We would like to thank the editor and all referees for their comments to improve our paper. The following main adjustments were made based on these comments:

- Sections 3.1.2 and 3.1.3: Both sections were expanded to clarify more clearly why different model structural changes were applied and the role of satellite observations in this process.
- Section 3.3: This section was expanded to explain why the Monte-Carlo parameter sampling strategy was chosen.
- Section 4.1.3: This section was expanded to avoid any confusion when comparing the spatial pattern in total water storage of different models.
- Section 5: The discussion section was expanded to include a more detailed discussion on spatially distributing calibration parameters, incorporating lateral sub-surface flow, the correction factor to close the long-term water balance and the sensitivity of the model performance metric E_{SP} related to the spatial pattern.

More details on the individual adjustments can be found below in the responses and the marked-up version of the revised manuscript.

Responses to comments by the Editor

Comment:

The paper is of broader interest and already well presented. However, the reviewer pointed out a couple of more major points that should be considered in the revisions of the paper. I also think that the pattern of areas with high ET in the remote sensing product could not be reproduced by the model.

Reply:

Thank you for this positive assessment. We have incorporated the comments of the reviewers in the revised manuscript as shown in the marked-up version below and mentioned in the responses to the reviewers. We would like to underline that the objective of this study was to improve the overall model performance with respect to multiple individual hydrological signatures, rather than only the spatial pattern of evaporation. Comparison of the two calibration methods (with respect to discharge only vs. multiple variables) and six model scenarios significantly improved the model's skill to reproduce multiple hydrological signatures, in particular with respect to the temporal variability. As highlighted by the reviewers and editor, the spatial pattern of the evaporation and total water storage indeed improved only slightly and remained rather modest. This is a result of the combined uncertainties in the input data, model structure and parametrization as well as of the spatial distribution of model parameters as described in the discussion.

For example, the precipitation significantly impacts the spatial pattern of the evaporation. To illustrate this, the precipitation data used in this study (P_{V1}) was compared to the precipitation data used for WaPOR (P_{V2}) which is available online (https://wapor.apps.fao.org). Changing the precipitation data in the hydrological model affected the modelled spatial pattern in the evaporation significantly, as shown in Figure 1 here below. The dry season precipitation according to P_{V1} was on average highest in the south resulting in higher evaporation (Figure 1a and d). Whereas with P_{V2} the precipitation was higher near the western border of the basin (Figure 1b) resulting in higher evaporation (Figure 1e) similar to the observation (Figure 1c). This illustrates the role of the precipitation on the spatial pattern using Model F and a random parameter set as an example. It is important to keep in mind that the "observed" evaporation according to WaPOR is in itself a model result which is subject to considerable uncertainties as well. We included this aspect in the discussion section of the paper (line 576 in the marked-up version below).

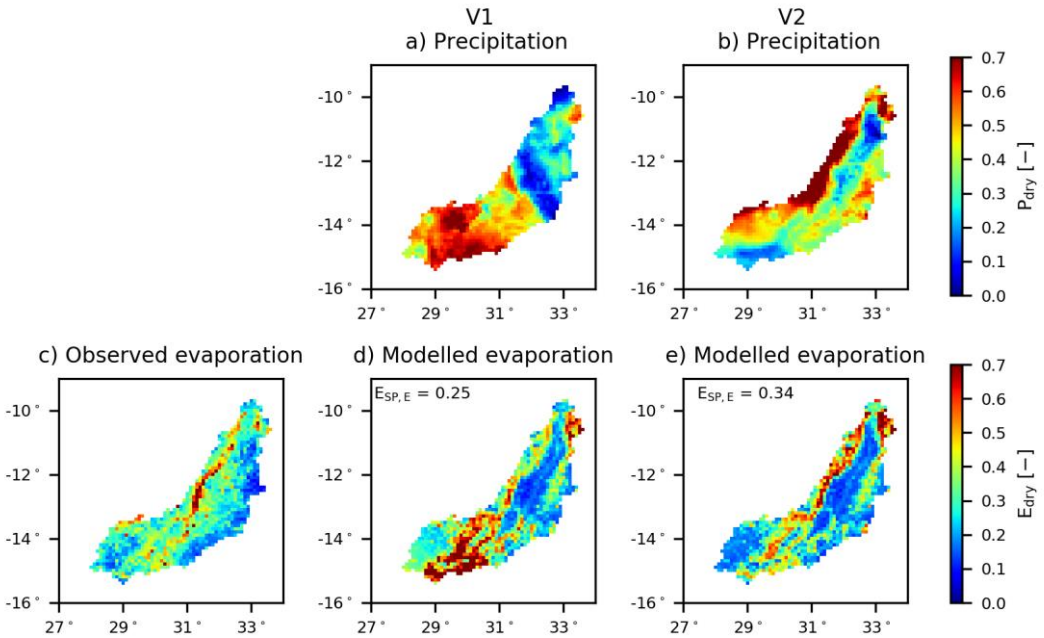

Figure 1: Effect of precipitation on the modelled evaporation with normalised a) precipitation originally used in the hydrological model (P_{V1}), b) precipitation used for WaPOR (P_{V2}), c) observed evaporation according to WaPOR, d) modelled evaporation using P_{V1}, and e) P_{V2}. All sub-figures show the spatial pattern averaged over all days within the dry season.

<u>*Comment:*</u>

I also wonder if your proposed missing process could be tested with a modification of the model structure. I know that this is not so easy in a conceptualized model structure, but there have been many successful ways proposed by researchers in the last years. If this is not possible for the whole domain, it would certainly be helpful to provide some smaller scale proof of concept. I think this would significantly strengthen the paper.

<u>Reply:</u>

We agree, it would be interesting to include lateral sub-surface flow into the hydrological model to assess its influence on different signatures including the spatial pattern of the evaporation. In principle, it is possible to add this process to the model. However, to do this in a meaningful way, multiple research papers are needed as this is a major research topic and cannot be incorporated with merely one additional model hypothesis in this study.

Lateral subsurface flow is driven by gradients and resistances in the sub-surface. However, conceptual models, such as the one used in this study, mimic gradients <u>*within*</u> grid cells, but <u>*not between*</u> adjacent cells. As a result, the head difference between neighbouring cells remains unknown which means the amount and direction of lateral exchange between two cells is unknown. Therefore, many additional calibration parameters would be needed to incorporate lateral subsurface flow. For Model F, where the groundwater system was fully distributed, this would result in at least 30(!) additional calibration parameters. This increases the degree-of-freedom of the model significantly which may (or may not) lead to improved model performances. However, the available data is insufficient to support incorporating lateral flow as we cannot test whether the additional calibration parameters and modelled lateral flow are physically plausible. As a result, water may flow against real-world elevation and/or pressure gradients despite good model performance metrics. These unspecified boundary fluxes across grid cells are at the core of the closure problem (Beven, 2006) and touch on the limits of what can be done in hydrology with our current observational technology and the available data. We included this in the discussion of the paper (line 560 in the marked-up version below).

Comment:

In addition, the point from reviewer #2 - I strongly suggest that you add a set of model setups that reflect different spatial parameterization schemes - should be considered in the revised versions.

Reply:

We agree, applying spatially distributed calibration parameters could improve the spatial pattern of the evaporation. However, this will increase the number of calibration parameters and hence the degree-of-freedom of the model. Therefore, it is important to have sufficient data to warrant spatially distributed parameters, to avoid excessive problems of equifinality and to ensure the consistency of the model. Transfer function approaches with global parameters, such as the MPR scheme developed for the MHM model (Samaniego et al., 2010; Kumar et al., 2013), could prove highly valuable. However, the design and choice of suitable and meaningful transfer functions would require substantial additional analysis to assess the information content of different variables to support spatial parameter distribution (for example NDVI, LAI, topography, soil type, vegetation type or climate) which would warrant probably several standalone research papers.

However, as a preliminary test, we here distributed the parameter I_{max} (maximum interception storage) in an additional Model G using a linear transfer function with LAI data similar to previous studies (Samaniego et al., 2010) and using Model F as basis. As this did not result in obvious improvements, as shown in Figure 2 below, we did not add this as a model hypothesis in the revised version of the manuscript. With the limited data availability in the study region, analysing additional parameter distribution strategies was considered outside the scope of this study. We included this in the discussion of the paper (line 551 in the marked-up version below).

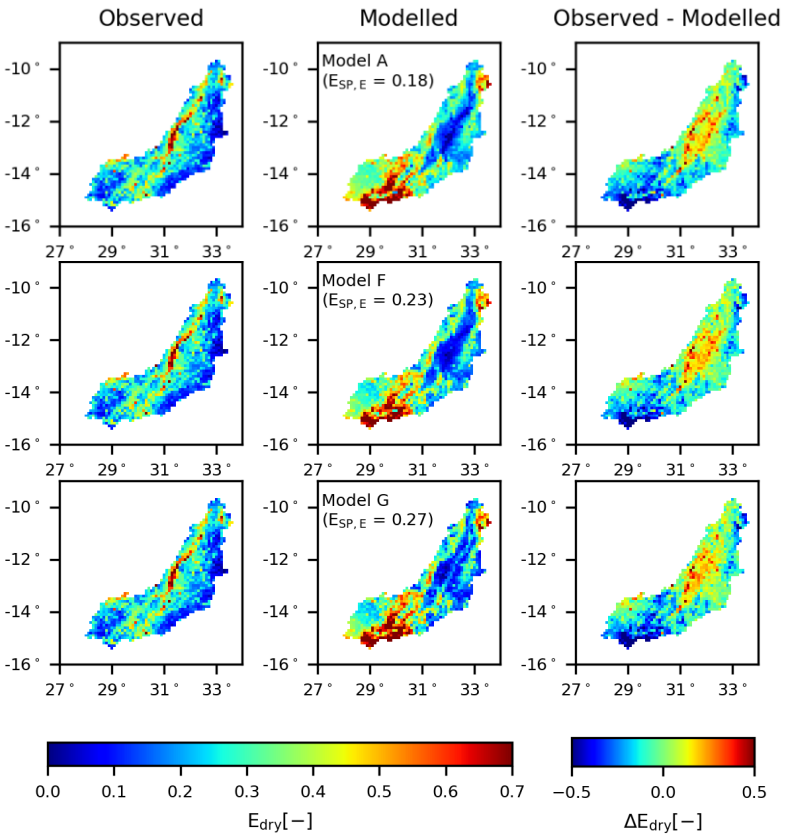

Figure 2: Spatial variability of the normalised total evaporation for Models A, F and G averaged over all days within the dry season. The left panel shows the observation according to WaPOR data, the middle panel the model result using the "optimal" parameter set with respect to <u>multiple variables ($D_{E,ESQcal}$)</u>, and the right panel the difference between the observation and model.

Responses to comments Anonymous Referee #1

We thank the reviewer for his/her interest in our work and for the thoughtful and detailed feedback provided.

Comment:

This manuscript reports on a comprehensive calibration and validation experiment of a hydrological model at large spatial scales. The value of this manuscript is less on learning on a particular model, on the hydrology of a river basin, or on how a suitable and well performing hydrological model should look like for this particular region, but its value is much more on presenting a well-defined procedure of a step-wise multi-variable and multi-criterial calibration scheme towards improving model structure. The study illustrates the use of even coarse and uncertain remote sensing data, including the spatial patterns of state and flux variables (here water storage variations and evapotranspiration) in the calibration and model adjustment approach. In this respect, it provides a valuable example and guideline for other studies in future. I therefore recommend its publication in HESS after considering some comments as listed below

Reply:

We highly appreciate this positive assessment of our manuscript. We will in the following address all specific comments in detail.

Comment:

A thematic/scientific drawback of the study is that a significant improvement of the spatial patterns of simulated ET and storage anomalies could not be achieved within the set of model modifications tested here, in spite of some increase in the performance criterion. In particular, the pattern of areas with high ET in the remote sensing product could not be reproduced by the model. The authors argue that missing lateral sub-surface flow between modelling units could be a reason for this. Can a related modification of the model structure additionally be tested? A more convincing outcome in this direction could also be of benefit for the paper as a whole in demonstrating the value of the multi-criterial calibration approach on spatial patterns.

