⁰ /3h	https://wci.earth2observe.eu/portal/
	3B42V(7)	0.25 ⁰ /3h	Huffman et al. (2007)
	CMORPH	0.25 ⁰ /3h	Joyce et al. (2004)
	PERSIANN	0.25 ⁰ /3h	Sorooshian et al. (2000)

Table 2: Details of the modelling systems.

Model	Interception	Evapotranspiration	Soil layers	Ground water	Runoff	Reservoirs/ lakes	Routing	Model Time step
JULES	Single reservoir, potential evapotranspiration	Penman-Monteith	4	No	Saturation and infiltration excess	No	No	1hr
ORCHIDEE	Single reservoir structural resistance to evapotranspiration	Bulk ETP (Barella-Ortiz et al. 2013)	11	Yes	Green-Ampt infiltration	No	linear cascade of reservoirs (sub-grid)	900s energy balance, 3hours routing
SURFEX	Single reservoir, potential evapotranspiration	Penman-Monteith	14	Yes	Saturation and infiltration excess	No	TRIP with stream and deep-water reservoir at 0.5°	900s for ISBA 3600s for TRIP
WATERGA P3	Single reservoir	Priestley-Taylor	1	Yes	Beta function	yes	Manning Strickler	1 day
HTESSEL	Single reservoir, potential evapotranspiration	Penman-Monteith	4	No	Saturation excess	No	CaMa-Flood	1hr

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