Reply:

This is indeed a very important point raised by the reviewer. It is true that even after rather extensive model testing and adaption, the representation of spatial pattern did only slightly improve. We also think that it is not implausible to assume that lateral exchange between the model units may explain some of these model deficiencies. Adding such lateral exchange to the model is of course possible, in principle. However, it is not a trivial thing to do in a meaningful way. We believe that this is in itself is a major research topic which warrants several in-depth research papers on its own and which cannot be done as a mere additional hypothesis in this analysis. The underlying reason for this is partly implicit in the nature of the model type used here and partly in the data that are available with current observation technology. Lateral exchange fluxes are (as any fluxes) driven by the interplay between continuous gradients and resistances. Conceptual type models are based on simplified expressions that mimic gradients *within* a model domain only. If such a model is implemented in a spatially distributed way, the individual model domains are the model grid cells. Gradients are thus only defined *within* these grid cells, but not across them. Thus, the head difference between adjacent model grid cells is undefined. In the absence of such gradients it therefore remains unknown between which grid cells such lateral exchange fluxes occur, into which direction and at which rates. As a consequence, these fluxes can only be expressed on basis of free calibration parameters. Depending

on the degree of spatial discretization at the very least 4 additional free calibration parameters (Model E) would here be needed to represent exchange fluxes between the model grid cells. This does not yet include potential exchange fluxes of each grid cell with adjacent grid cells outside the Luangwa basin. In comparison, the fully distributed Model F would even require at least 30 additional calibration parameters. In the model calibration process, these additional parameters and the associated increase in the degree-of-freedom of the model, will very likely lead to improved model performances. This may even extend to the model validation period. Yet, the inclusion of such processes will not be warranted by the available data, as we will have no means of testing whether the additional calibration parameters and the associated exchange fluxes are physically plausible. We may end up with a model that features nice performance metrics for calibration and potentially also for validation, but in which water may flow against real-world elevation and/or pressure gradients or, to express it in a pointed way, water may flow uphill. These unspecified boundary fluxes across grid cells are at the core of the closure problem (Beven, 2006) and touch on the limits of what can be done in hydrology with our current observational technology and the available data. We included this in the discussion of the paper (line 560 in the marked-up version below).

<u>*Comment:*</u>

In this respect, the authors discuss the dominance of the discharge performance criterion within the overall performance measure that was used for calibrating against all variables and criteria. Has the ability of the model to reproduce that spatial ET patterns been tested with varying weights among the different criteria in the overall measure, or for single-criterion calibration the ET patterns only? The (in)ability of the model to represent this feature and the trade-offs relative to other criteria could be another good indicator of structural model deficits.

<u>Reply:</u>

We agree that, as discussed in the paper and mentioned by the Reviewer, the discharge performance criterion had a dominant influence on the multi-criteria model performance. This was especially visible when comparing different models with each other (see Figures 3 and 8 in the manuscript) and could indeed be one of the reasons for the poor simulation of the spatial pattern in the evaporation. To test this, the models were also calibrated with respect to the spatial pattern in the evaporation only. This did improve this variable, but only to a certain extent (Figure 3 below). We discussed this in Section 5 of the original manuscript, where we emphasized that it is plausible to assume that the poor simulation of the spatial pattern was more likely a result of using the same parameters within a specific HRU for all grid cells throughout the basin as also observed in previous studies (Stisen et al., 2018). We expanded the discussion of that issue in the revised manuscript (line 589 in the marked-up version below) and provide Figure 3 below as supplementary material to the manuscript.

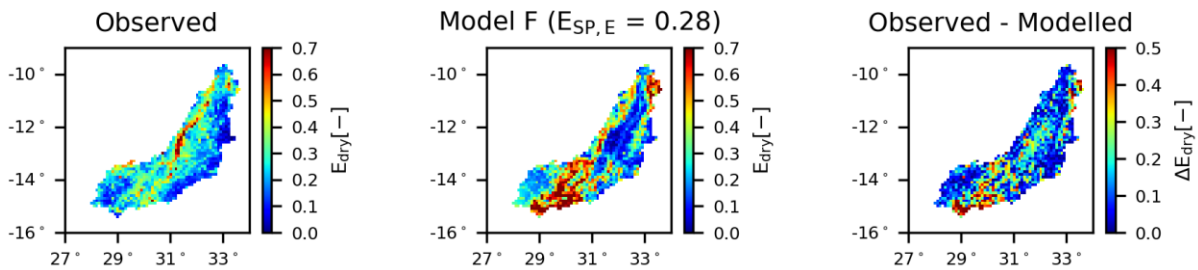

Figure 3: Spatial variability of the normalised total evaporation for Model F averaged over all days within the dry season. The left panel shows the observation according to WaPOR data, the middle panel the model result using the "optimal" parameter set with respect to the spatial pattern in the evaporation ($E_{SP,E}$), and the right panel the difference between the observation and model.

Comment:

The satellite-based data product used here for calibration and validation is an actual evapotranspiration product, isn't it? I suggest to change the term evaporation to ET throughout the manuscript.

Reply:

Thank you for pointing this out. This study used the satellite product WaPOR for calibration and validation. This product describes the actual total evaporation as the sum of the individual components interception, evaporation, soil evaporation and plant transpiration (FAO, 2018). While many studies use the term "evapotranspiration" to describe the combination of different evaporation processes, other studies use the term "evaporation" as overarching term. The FAO defines "evapotranspiration" as the sum of evaporation from different surfaces and transpiration from plants. However, as argued by Savenije (2004), interception and soil evaporation, on the one hand, are functionally completely different processes than transpiration, on the other hand. While the latter is constrained by moisture in the root zone and contains a biological component of water released by stomata before the physical processes of evaporation from the surfaces of leaves occurs, interception and soil evaporation are purely physical processes. We therefore prefer to keep the term "evaporation" as an overarching term as, strictly spoken, there is no single process that can be referred to as "evapotranspiration" (Brutsaert, 1982; Savenije, 2004; 2005).

Comment:

line 114: "In this study, the long-term bias between the discharge, evaporation (WaPOR) and total water storage anomalies (GRACE) was corrected by multiplying the evaporation with a correction factor of 1.08 to close the long-term water balance." What about precipitation? Its amount is required to close the water balance.

Reply:

In general, an open long-term water balance could indeed be a result of uncertainties in precipitation, evaporation and/or discharge. As a result of limited ground observations, it was not possible to validate the satellite-based observations to correct for errors such as bias. In this study, the hydrological model and satellite-based evaporation product WaPOR used the same precipitation product CHIRPS (FAO, 2018). As a result, any bias between modelled and satellite-based evaporation cannot be a result of the precipitation (even though it could be a reason for the water balance non-closure), but can be a result of different underlying methodologies. That is why we chose to only correct the evaporation.

As simple comparison, the model was run with a random parameter set adjusting 1) the observed evaporation (factor 1.08) and 2) the precipitation only (factor 0.93). The modelled evaporation decreased slightly in Scenario 2 compared to Scenario 1 as it decreased with an average of 0.1 mm/d and a maximum of 0.5 mm/d (Figure 4 here below). The model performance with respect to the temporal variation in the evaporation was also very similar to each other with $E_{NS,Basin,E}$ = 0.65 for Scenario 1 and $E_{NS,Basin,E}$ = 0.66 for Scenario 2 since normalised values were used as explained in the paper. We included this in the discussion of the paper (line 579 in the marked-up version below).

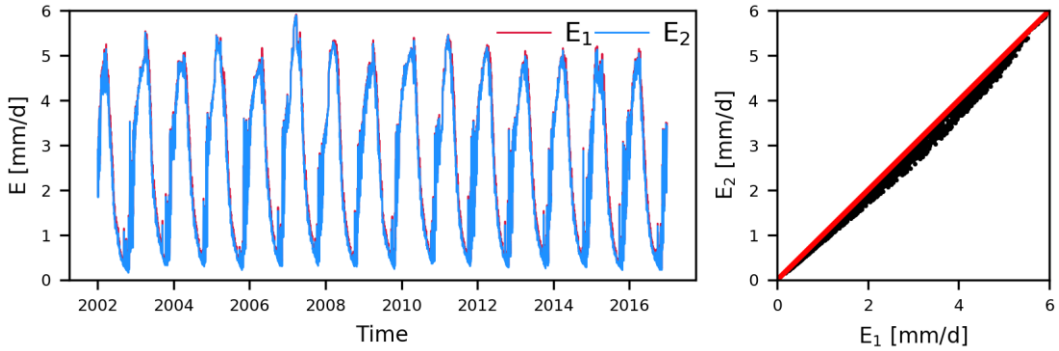

Figure 4: Modelled evaporation for one random simulation when adjusting the 1) observed evaporation (corresponding to E_1), or 2) precipitation only (corresponding to E_2) to close the long term water balance. The red line in the right panel indicates the 1:1 line.

<u>*Comment:*</u>

Figure 5, caption: "Range of model solutions for Models A to F." This should read "Model A" only.

<u>Reply:</u>

Thank you for pointing this out. This is corrected in the revised version of the manuscript.

<u>*Comment:*</u>

Figure 7 and 12: "Spatial variability of the normalised total water storage anomalies for Model A averaged over all days within the dry season."

<u>Reply:</u>

In Figures 7 and 12, the spatial variability of the normalised total water storage anomalies was visualised for Model A. In Figure 12, also Models C and F were included. The difference between both figures is that in Figure 7, the "optimal" parameter set was selected based on discharge data only ($D_{E,Qcal}$), while in Figure 12 multiple-variables were used to for this purpose ($D_{E,ESQcal}$). This was indicated in the second part of the figure caption for both figures. We clarified this in the revised manuscript.

<u>*Comment:*</u>

line 403: "…since the model significantly overestimated storage anomalies in large parts of the basin." This statement can be misleading. After normalisation with Eq.33, a higher value of the model compared to GRACE indicates that the negative storage anomaly of the model is less pronounced than the one of GRACE because the averaging period considered here is the dry season?

<u>Reply:</u>

Thank you for pointing this out. This statement can indeed be confusing. With respect to the spatial pattern, spatially normalised values were compared with each other instead of absolute values. As a result, a higher normalised model value compared to the observation does not necessarily mean the actual (non-normalised) model value was also higher. However, it does mean the simulation results in this cell/region were high relative to the remaining of the basin compared to the observation.

To illustrate this, the simulated and observed dry season total water storage anomalies was visualised considering their normalised values (Figure 5 here below) and actual values (hence non-normalised,

Figure 6 here below). Figure 5 shows that for Model A several cells have higher normalised values compared to the observation (e.g. the marked cell), while the actual modelled values are lower than the observation as shown in Figure 6 (please note the scale bar in Figure 6 is different for the observation and model). However, both Figures 5 and 6 show similar spatial pattern. For example in Figure 6, the marked cell in the modelled map shows a high value compared to the remaining of the basin, which was also the case in Figure 5. As a result, the spatial pattern was preserved when normalising the maps, also when calculating only with negative values as is the case when considering the total water storage map averaged over the dry season.

We reformulated this statement to highlight this and avoid any confusion (line 416 in the marked-up version below).

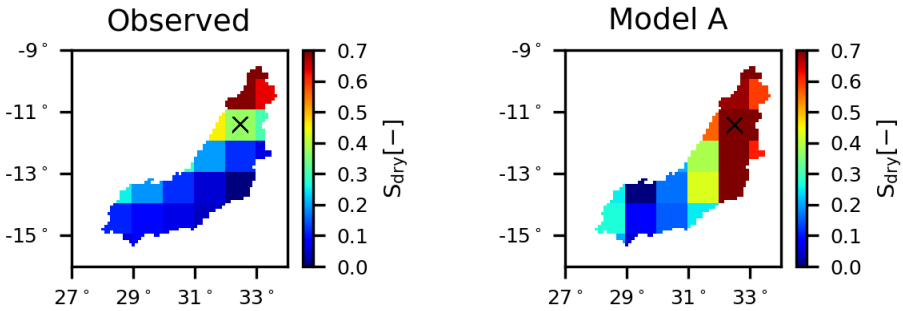

Figure 5: Spatial variability of the *normalised* total water storage anomalies for Model A averaged over all days within the dry season. The left panel shows the observation according to GRACE data, and the right panel the model result using the "optimal" parameter set with respect to discharge ($D_{E,Qcal}$).

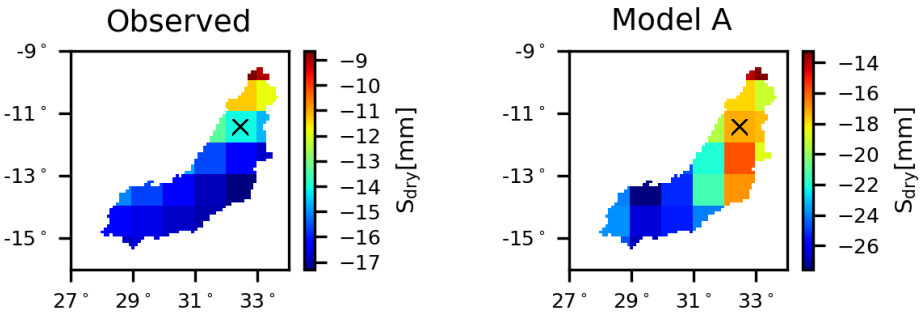

Figure 6: Spatial variability of the total water storage anomalies (*not normalised*) for Model A averaged over all days within the dry season. The left panel shows the observation according to GRACE data, and the right panel the model result using the "optimal" parameter set with respect to discharge ($D_{E,Qcal}$).

<u>*Comment:*</u>

For model calibration, a simple Monte-Carlo parameter sampling strategy is applied in spite of the fact that there are effective multi-criterial calibration methods around that can be expected to result in parameters sets with higher model performance than obtained here, such as Borg or other evolutionary algorithms. While I am not necessarily recommending to use such algorithms for the present study as its aim is rather on comparative model evaluation and development than on pure parameter optimization, the authors may explain their choice.

<u>Reply:</u>

Thank you for this comment. There are indeed many multi-criteria calibration methods that can be very useful to find the "optimal" parameter set and associated posterior parameter distributions. However, the goal of this study was to explore the information content of multiple variables using multiple model evaluation criteria for step-wise model structure development and calibration. For this

purpose, it was important to use the same parameter sets for all models as common starting point to rule out the effect of different parameter sets. This was efficiently possible with the Monte-Carlo parameter sampling strategy, which, in addition also allowed a relatively straight-forward and intuitive interpretation and communication of the results. We added an explanation of this choice in the revised manuscript (line 275 in the marked-up version below).

Responses to comments Anonymous Referee #2

We thank the reviewer for his/her interest in our work and for the thoughtful and detailed feedback provided.

<u>*Comment:*</u>
The manuscript is very well written and nicely illustrated. It deals with an interesting topic of model structure and gaining information from satellite data in a data sparse basin.

<u>Reply:</u>
We highly appreciate this positive assessment of our manuscript. We will in the following address all specific comments in detail.

<u>*Comment:*</u>
It makes the paper less interesting that there are essentially no major changes to the simulated spatial patterns of ET across Model A-F (e.g. Figure 11) and that the general simulated spatial pattern does not resemble the observed in any way. It seems that you are not addressing the most important issues in your set of alternative models (B-F). The general interest of the manuscript would increase greatly if some of your hypothesis would at least produce a different pattern from Model A.
The simulated spatial pattern will be a reflection of both model structure and parametrizations scheme, in my experience mainly the latter. Therefore, I strongly suggest that you add a set of model setups that reflect different spatial parameterization schemes. In your discussion you address this limitation nicely, but I also feel that the manuscript would benefit greatly from an additional analysis illustrating the importance of model parameterization and parameter distribution on the simulated spatial patterns. Basically, even the most sophisticated model structure cannot be expected to reproduce a correct spatial pattern without a sound, flexible and spatially explicit parametrizations scheme.
I think you can logically add such an analysis to your manuscript in line with the idea of learning from satellite observations, by letting the observed spatial patterns guide your spatial parametrization approach. Such a parametrization scheme could also include transfer functions or simple spatial relations to known variables such as elevation, slope, soiltype, LAI etc.

<u>Reply:</u>
We completely agree with the observation of the Reviewer that there are indeed only limited improvements with respect to the spatial pattern of the evaporation when looking at Figure 11 in the manuscript. However, this figure includes only a selection of models with the best results applying the second calibration strategy using multiple variables. Additional figures were included in the Supplementary Material showing the spatial pattern for all Models A – F for both calibration strategies, hence using discharge (Figure S6 in the Supplementary Material) or multiple variables (Figure S10 in the Supplementary Material). With these graphs the effect of different model structures and calibration strategies on the spatial variability of the evaporation was illustrated.
On the one hand, when calibrating with respect to discharge only, the spatial pattern of the evaporation changed depending on the model structure, but remained poorly reproduced for all Models B – F compared to the benchmark Model A (Figure S6 in the Supplementary Material). On the

other hand, when calibrating with respect to multiple variables, the effect of the model structure was less significant (Figure S10 in the Supplementary Material). Only Model D showed clear differences compared to Model A, for example the dry season average evaporation was significantly overestimated in the wetland areas along the river in contrast to the observation (highlighted in Figure 7 here). In other words, the results in this study illustrate the spatial pattern of the evaporation did change with when changing the model structure or applying different calibration strategies.

However, the improvements remained very limited compared to the benchmark and the modelled spatial pattern remained poorly reproduced. We of course also completely agree with the reviewer, that at least some of the remaining problems are likely to be related to the actual distribution of parameters. As recommended by the Referee and mentioned in the discussion of our manuscript, this could, among others, be further improved by applying spatially distributed parameter sets. However, this will increase the number of calibration parameters considerably and hence also the degree of freedom such that many different combinations of parameters result in similar model performances, but do not necessarily reproduce all hydrological processes well. Therefore, it is important to have sufficient data to support spatially distributed parameters to avoid this problem of equifinality and improve the model realism. To limit the problems related to equifinalty, indeed a transfer function approach with global parameters, such as the MPR scheme developed for the mhm model (Samaniego et al., 2010; Kumar et al., 2013), could prove highly valuable. However, the design and choice of suitable and meaningful transfer functions in itself would require substantial additional analysis to assess the information content of different variables to support spatial parameter distribution (for example NDVI, LAI, topography, soil type, vegetation type or climate) and to test different distribution methods, which would warrant probably several standalone research papers. Therefore, as a first test, we analysed the effect of spatially distributing one calibration parameter related to the evaporation, the maximum interception storage (I_{max}), using a linear transfer function with LAI data similar to previous studies (Samaniego et al., 2010) and using Model F as basis. This did not result in obvious improvements as shown in Figure 8 here.

We added an in-depth discussion on the risks and potentials of parameter distribution strategies in the revised manuscript (line 551 in the marked-up version below). However, this paper focused on the added value of satellite-based evaporation and total water storage observations for model structure development and parameter selection. Therefore, additional analysis on parameter distribution strategies was considered outside the scope of this study.

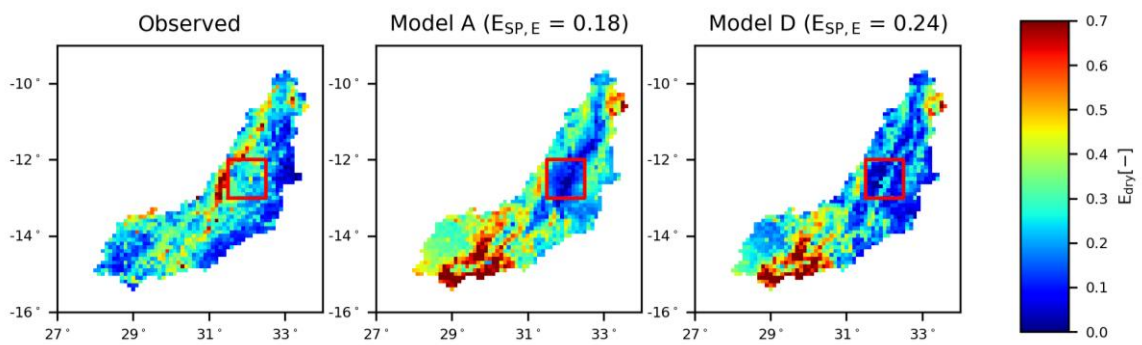

Figure 7: Observed and modelled spatial variability of the normalised total evaporation averaged over all days within the dry season for Models A and D using the "optimal" parameter set with respect to multiple variables ($D_{E,ESQcal}$).

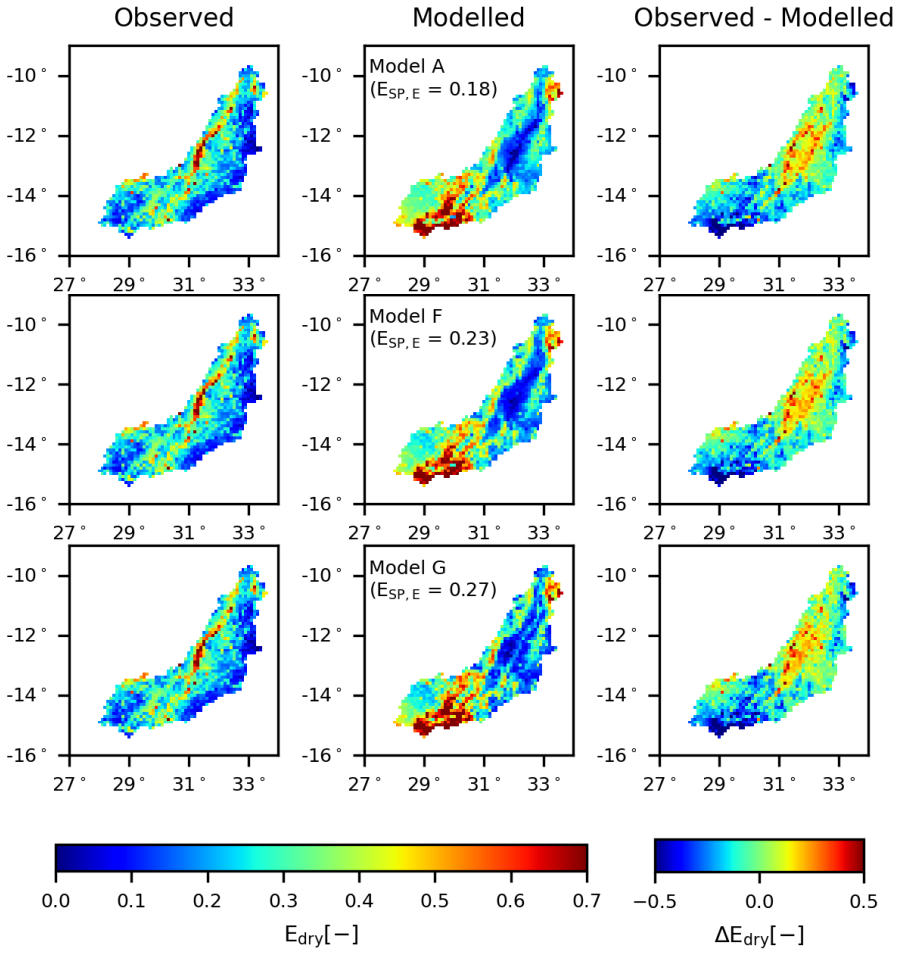

Figure 8: Spatial variability of the normalised total evaporation for Models A, F and G averaged over all days within the dry season. The left panel shows the observation according to WaPOR data, the middle panel the model result using the "optimal" parameter set with respect to multiple variables ($D_{E,ESQcal}$), and the right panel the difference between the observation and model.

Comment:

In sections 3.1.2 and 3.1.3 it is unclear why the different structural changes were applied. The title suggests that you are learning from satellite data, but it is not clear to me how you learn and how you used the satellite data to make new hypothesis about model structure. It is mentioned several times that you diagnose model deficiencies, however it is unclear to me how this is done. I believe this should be elaborated in a revised manuscript.

Reply:

In this study, the model structure was adapted iteratively based on the results of the benchmark Model A or subsequently developed models. Therefore, the paper was structured such that first the benchmark Model A was explained (Section 3.1.1), followed by a brief description of the model adaptations (Section 3.1.2 and 3.1.3). Based on the deficiencies of the benchmark Model A diagnosed and highlighted in Section 4.1.3, the first set of model adaptations were developed (Models B – D) as explained in Section 4.2. Similarly, based on

the deficiencies diagnosed in Models B – D as explained in Section 4.2.3, the second set of model adaptations were developed (Models E – F) as explained in Section 4.3. Therefore, as the model adaptations depended on the model results, they were explained only briefly in Section 3 and more detailed in Section 4.
However, we updated the manuscript to more specifically and explicitly emphasize the role of satellite observations when diagnosing deficiencies and changing the model structure. The satellite-based evaporation and total water storage observations were used for model evaluation with respect to their spatial and temporal variability to detect model deficiencies in these system-internal variables. In addition, satellite-based evaporation data was used to evaluate whether temporal variations in the evaporation from a specific hydrological response unit, in this case wetland dominated areas, were reproduced well. In all cases, the variables were normalised to focus on dynamic fluctuations and spatial pattern rather than absolute values to avoid incorporating bias uncertainties in the satellite data.

Comment:
An issue with the use of the SPAEF metric for the water storage anomaly might be, that the histogram component of the metric, might not be so meaningful when applied to the coarse spatial resolution of 1 deg., with very few grids. You could look into this by examining the three components of the metric separately. I do not suggest to put this analysis in the paper, but it might be mentioned in a discussion.

Reply:
Thank you for pointing this out. This could indeed provide some interesting insights. Upon closer inspection of $E_{SP,E}$ and $E_{SP,S}$ for the "optimal" parameter sets for Models A — F according to the first calibration strategy using discharge only, we discovered different ranges for the individual components as indicated in Table 1 here. According to these numbers, differences in E_{SP} were mainly a result of differences in β (coefficient of variation), whereas the component with the smallest difference was α (Pearson correlation coefficient). The range in γ (fraction of histogram intersection) is indeed smaller for the total water storage where the grid size is larger compared to the evaporation. For future studies, it would be interesting to examine the different components more detailed to assess the overall information content of this model performance metric E_{SP} to identify feasible parameter sets across different spatial scales. We elaborated on this in detail in the discussion (line 590 in the marked-up version below).

Table 1: Overview of model performance ranges with respect to the spatial pattern (E_{SP}) of evaporation and total water storage including the corresponding individual components (α: Pearson correlation coefficient, β: coefficient of variation and γ: fraction of histogram intersection) using the "optimal" parameter sets according to the first calibration strategy using discharge only for Models A – F.

	Evaporation	Total water storage
α	0.12 – 0.23	0.43 – 0.54
β	0.55 – 1.23	0.62 – 1.16
γ	0.43 – 0.81	0.07 – 0.23
E_{SP}	-0.04 – 0.17	-0.17 – 0.08

<u>*Comment:*</u>

Did you perform any sensitivity analysis to explore which model parameters, structures or compartments were most important for simulating spatial patterns and temporal dynamics?

<u>Reply:</u>

While we agree that an analysis of the respective sensitivities of individual aspects in the modelling processes could indeed provide additional insights into factors influencing the spatial and temporal variability we did not explicitly perform such a detailed analysis as this would have further inflated an already long, detailed and complex manuscript. However, the model results did shed light into the importance of several different aspects. For instance, when considering the model parameter sensitivity, of the generated parameter sets, the best 5% were selected with respect to discharge or multiple variables. Other combinations of variables to identify feasible parameter sets, for example discharge and evaporation or only evaporation, were also tested but excluded from the manuscript as they did not add further value and to keep the story concise. Regardless of the calibration strategy, the modelled spatial pattern of the evaporation and total water storage remained significantly different from the observation when using the benchmark model. Also, the evaporation from wetland areas was reproduced poorly regardless of which variables were combined with discharge in the calibration procedure. This indicated these deficiencies were more likely a result of uncertainties in the model structure, parameterization or data rather than of the selected parameter sets. That is why the model structure was adjusted stepwise. While the spatial pattern mainly improved when incorporating multiple variables in the calibration procedure (compare Figures S6 and S10 in the Supplementary Material), the evaporation from wetland areas benefited the most from the changed model structure (Figure 10 in the manuscript).

A more systematic sensitivity analysis could provide valuable information on how to further improve the spatial and temporal variability of the system-internal variables, but this was considered outside the scope of this study. We included this as recommendation in the revised manuscript (line 610 in the marked-up version below).

<u>*Comment:*</u>

3.1.2 First model adaptation (Models B – D): Please describe what made you chose to make exactly these structural changes?

Reply:
The first set of model adaptations (Models B—D) depended on the results of the benchmark Model A. Therefore, the choice of adaptions was explained after having highlighted the deficiencies of Model A (Section 4.1.3) in Section 4.2. See also our reply on a previous comment on Sections 3.1.2 and 3.1.3. We acknowledge that this is not a conventional paper set-up, but we believe an iterative analysis warrants a partly iterative description of the steps.

Comment:
Line 522: How can you argue that you significantly improve the spatial pattern of ET? Your $E_{SP,ET}$ might increase slightly from 0.18 to 0.23, but looking at the maps in Figure 11, Model F has the same pattern as Model A and none of them resemble the observed pattern.

Reply:
In this paper, the effect of using 1) multiple variables for model calibration and 2) alternative model structures on the spatial-temporal variability of among others evaporation was assessed. With respect to the spatial pattern, the results were illustrated with respect to the model performance values ($E_{SP,E}$) and figures showing the spatial pattern. In the manuscript, only a selection of these figures was shown (Figure 11), whereas in the Supplementary Material all remaining figures were included (Figures S6 and AS10).
In Line 522, we compared both calibration strategies for Model F. When calibrating Model F using discharge only, the spatial pattern of the evaporation was poorly reproduced (Figures 9b here and S6 in the Supplementary Material). This improved considerably when calibrating using multiple variables (Figures 9c here and 11 in the manuscript) as the evaporation was lower in the south-west and east of the basin similar to the observation. We clarified this in the revised manuscript to avoid any confusion and also tone down the language to avoid confusion and misleading interpretation of our descriptions by the reader (line 537 in the marked-up version below).
We absolutely agree with the Referee that the spatial pattern in the evaporation remain poorly reproduced. However, the goal of the statement mentioned by the Reviewer was to illustrate the added value of satellite observations to improve the representation of spatial *and* temporal variability of *multiple variables*. This paper showed that only limited improvements were observed in the spatial pattern with the chosen model structures and parameterization.

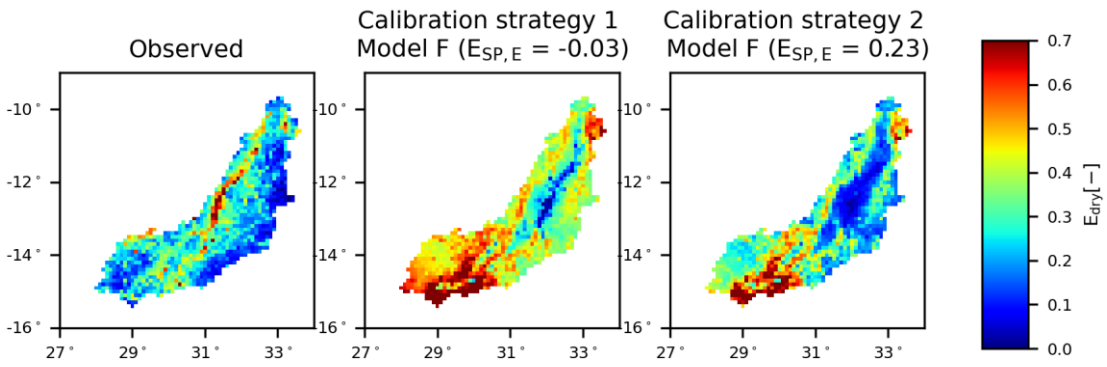

Figure 9: Spatial variability of the normalised total evaporation averaged over all days within the dry season according to WaPOR (observation) and Model F for both calibration strategies using discharge (Calibration strategy 1, $D_{E,Qcal}$) or multiple variables (Calibration strategy 2, $D_{E,ESQcal}$).

Comment:

Figure 11 and similar figures: I suggest that you condense the figures to make less white space and thereby allow the reader to make a better visual examination of the observed and simulated patterns. You can skip the lat long degree for instance, they can be added to figure 1 instead.

Reply:

Thank you for this feedback. We condensed these figures as much as possible to allow for a better visual comparison.

Comment:

Line 59: " to spatial pattern of" change to " to the spatial pattern of" or to " to spatial patterns of" Also in line 66 + 79 "spatial pattern and temporal dynamics" I suggest writing "spatial patterns"

Reply:

Thank you for pointing this out. We corrected this in the revised manuscript.

Comment:

Line 78: "for a large river systems" change to "for a large river system"

Reply:

Thank you for pointing this out. We corrected this in the revised manuscript.

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Marked-up version of the revised manuscript

Learning from satellite observations: increased understanding of catchment processes through stepwise model improvement

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Abstract. Satellite observations can provide valuable information for a better understanding of hydrological processes and thus serve as valuable tools for model structure development and improvement. While model calibration and evaluation has in recent years started to make increasing use of spatial, mostly remotely-sensed information, model structural development largely remains to rely on discharge observations at basin outlets only. Due to the ill-posed inverse nature and the related equifinality issues in the modelling process, this frequently results in poor representations of the spatiotemporal heterogeneity of system-internal processes, in particular for large river basins. The objective of this study is thus to explore the value of remotely-sensed, gridded data to improve our understanding of the processes underlying this heterogeneity and, as a consequence, their quantitative representation in models through a stepwise adaptation of model structures and parameters. For this purpose, a distributed, process-based hydrological model was developed for the study region, the poorly gauged Luangwa river basin. As a first step, this benchmark model was calibrated to discharge data only and, in a post-calibration evaluation procedure, tested for its ability to simultaneously reproduce (1) the basin-average temporal dynamics of remotely-sensed evaporation and total water storage anomalies, and (2) their temporally-averaged spatial patterns. This allowed the diagnosis of model structural deficiencies in reproducing these temporal dynamics and spatial patterns. Subsequently, the model structure was adapted in a step-wise procedure, testing five additional alternative process hypotheses that could potentially better describe the observed dynamics and pattern. These included, on the one hand, the addition and testing of alternative formulations of groundwater upwelling into wetlands as function of the water storage and, on the other hand, alternative spatial discretizations of the groundwater reservoir. Similar to the benchmark, each alternative model hypothesis was, in a next step, calibrated to discharge only and tested against its ability to reproduce the observed spatiotemporal pattern in evaporation and water storage anomalies. In a final step, all models were re-calibrated to discharge, evaporation and water storage anomalies simultaneously. The results indicated that (1) the benchmark model (Model A) could reasonably well reproduce the time series of observed discharge, basin-average evaporation and total water storage. In contrast, it poorly represented time series of evaporation in wetland dominated areas as well as the spatial pattern of evaporation and total water storage. (2) Step-wise adjusting the model structure (Models B – F) suggested that Model F, allowing for upwelling groundwater from a distributed representation of the groundwater reservoir and (3) simultaneously calibrating the model with respect to multiple variables, i.e. discharge, evaporation and total water storage anomalies, provided the best representation of all these variables with respect to their temporal dynamics and spatial patterns, except for the basin-average temporal dynamics in the total water storage anomalies. It was shown that satellite-based evaporation and total water storage anomaly data are not only valuable for multi-criteria calibration, but can play an important role in improving our understanding of hydrological processes through diagnosing model deficiencies and step-wise model structural improvement.

1. Introduction

Traditionally, discharge observations at basin outlets are used for hydrological model development and calibration, which can be a robust strategy in small watersheds with relatively uniform characteristics such as topography and land cover, but not for larger, heterogeneous basins (Blöschl and Sivapalan, 1995; Daggupati et al., 2015). As a result, temporal dynamics of discharge may be well reproduced. This however, does not ensure that the spatial patterns and temporal dynamics of model internal storage and flux variables provide a meaningful representation of their real pattern and dynamics (Beven, 2006b; Kirchner, 2006; Clark et al., 2008; Gupta et al., 2008; Hrachowitz et al., 2014; Garavaglia et al., 2017). Especially in large, poorly gauged basins this traditional model calibration and testing method is likely to result in a poor representation of spatial variability (Daggupati et al., 2015) due to equifinality and the related the boundary flux problem (Beven, 2006b).

An increasing number of satellite-based observations have become available over the last decade, giving us insight into a wide range of hydrology-relevant variables, including precipitation, total water storage anomalies, evaporation, surface soil moisture or river width (Xu et al., 2014; Jiang and Wang, 2019). These data are increasingly used as model forcing or for parameter selection and model calibration (e.g. Li et al., 2015; Mazzoleni et al., 2019; Tang et al., 2019).

Many studies used a single satellite product in the calibration procedure, some of them additionally using discharge data, others not. For instance, hydrological models have been calibrated with respect to evaporation (e.g. Immerzeel and Droogers, 2008; Winsemius et al., 2008; Vervoort et al., 2014; Bouaziz et al., 2018; Odusanya et al., 2019), water storage anomalies from GRACE (Gravity Recovery and Climate Experiment, Werth et al., 2009), river width (Revilla-Romero et al., 2015; Sun et al., 2018) or river altimetry (Getirana, 2010; Michailovsky et al., 2013; Sun et al., 2015; Hulsman et al., 2019).

Other studies simultaneously calibrated hydrological models with respect to multiple remotely-sensed variables, but only exploiting basin-average time series, without consideration for spatial patterns (e.g. Milzow et al., 2011; López et al., 2017; Kittel et al., 2018; Nijzink et al., 2018). On the other hand, some studies exclusively calibrated models to spatial patterns of ~~the~~ observed variables (Stisen et al., 2011; Koch et al., 2016; Mendiguren et al., 2017; Demirel et al., 2018; Zink et al., 2018). As most satellite-based observations such as evaporation are not measured directly but are themselves a result of underlying models using satellite data as input (Xu et al., 2014), more focus has been recently placed on calibration to the relative spatial variability instead of using absolute magnitudes (Stisen et al., 2011; van Dijk and Renzullo, 2011; Dembélé et al., 2020).

To fully exploit the information content of satellite-based observations, simultaneous model calibration on both, temporal dynamics and spatial patterns of multiple variables has the potential to improve the representation of spatiotemporal variability and, linked to that, their underlying model internal processes and therefore the model realism (Rientjes et al., 2013; Rakovec et al., 2016; Herman et al., 2018). Strikingly, only a few studies so far used satellite-based observations to calibrate with respect to the temporal and spatial variation simultaneously (Rajib et al., 2018; Dembélé et al., 2020).

In general, most studies that made use of remotely-sensed data for model applications have exclusively addressed the problem of parameter selection and thus model calibration. However, as models are always abstract and simplified representations of reality, every model structure needs to be understood as a hypothesis to be tested (Clark et al., 2011; Fenicia et al., 2011; Hrachowitz and Clark, 2017). Yet, most studies on model structural improvement have so far only relied on spatially aggregated variables (Fenicia et al., 2008; Kavetski and Fenicia, 2011; Hrachowitz et al., 2014; Nijzink et al., 2016), while spatial data remain rarely used for that purpose (e.g. Fenicia et al., 2016; Roy et al., 2017).

The overall objective of this paper is therefore to explore the simultaneous use of spatial patterns and temporal dynamics of satellite-based evaporation and total water storage observations for a step-wise structural improvement and calibration of hydrological models for a large river system~~s~~ in a semi-arid, data scarce region. More specifically, we tested the research hypotheses that (1) spatial patterns and temporal dynamics in satellite-based evaporation and water storage anomaly data contain relevant information to diagnose and to iteratively improve on model structural deficiencies and that (2) these data, when simultaneously used with discharge data for calibration, do contain sufficient information for a more robust parameter selection.

2. Site description

The Luangwa River in Zambia is a large, mostly unregulated tributary of the Zambezi with a length of about 770 km (Figure 1). This poorly gauged river basin has an area of 159,000 km^2 which is mostly covered with deciduous forest, shrubs and savanna and where an elevation difference up to 1850 m can be found between the highlands and low lands along the river (The World Bank, 2010; Hulsman et al., 2019). In this semi-arid basin, the mean annual evaporation (1555 mm yr^{-1}) exceeds the mean annual precipitation (970 mm yr^{-1}).

The Luangwa River flows into the Zambezi upstream of the Cahora Bassa Dam which is used for hydropower production, and flood and drought protection. The operation of this dam is very difficult since there is only limited information available from the poorly gauged upstream tributaries (SADC, 2008; Schleiss and Matos, 2016). As a result, the local population has in the past suffered from severe floods and droughts (ZAMCOM et al., 2015; Schumann et al., 2016).

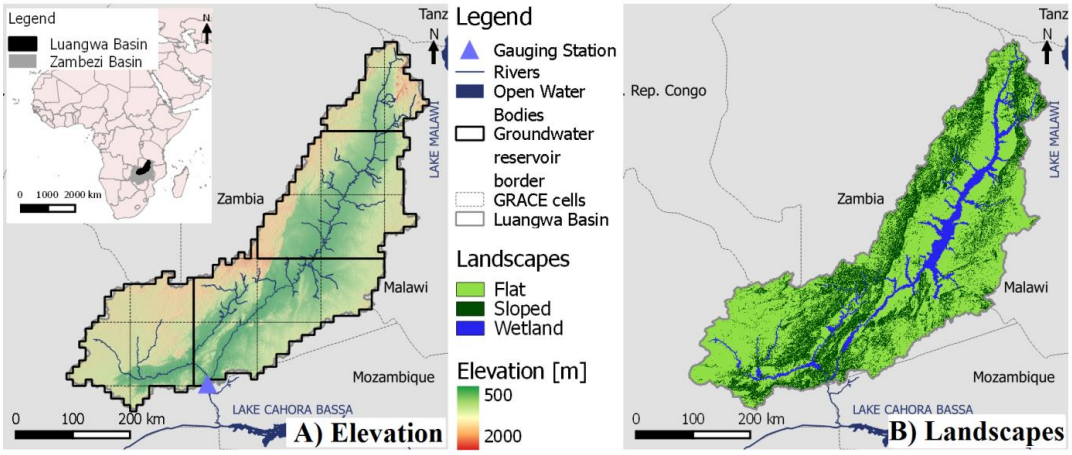

Figure 1: Map of the Luangwa River Basin in Zambia with A) the elevation, groundwater reservoir units at 0.1° resolution and 1° grid according to GRACE, and B) the main landscape types

2.1 Data availability

2.1.1 In-situ discharge observations

Historical daily in-situ discharge data was available from the Zambian Water Resources Management Authority at the Great East Road Bridge gauging station, located at 30º 13’ E and 14º 58’ S (Figure 1), for the time period 2004 to 2016 yet containing considerable gaps resulting in a temporal coverage of 31%.

2.1.2 Spatially gridded observation

Spatially gridded data were used for a topography-based landscape classification into hydrological response units (HRU, Savenije, 2010), as model forcing (precipitation and temperature) and for parameter selection (evaporation and total water storage, see Table 1).

More specifically, topography was extracted from GMTED with a spatial resolution of 0.002º (Danielson and Gesch, 2011). Daily precipitation data was extracted from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) with a spatial resolution of 0.05º. Monthly temperature data extracted from CRU at a spatial resolution of 1º was used to estimate the potential evaporation applying the Hargreaves method (Hargreaves and Samani, 1985; Hargreaves and Allen, 2003). These monthly observations were interpolated to daily timescale using daily averaged in-situ temperature measured at two locations with the coordinates 28º 30’ E, 14º 24’ S and 32º 35’ E, 13º 33’ S. The satellite-based total evaporation data was extracted from WaPOR (Water Productivity Open-access portal, FAO, 2018) version 1.1 as it proved to perform well in African river basins (Weerasinghe et al., 2019). This product was available on 10-day temporal and 250 m spatial resolution. Satellite-based observations on the total water storage anomalies were extracted from the Gravity Recovery and Climate Experiment

(GRACE). With two identical GRACE satellites, the variations in the Earth's gravity field were measured to detect regional mass changes which are dominated by variations in the terrestrial water storage after having accounted for atmospheric and oceanic effects (Landerer and Swenson, 2012; Swenson, 2012). In this study, the long-term bias between the discharge, evaporation (WaPOR) and total water storage anomalies (GRACE) was corrected by multiplying the evaporation with a correction factor of 1.08 to close the long-term water balance.

The gridded information provided for the precipitation, temperature and evaporation were rescaled to the model resolution of 0.1°. If the resolution of the satellite product was higher than 0.1°, then the mean of all cells located within each model cell was used. Otherwise, each cell of the satellite product was divided into multiple cells such that the model resolution is obtained, retaining the original value. In contrast, the modelled total water storage was rescaled to 1°, the resolution of the GRACE data set, by taking the mean.

Table 1: Data used in this study

	Time period	Time Resolution	Spatial resolution	Product Name	Source
Digital elevation map	NA	NA	0.002°	GMTED	(Danielson and Gesch, 2011)
Precipitation	2002 – 2016	Daily	0.05°	CHIRPS	(Funk et al., 2014)
Temperature	2002 – 2016	Monthly	0.5°	CRU	(University of East Anglia Climatic Research Unit et al., 2017)
Evaporation	2009 – 2016	10-day	0.00223°	WaPOR	(FAO, 2018; FAO and IHE Delft, 2019)
Total water storage	2002 – 2016	Monthly	1°	GRACE	(Swenson and Wahr, 2006; Landerer and Swenson, 2012; Swenson, 2012)
Discharge (Luangwa Bridge gauging station)	2004 – 2016	Daily	NA	NA	WARMA

3. Modelling approach

A previously developed and tested (Hulsman et al., 2019) distributed, process-based hydrological model was implemented for the Luangwa Basin, see Section 3.1 for more information. This benchmark model (Model A) was calibrated with respect to discharge for the time period 2002 – 2012 and validated for the time period 2012 – 2016 with respect to discharge, evaporation and total water storage anomalies. Then, the model was calibrated with respect to all above variables, hence discharge, evaporation and total water storage anomalies simultaneously, for the time period 2002 – 2012 and validated with respect to the same variables for the time period 2012 – 2016. Model deficiencies were then diagnosed for this benchmark model (Model A) based on the results of both calibration strategies.

Next, model structure changes were applied creating Models B – D to improve the deficiencies found in Model A. These changes concerned the groundwater upwelling into the unsaturated zone as explained in Section 4.2.1. The same calibration and validation strategies as applied to Model A were applied to Models B – D. Model improvements were evaluated and further deficiencies were diagnosed for these models based on the calibration and validation results.

To improve the deficiencies diagnosed in Models B – D, further model structural changes, i.e. increased levels of spatial discretisation of the saturated zone as explained in Section 4.3.1, resulted in Models E and F. Similar to the previous models, the same calibration and validation strategies were applied to Models E and F, and model improvements and deficiencies were diagnosed based on the calibration and validation model performances.

The calculation of the model performance with respect to discharge, evaporation and total water storage are explained in Section 3.2. The calibration and validation procedures are described in Sections 3.3 and 3.4.

3.1 Hydrological models

3.1.1 Benchmark model (Model A)

This model is a process-based hydrological model developed in a previous study by Hulsman et al. (2019) for the Luangwa basin. In this model, the water accounting was distributed by discretizing the basin and using spatially distributed forcing data while the same model structure and parameter set were used for the entire basin. Each 0.1° x 0.1° model cell was then further discretized into functionally distinct landscape classes, i.e. hydrological response units (HRU), inferred from topography (Figure 1B), but connected by a common groundwater component (Euser et al., 2015) following the FLEX-Topo modelling concept (Savenije, 2010) which was previously successfully applied in many different and climatically contrasting regions (Gao et al., 2014; Gharari et al., 2014; 2016; Nijzink et al., 2016). Here, the landscape was classified based on the local slope and "Height-above-the-nearest-drainage" (HAND, Rennó et al., 2008) into sloped areas (slope ≥ 4%), flat areas (slope < 4%, HAND ≥ 11 m) and wetlands (slope < 4%, HAND < 11 m). For this purpose, the drainage network was derived from a digital elevation map extracted from GMTED (Section 2.1.2) using a flow accumulation map after having burned-in a river network map extracted from OpenStreetMap (https://wiki.openstreetmap.org/wiki/Shapefiles) to obtain an as accurate as possible drainage network as done successfully in previous studies (Seyler et al., 2009). According to this classification, the wetland areas covered 8% of the basin, flat areas 64% and sloped areas 28% (Figure 1).

The model consisted of different storage components schematised as reservoirs representing interception and unsaturated storage, as well as a slow responding reservoir, representing the groundwater and a fast responding reservoir (Figure 2). The water balance for each reservoir and the associated constitutive equations are summarised in Table 2. The individual model structures of each parallel HRU were very similar. Functional differences between HRUs were thus mostly accounted for by different parameter sets. To allow the use of partly overlapping prior parameter distributions while maintaining relationships between parameters of individual HRUs that are consistent with our physical understanding of the system and to limit equifinality, model process constraints (Gharari et al., 2014; Hrachowitz et al., 2014) were applied for several parameters (Table 3). For instance, in the Luangwa Basin, the sloped areas are dominated by dense vegetation, suggesting higher interception capacities and larger storage capacities in the unsaturated zone compared to the remaining part of the basin. In addition, for each HRU the model structure was adjusted where necessary to include processes unique to that area. For instance, water percolates and recharges the groundwater system in sloped and flat areas whereas in wetlands this was assumed to be negligible due to groundwater tables that are very shallow and thus close to the surface.

The runoff was first calculated for each individual grid cell. A simple routing scheme based on the flow direction and constant flow velocity as calibration parameter was applied to estimate the flow at the outlet. In total, this model consisted of 16 calibration parameters with uniform prior distributions and constraints as summarized in Table 3.

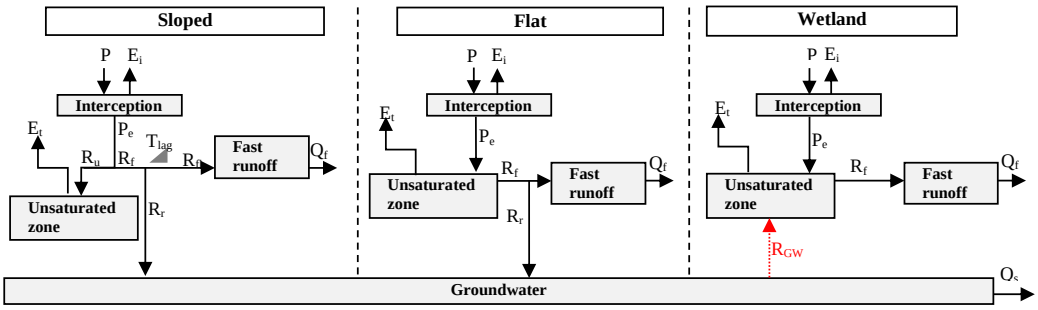

Figure 2: Schematisation of the model structure applied to each grid cell. Symbol explanation: precipitation (*P*), effective precipitation (P_e), interception evaporation (E_i), plant transpiration (E_t), infiltration into the unsaturated root zone (R_u), drainage to fast runoff component (R_f), delayed fast runoff (R_{fl}), lag time (T_{lag}), groundwater recharge (R_r), upwelling groundwater flux (R_{GW}), fast runoff (Q_f), groundwater/slow runoff (Q_s).

Table 2: Equations applied in the hydrological model. <u>Fluxes</u> [mm d^{-1}]: precipitation (P), effective precipitation (P_e), potential evaporation (E_p), interception evaporation (E_i), plant transpiration (E_t), infiltration into the unsaturated zone (R_u), drainage to fast runoff component (R_f), delayed fast runoff (R_{fl}), groundwater recharge (R_r for each relevant HRU and $R_{r,tot}$ combining all relevant HRUs), groundwater upwelling (R_{GW} for each relevant HRU and $R_{GW,tot}$ combining all relevant HRUs), fast runoff (Q_f for each HRU and $Q_{f,tot}$ combining all HRUs), groundwater/slow runoff (Q_s), total runoff (Q_m). <u>Storages</u> [mm]: storage in interception reservoir (S_i), storage in unsaturated root zone (S_u), storage in groundwater/slow reservoir (S_s), storage in fast reservoir (S_f). <u>Parameters</u>: interception capacity (I_{max}) [mm], maximum upwelling groundwater (C_{max}) [mm d^{-1}], maximum root zone storage capacity (S_{umax}) [mm], reference storage in the saturated zone ($S_{s,ref}$) [mm], splitter (W) [-], shape parameter (β) [-], transpiration coefficient (C_e) [-], time lag (T_{lag}) [d], exponent (γ) [-], reservoir time scales [d] of fast (K_f) and slow (K_s) reservoirs, areal weights for each grid cell (p_{HRU}) [-],time step (Δt) [d]. Model calibration parameters are shown in bold letters in the table below. The equations were applied to each hydrological response unit (HRU) unless indicated differently.

Reservoir system	Water balance equation	Equation	Process functions	Equation
Interception	$\frac{\Delta S_i}{\Delta t} = P - P_e - E_i$	(1)	$E_i = \min\left(E_p, \min\left(P, \frac{\boldsymbol{I_{max}}}{\Delta t}\right)\right)$	(2)
			$P_e = P - E_i$	(3)
Unsaturated zone	Sloped: $\frac{\Delta S_u}{\Delta t} = R_u - E_t$	(4)	$E_t = \min\left((E_p - E_i), \min\left(\frac{S_u}{\Delta t}, (E_p - E_i) \cdot \frac{S_u}{\boldsymbol{S_{u,max}}} \cdot \frac{1}{\boldsymbol{C_e}}\right)\right)$	(5)
	Flat: $\frac{\Delta S_u}{\Delta t} = P_e - E_t - R_f$	(6)	Model A: $R_{GW} = 0$	(7)
	Wetland: $\frac{\Delta S_u}{\Delta t} = P_e - E_t - R_f + R_{GW}$	(8)	Model B: $R_{GW} = \min\left(\left(1 - \frac{S_u}{\boldsymbol{S_{u,max}}}\right) \cdot \boldsymbol{C_{max}}, \frac{\frac{S_s}{\Delta t}}{p_{HRU}}\right)$	(9)
			Model C, E, F: $R_{GW} = \min\left(\frac{\min(S_s, \boldsymbol{S_{s,ref}})}{\boldsymbol{S_{s,ref}}} \cdot \boldsymbol{C_{max}}, \frac{\frac{S_s}{\Delta t}}{p_{HRU}}\right)$	(10)
			Model D: $R_{GW} = \min\left(\left(\frac{\min(S_s, \boldsymbol{S_{s,ref}})}{\boldsymbol{S_{s,ref}}}\right)^{\gamma} \cdot \boldsymbol{C_{max}}, \frac{\frac{S_s}{\Delta t}}{p_{HRU}}\right)$	(11)
			if $S_u + R_{GW} \cdot \Delta t > S_{u,max}$: $R_{GW} = \frac{S_{u,max} - S_u}{\Delta t}$	(12)
			Sloped: $R_u = (1 - C) \cdot P_e$	(13)
			$C = 1 - \left(1 - \frac{S_u}{\boldsymbol{S_{u,max}}}\right)^{\boldsymbol{\beta}}$	(14)
Fast runoff	$\frac{\Delta S_f}{\Delta t} = R_{fl} - Q_f$	(15)	$Q_f = \frac{S_f}{K_f}$	(16)
			Flat/Wetland: $R_f = \frac{\max(0, S_u - \boldsymbol{S_{u,max}})}{\Delta t}$	(17)
			$R_{fl} = R_f$	(18)
			Sloped: $R_f = (1 - \boldsymbol{W}) \cdot C \cdot P_e$	(19)
			$R_{fl} = R_f * f(\boldsymbol{T_{lag}})$	(20)
Groundwater	$\frac{\Delta S_s}{\Delta t} = R_{r_{tot}} - R_{GW_{tot}} - Q_s$	(21)	$R_r = \boldsymbol{W} \cdot C \cdot P_e$	(22)
			$R_{r_{tot}} = \sum_{HRU} p_{HRU} \cdot R_r$	(23)
			$R_{GW_{tot}} = \sum_{HRU} p_{HRU} \cdot R_{GW}$	(24)
			$Q_s = \frac{S_s}{K_s}$	(25)
Total runoff	$Q_m = Q_s + Q_{f_{tot}}$	(26)	$Q_{f_{tot}} = \sum_{HRU} p_{HRU} \cdot Q_f$	(27)
Supporting literature	(Gao et al., 2014; Gharari et al., 2014; Euser et al., 2015; Hulsman et al., 2019)			

Table 3: Model parameter and ranges (Hulsman et al., 2019)

Landscape class	Parameter	min	max	Unit	Constraint	Comment
Entire basin	C_e	0	1	-		
	K_s	50	200	d		
	S_{sref}	100	500	mm		Only for Models C to F
Flat	I_{max}	0	5	mm d^{-1}		
	$S_{u,max}$	300	1000	mm		
	K_f	10	12	d		
	W	0.5	0.95	-		
Sloped	I_{max}	0	5	mm d^{-1}	$I_{max,sloped} > I_{max,flat}$	
	S_{umax}	300	1000	mm	$S_{umax,sloped} > S_{umax,flat}$	
	β	0	2	-		
	T_{lag}	1	5	d		
	K_f	10	12	d		
	W	0.5	0.95	-	$W_{sloped} > W_{flat}$	
Wetland	I_{max}	0	5	mm d^{-1}	$I_{max,wetland} < I_{max,sloped}$	
	S_{umax}	10	500	mm	$S_{umax,wetland} < S_{umax,sloped}$	
	K_f	10	12	d		
	C_{max}	0.1	5	mm d^{-1}		Only for Models B to F
	γ	0.01	0.5	-		Only for Model D
River profile	v	0.01	5.0	m s^{-1}		

3.1.2 First model adaptation: Adding groundwater upwelling (Models B – D)

Satellite-based evaporation and total water storage observations were used to evaluate the benchmark Model A with respect to the spatial and temporal variability visually and using model performance metrics as described in Section 3.2 to detect model deficiencies in these system-internal variables. The first model adaptation was applied to improve the hydrological model with respect to the deficiencies detected in Model A. Therefore, a detailed description of the reasoning behind the first model adaptation was explained in Section 4.2 after having described the deficiencies in Model A in Section 4.1.3.

~~As first model adaption~~In short, groundwater upwelling (R_{GW}) was added in wetland areas (see Figure 2). This upwelling groundwater was made (1) a linear function of the water content in the unsaturated reservoir (Model B, Eq.9 in Table 2), (2) a linear function of the water content in the slow responding reservoir (Model C, Eq.10) and (3) a non-linear function of the water content in the slow responding reservoir (Model D, Eq.11). As a result, upwelling water from the saturated zone feeds the unsaturated zone, controlled by the water content in the unsaturated (Model B) or in the saturated zone (Models C and D), and thus increasing the water availability for transpiration from the unsaturated zone in wetland areas. Compared to the benchmark Model A, Model B introduces one additional calibration parameter, Model C two and Model D three (Tables 2 and 3). ~~See Section 4.2 for more detailed information on the reasons for and processes behind these model adjustments.~~

3.1.3 Second model adaptation: Discretizing the groundwater system (Models E – F)

Similar to the first model adaptation, the second model adaptation was developed to improve deficiencies detected in Models B – D. Therefore, a detailed description of the reasoning behind the second model adaptation was explained in Section 4.3 after having described the deficiencies in Models B – D in Section 4.2.3.

~~As second model adaptation~~In short, the spatial resolution of the slow responding reservoir was gradually increased from lumped (Models A – D) to semi-distributed (Model E) and fully distributed (Model F). In Model E, the slow responding reservoir was divided into four units as visualised in Figure 1A, whereas in Model F it was further discretized into a grid of 10 x 10 km^2, equivalent to the remaining parts of the model. For both alternative formulations, Models E and F respectively, the slow reservoir timescales K_s remained constant throughout the basin to limit the number of calibration parameters. For both Models E and F, groundwater upwelling was included according to Eq.10 (Table 2), hence using Model C as basis, introducing two additional calibration parameters compared to the benchmark Model A (Tables 2 and 3). ~~See Section 4.3 for more detailed information on the reasons for and processes behind these model adjustments.~~

3.2 Model performance metrics

3.2.1 Discharge

The model performance with respect to discharge was evaluated using eight distinct signatures simultaneously characterizing the observed discharge data (Euser et al., 2013; Hulsman et al., 2019). The model performance measure was based either on the Nash-Sutcliffe efficiency ($E_{NS,\theta}$, Eq.28 in Table 4) or the relative error ($E_{R,\theta}$, Eq.29) depending on the individual signature. The resulting performance metrics for the eight signatures then included the Nash-Sutcliffe efficiencies of the daily discharge time series ($E_{NS,Q}$), its logarithm ($E_{NS,logQ}$), the flow duration curve ($E_{NS,FDC}$), its logarithm ($E_{NS,logFDC}$) and of the autocorrelation function of daily flows ($E_{NS,AC}$) and the relative errors of the mean seasonal runoff coefficient during dry and wet periods ($E_{R,RCdry}$, $E_{R,RCwet}$) and of the rising limb density of the hydrograph ($E_{R,RLD}$). All these signatures were combined into an overall performance metric based on the Euclidian distance to the "perfect" model ($D_{E,Qcal}$, Eq.31). In absence of more information and to obtain balanced solutions, all individual performance metrics were equally weighted in Eq.31. Here, a $D_{E,Qcal}$ = 1 indicates a perfect fit.

The discharge data availability was very limited during the validation time period (2012 – 2016). As a result, hydrological years were not fully captured resulting in incomplete information on the hydrologic signatures such as rising limb density or

auto correlation function. That is why the overall model performance ($D_{E,Qval}$) was calculated using the signatures $E_{NS,Q}$, $E_{NS,logQ}$, $E_{NS,FDC}$ and $E_{NS,logFDC}$ excluding $E_{R,RCdry}$, $E_{R,RCwet}$, $E_{R,RLD}$ and $E_{NS,AC}$. It is therefore important to note that $D_{E,Qcal}$ cannot be meaningfully compared with $D_{E,Qval}$. Instead, following the overall objective of the analysis, $D_{E,Qval}$ of the different alternative model hypothesis were compared to evaluate the differences between the models.

Table 4: Overview of equations used to calculate model performance

Name	Objective Function	Equation	Variable explanation
Nash-Sutcliffe efficiency	$E_{\mathrm{NS},\theta} = 1 - \frac{\sum_t(\theta_{\mathrm{mod}}(t)-\theta_{\mathrm{obs}}(t))^2}{\sum_t(\theta_{\mathrm{obs}}(t)-\overline{\theta_{\mathrm{obs}}})^2}$	(28)	θ variable
Relative error	$E_{\mathrm{R},\theta} = 1 - \frac{\lvert\theta_{\mathrm{mod}}-\theta_{\mathrm{obs}}\rvert}{\theta_{\mathrm{obs}}}$	(29)	
Spatial efficiency metric	$E_{\mathrm{SP}} = \frac{1}{\mathrm{t_{max}}} \cdot \sum_t 1 - \sqrt{(\alpha-1)^2 + (\beta-1)^2 + (\gamma-1)^2}$ With: $\alpha = \rho(\varphi_{\mathrm{obs}}, \varphi_{\mathrm{mod}})$ $\beta = \frac{\sigma_{\mathrm{obs}}/\mu_{\mathrm{obs}}}{\sigma_{\mathrm{mod}}/\mu_{\mathrm{mod}}}$ $\gamma = \left(\sum_{i=0}^{i=n} \min(K_i, L_i)\right) \cdot \left(\sum_{i=0}^{i=n} K_{\mathrm{i}}\right)^{-1}$	(30)	α Pearson correlation coefficient φ_{obs}, φ_{mod} observed/modelled map β coefficient of variation σ standard deviation μ mean γ fraction of histogram intersection between K and L K observed histogram L modelled histogram n = 100 bins t time step within the dry season with maximum t_{max}
Euclidian distance over multiple signatures	$D_{\mathrm{E,Q}} = 1 - \sqrt{\frac{1}{(N+M)}\left(\sum_n\left(1-E_{\mathrm{NS},\theta_{\mathrm{n}}}\right)^2 + \sum_m\left(1-E_{\mathrm{R},\theta_{\mathrm{m}}}\right)^2\right)}$	(31)	n signatures evaluated with Eq.28 with maximum N m signatures evaluated with Eq.29 with maximum M
Euclidian distance over multiple variables	$D_{\mathrm{E,ESQ}} = 1 - \sqrt{\frac{1}{N}\left(\sum_n(1-E_{\mathrm{n}})^2\right)}$	(32)	n variables maximum N E_n model performance metric of variable n

3.2.2 Evaporation and total water storage

The model performance was also evaluated with respect to both the temporal dynamics and the spatial pattern of evaporation and total storage, respectively. For this purpose, satellite-based evaporation data (WaPOR) was used on 10-day time scale, and total water storage anomaly data (GRACE) on monthly time scale.

Temporal variation

To quantify the models' skill to reproduce the temporal dynamics of evaporation and total water storage anomalies, the respective Nash-Sutcliffe efficiencies (Eq. 28) were used as performance metrics. This performance metric was applied to assess the models' skill to reproduce the basin-average time series of evaporation and total water storage anomalies, i.e. $E_{NS,Basin,E}$ and $E_{NS,Basin,S}$, respectively. Similarly, the models' performance to mimic the dynamics of evaporation in all grid cells dominated by the wetland HRU was calculated with the Nash-Sutcliffe efficiency ($E_{NS,Wetland,E}$). Grid cells were considered as wetland dominated if they were completely covered by wetlands, hence if p_{HRU} = 1 with p_{HRU} the areal weight of wetland areas within that cell. With respect to evaporation, the flux was normalised first with Eq.33 to emphasize temporal variations rather than absolute values in an attempt to reduce bias related errors in the observation:

$$E_{\text{normalised}} = \frac{E - E_{\min}}{E_{\max} - E_{\min}} \tag{33}$$

Spatial variation

The model performance with respect to the spatial pattern of evaporation and total water storage anomalies was calculated with the spatial efficiency metrics $E_{SP,E}$ and $E_{SP,S}$ (Eq.30), respectively, which was successfully used in previous studies (Demirel et al., 2018; Koch et al., 2018). The spatial model performance was first calculated for each time step within the dry period which was in September/October and then averaged to obtain the overall model performance (E_{SP}, Eq.30). The spatial pattern was averaged over the dry season to minimize the effect of precipitation errors.

3.2.3 Multi-variable

The overall potential of the models to simultaneously reproduce the temporal dynamics as well as the spatial patterns of all observed variables, i.e. discharge, evaporation and total water storage anomalies, was tested with the overall model performance metric $D_{E,ESQ}$. This metric was the Euclidian distance (Eq.32) of the following individual metrics: the temporal variation of the basin-average evaporation ($E_{NS,Basin,E}$) and total water storage anomalies ($E_{NS,Basin,S}$), spatial pattern of the evaporation ($E_{SP,E}$) and total water storage anomalies ($E_{SP,S}$) as well as discharge ($D_{E,Q}$). See Table 5 for an overview of all model performance metrics used in this study.

Table 5: Overview of the applied model performance metrics

Data	Temporal dynamics/ Spatial pattern	Performance metric	Symbol and equation nr.	Calibration/validation
Discharge	Temporal dynamics	Euclidian distance over multiple signatures (combining $E_{NS,Q}$, $E_{NS,logQ}$, $E_{NS,FDC}$, $E_{NS,logFDC}$, $E_{NS,AC}$, $E_{R,RCdry}$, $E_{R,RCwet}$ and $E_{R,RLD}$)	$D_{E,Qcal}$ (Eq.31)	Calibration (2002 – 2012)
	Temporal dynamics	Euclidian distance over multiple signatures (combining $E_{NS,Q}$, $E_{NS,logQ}$, $E_{NS,FDC}$ and $E_{NS,logFDC}$)	$D_{E,Qval}$ (Eq.31)	Validation (2012 – 2016)
Evaporation	Temporal dynamics (basin-average)	Nash-Sutcliffe efficiency	$E_{NS,Basin,E}$ (Eq.28)	Validation (2012 – 2016)
	Temporal dynamics (wetland areas)	Nash-Sutcliffe efficiency	$E_{NS,Wetland,E}$ (Eq.28)	Validation (2012 – 2016)
	Spatial pattern	Spatial efficiency metric	$E_{SP,E}$ (Eq.30)	Validation (2012 – 2016)
Total water storage anomalies	Temporal dynamics (basin-average)	Nash-Sutcliffe efficiency	$E_{NS,Basin,S}$ (Eq.28)	Validation (2012 – 2016)
	Spatial pattern	Spatial efficiency metric	$E_{SP,S}$ (Eq.30)	Validation (2012 – 2016)
Multi-variable (discharge, evaporation and total water storage anomalies)	Combination	Euclidian distance over multiple variables (combining $D_{E,Qcal}$, $E_{NS,Basin,E}$, $E_{SP,E}$, $E_{NS,Basin,S}$ and $E_{SP,S}$)	$D_{E,ESQcal}$ (Eq.32)	Calibration (2002 – 2012)
	Combination	Euclidian distance over multiple variables (combining $D_{E,Qval}$, $E_{NS,Basin,E}$, $E_{SP,E}$, $E_{NS,Basin,S}$ and $E_{SP,S}$)	$D_{E,ESQval}$ (Eq.32)	Validation (2012 – 2016)

3.3 Model calibration

In general, the model was calibrated by first running the model with $5 \cdot 10^{5}$~~4~~ random parameter sets generated with a Monte-Carlo sampling strategy from uniform prior parameter distributions (Table 3). Then, the optimal and 5% best-performing parameter sets were selected according to the model performance metric as described in the previous section. The model was calibrated within the time period 2002 – 2012 with respect to 1) discharge ($D_{E,Qcal}$) and 2) all variables simultaneously ($D_{E,ESQcal}$). As the objective of this study was to explore the information content of multiple variables using multiple model

evaluation criteria for step-wise model structure development and calibration, it was important to use the same parameter sets for all models as common starting point to rule out the effect of different parameter sets. This was efficiently possible with the Monte-Carlo parameter sampling strategy, which, in addition also allowed a relatively straight-forward and intuitive interpretation and communication of the results.

3.4 Model validation

The model was validated with respect to discharge, evaporation and total water storage anomalies for the time period 2012 – 2016. During validation each variable was evaluated separately both temporally and spatially. This included the temporal variation of the basin-average evaporation ($E_{NS,Basin,E}$) and total water storage anomalies ($E_{NS,Basin,S}$), evaporation in wetland areas ($E_{NS,Wetland,E}$), spatial pattern of the evaporation ($E_{SP,E}$) and total water storage anomalies ($E_{SP,S}$) as well as discharge ($D_{E,Qval}$). In addition, the model was evaluated with respect to the overall performance ($D_{E,ESQval}$). This was done for the solutions from both calibration strategies.

4. Model results

4.1 Benchmark model (Model A)

4.1.1 Discharge based calibration

For the benchmark model (Model A), the model performance of all model realizations following the first calibration strategy, i.e. calibrating to discharge, resulted in an optimum $D_{E,Qcal,opt}$ = 0.76 and $D_{E,Qval}$ = 0.37 during validation (Table 6, Figure 3). As shown in Figure 4, the main features of the hydrological response were captured reasonably well. However, particularly in the validation period, low flows were somewhat underestimated. Note that in 2013, the observed high flows were probably underestimated due to failures in the recording which resulted in a truncated top in the hydrograph and flat top in the flow duration curve during the validation time period (Figure 4) and which affect the validated model performance values ($D_{E,Qval}$). The range in the calibrated model performance with respect to each discharge signature separately is visualised in Figure S1 in the supplementary material.

The basin-average evaporation ($E_{NS,\ Basin,E}$ = 0.54) and total water storage anomalies ($E_{NS,\ Basin,S}$ = 0.74) were in general also reproduced rather well (Figures S3 and S5). In contrast, the model failed to mimic the evaporation dynamics in wetland dominated areas as it decreased rapidly to zero in the dry season in contrast to the observations ($E_{NS,Wetland,E}$ = 0.25, Figure 5). Similarly, the spatial variability in evaporation ($E_{SP,E}$ = 0.17) and water storage anomalies ($E_{SP,S}$ = -0.02) were poorly captured as several areas were over- or underestimated (Figures 6 and 7). Note that in both figures the normalised evaporation and total water storage anomalies were plotted applying Eq.33 to emphasize relative spatial differences rather than absolute values.

Table 6: Summary of model performance with respect to evaporation ($E_{NS,Basin,E}$, $E_{NS,Wetland,E}$ and $E_{SP,E}$), total water storage anomalies ($E_{NS,Basin,S}$ or $E_{SP,S}$), discharge ($D_{E,Qcal}$ and $D_{E,Qval}$) and all variables combined ($D_{E,ESQval}$): The parameter sets were selected based on discharge ($D_{E,Qcal}$).

	Calibration (2002 – 2012)	Validation (2012 – 2016)						
	$D_{E,Qcal,opt}$ ($D_{E,Qcal,5/95\%}$)	$D_{E,Qval}$ ($D_{E,Qval,5/95\%}$)	$E_{NS,Basin,E}$ ($E_{NS,Basin,E,5/95}$)	$E_{NS,wetland,E}$ ($E_{NS,wetland,E,5/95}$)	$E_{SP,E}$ ($E_{SP,E,5/95}$)	$E_{NS,Basin,S}$ ($E_{NS,Basin,S,5/95}$)	$E_{SP,S}$ ($E_{SP,S,5/95}$)	$D_{E,ESQval}$ ($D_{E,ESQval,5/95}$)
A	0.76 (0.54 – 0.68)	0.37 (0.26 – 0.85)	0.54 (0.34 – 0.57)	0.25 (-0.14 – 0.58)	0.17 (-0.37 – 0.04)	0.74 (0.62 – 0.80)	-0.02 (-0.23 – 0.03)	0.30 (0.12 – 0.29)
B	0.75 (0.36 – 0.60)	0.08 (-3.9 – 0.78)	0.46 (0.34 – 0.63)	0.29 (0.09 – 0.65)	0.12 (-0.68 – 0.12)	0.69 (0.61 – 0.82)	-0.07 (-0.20 – 0.08)	0.21 (-1.3 – 0.27)
C	0.79 (0.58 – 0.70)	0.81 (0.27 – 0.85)	0.50 (0.34 – 0.58)	0.19 (-0.01 – 0.57)	0.10 (-0.39 – 0.06)	0.76 (0.62 – 0.81)	-0.08 (-0.23 – 0.04)	0.32 (0.12 – 0.30)
D	0.77 (0.53 – 0.68)	-1.7 (-2.4 – 0.84)	0.36 (0.33 – 0.60)	0.41 (0.11 – 0.62)	-0.04 (-0.57 – 0.10)	0.63 (0.61 – 0.82)	-0.17 (-0.22 – 0.06)	-0.41 (-0.72 – 0.28)
E	0.78 (0.58 – 0.70)	0.81 (0.27 – 0.85)	0.50 (0.34 – 0.58)	0.07 (-0.04 – 0.59)	0.05 (-0.39 – 0.05)	0.77 (0.62 – 0.81)	-0.08 (-0.23 – 0.04)	0.30 (0.12 – 0.29)
F	0.91 (0.86 – 0.89)	0.52 (0.12 – 0.74)	0.61 (0.45 – 0.63)	0.56 (-0.08 – 0.61)	-0.03 (-0.49 – 0.19)	0.66 (0.44 – 0.71)	0.08 (-0.07 – 0.13)	0.31 (0.12 – 0.34)

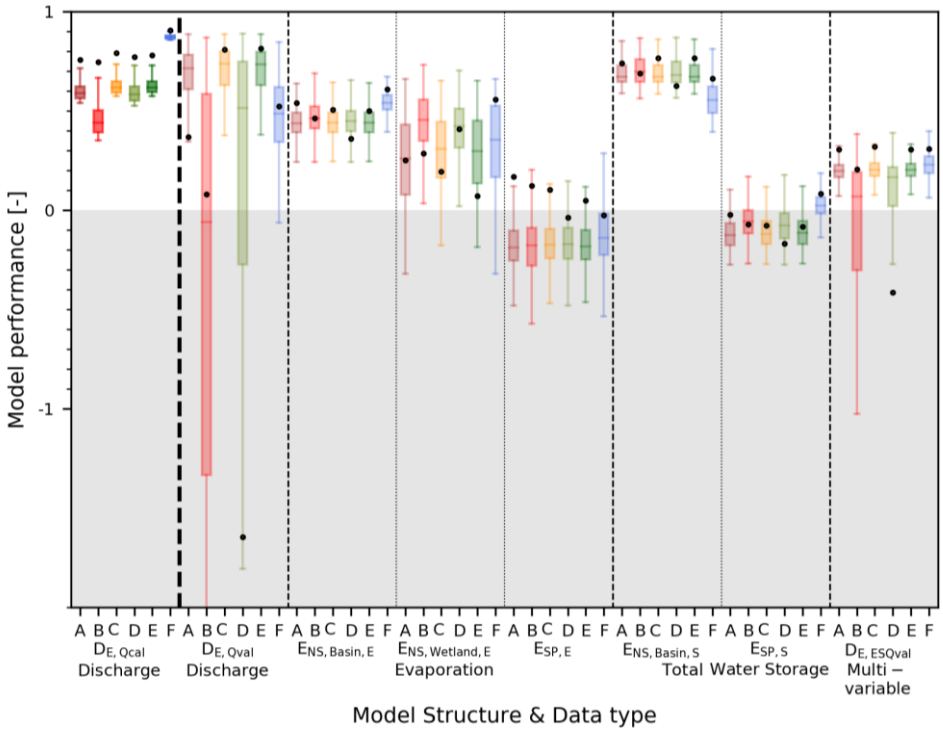

Figure 3: Model performance with respect to discharge, evaporation and storage for all models. The model is calibrated to discharge ($D_{E,Qcal}$, darker boxplots in the first column) and validated to the discharge, evaporation and storage (lighter boxplots). The dots represent the model performance using the "optimal" parameter set and the boxplot the range of the best 5% solutions both according to discharge ($D_{E,Qcal}$). The following performance metrics were used: 1) discharge using the overall model performance metric ($D_{E,Qcal}$ for calibration and $D_{E,Qval}$ for validation), 2) evaporation temporally basin-average ($E_{NS,Basin,E}$), 3) evaporation temporally wetland areas only ($E_{NS,Wetland,E}$), 4) evaporation spatially ($E_{SP,E}$), 5) storage temporally basin-average ($E_{NS,Basin,S}$), ~~6) storage temporally wetland areas only ($E_{NS,Wetland,S}$),~~ ~~7~~6) storage spatially ($E_{SP,S}$), and ~~8~~7) the combination of evaporation, storage and discharge (combined metric $D_{E,ESQval}$).

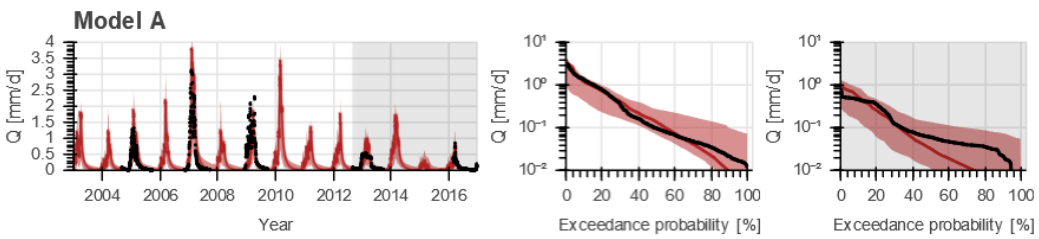

Figure 4: Range of model solutions for Model A. The left panel shows the hydrograph and the right panel the flow duration curve of the recorded (black) and modelled discharge: the line indicates the solution with the highest calibration objective function with respect to discharge ($D_{E,Qcal}$) and the shaded area the envelope of the solutions retained as feasible. The data in the white area were used for calibration and the grey shaded area for validation.

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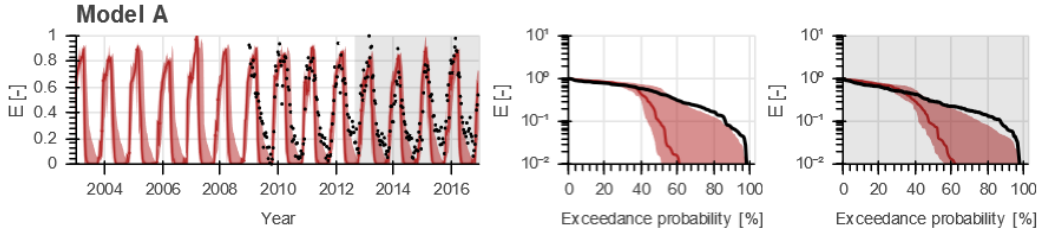

Figure 5: Range of model solutions for Model~~s~~ A ~~to F~~. The left panel shows the time series and the right panel the duration curve of the recorded (black) and modelled normalised evaporation for wetland dominated areas: the line indicates the solution with the highest calibration objective function with respect to discharge ($D_{E,Qcal}$) and the shaded area the envelope of the solutions retained as feasible. The data in the grey shaded area were used for validation.

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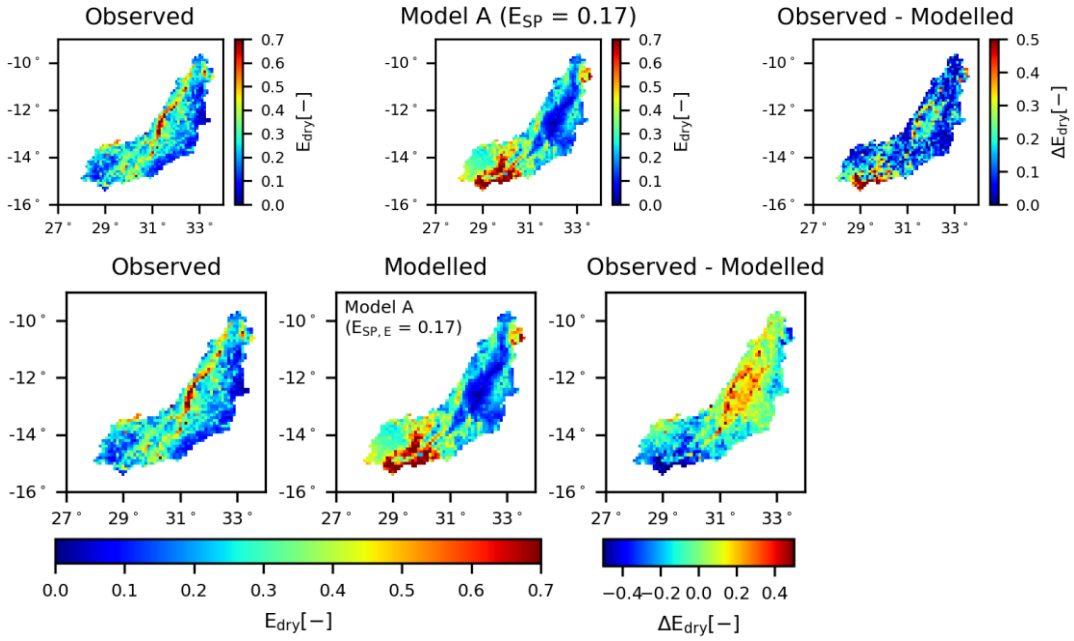

Figure 6: Spatial variability of the normalised total evaporation for Model A averaged over all days within the dry season. The left panel shows the observation according to WaPOR data, the middle panel the model result using the "optimal" parameter set with respect to discharge ($D_{E,Qcal}$), and the right panel the difference between the observation and model.

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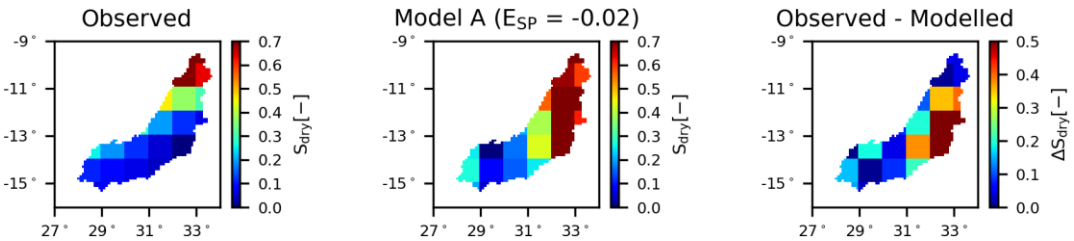

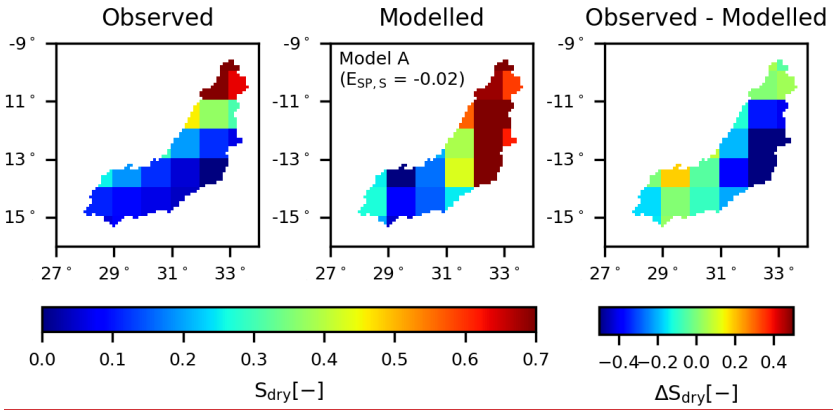

Figure 7: Spatial variability of the normalised total water storage anomalies for Model A averaged over all days within the dry season. The left panel shows the observation according to GRACE data, the middle panel the model result using the "optimal" parameter set with respect to discharge ($D_{E,Qcal}$), and the right panel the difference between the observation and model.

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4.1.2 Multi-variable calibration

Calibrating with respect to multiple variables simultaneously in the second calibration strategy, resulted in a reduced model skill to simultaneously reproduce all flow signatures in the validation period with $D_{E,Qval}$ = 0.07 (Table 7, Figures 8 and 9). Compared to the first calibration strategy, the simulated evaporation did not change significantly with respect to the temporal dynamics ($E_{NS,Wetland,E}$ = 0.27, $E_{NS,Basin,E}$ = 0.57) and spatial pattern ($E_{SP,E}$ = -0.18). Evaporation from wetland dominated areas remained underestimated in the dry season (Figure 10) and large areas in the basin were still under- or overestimated (Figure 11). The reproduction of the total water storage anomalies decreased though, mostly with respect to the spatial pattern ($E_{SP,S}$ = -0.14, Figure 12). On the other hand, when looking at the 5/95th percentile range instead of the "optimal" parameter set, then an improvement was observed in the spatial pattern in evaporation ($E_{SP,E,5/95}$ =-0.10 – 0.22) and in total water storage ($E_{SP,S,5/95}$ = -0.17 – 0.08, compare Tables 6 and 7).

Table 7: Summary of the model performance with respect to evaporation ($E_{NS,Basin,E}$, $E_{NS,Wetland,E}$ and $E_{SP,E}$), total water storage anomalies ($E_{NS,Basin,S}$ or $E_{SP,S}$), discharge ($D_{E,Qval}$) and all variables combined ($D_{E,ESQval}$): Parameter sets selected based on multiple variables simultaneously ($D_{E,ESQcal}$).

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	Calibration (2002 – 2012)	Validation (2012 – 2016)						
	$D_{E,ESQcal,opt}$ ($D_{E,ESQcal,5/95}$)	$D_{E,Qval}$ ($D_{E,Qval,5/95\%}$)	$E_{NS,Basin,E}$ ($E_{NS,Basin,E,5/95}$)	$E_{NS,wetland,E}$ ($E_{NS,wetland,E,5/95}$)	$E_{SP,E}$ ($E_{SP,E,5/95}$)	$E_{NS,Basin,S}$ ($E_{NS,Basin,S,5/95}$)	$E_{SP,S}$ ($E_{SP,S,5/95}$)	$D_{E,ESQval}$ ($D_{E,ESQval,5/95}$)
A	0.42 (0.28 – 0.36)	0.07 (-1.4 – 0.80)	0.57 (0.37 – 0.60)	0.27 (-0.05 – 0.61)	0.18 (-0.10 – 0.22)	0.72 (0.60 – 0.77)	-0.14 (-0.17 – 0.08)	0.21 (-0.25 – 0.32)
B	0.40 (0.23 – 0.33)	0.46 (-4.2 – 0.70)	0.55 (0.39 – 0.63)	0.56 (0.04 – 0.64)	0.16 (-0.14 – 0.25)	0.73 (0.61 – 0.79)	-0.16 (-0.17 – 0.09)	0.28 (-1.4 – 0.29)
C	0.44 (0.29 – 0.37)	0.61 (-1.6 – 0.79)	0.48 (0.37 – 0.61)	0.51 (0.08 – 0.60)	0.19 (-0.07 – 0.25)	0.70 (0.60 – 0.77)	-0.03 (-0.16 – 0.09)	0.33 (-0.31 – 0.33)
D	0.43 (0.27 – 0.36)	-0.08 (-3.5 – 0.75)	0.51 (0.38 – 0.62)	0.59 (0.06 – 0.61)	0.24 (-0.09 – 0.26)	0.69 (0.60 – 0.78)	-0.04 (-0.16 – 0.09)	0.21 (-1.1 – 0.32)
E	0.43 (0.29 – 0.36)	0.30 (-1.6 – 0.79)	0.43 (0.38 – 0.61)	0.30 (0.03 – 0.61)	0.17 (-0.08 – 0.25)	0.64 (0.60 – 0.77)	-0.02 (-0.16 – 0.10)	0.27 (-0.31 – 0.32)
F	0.52 (0.39 – 0.45)	0.51 (-0.24 – 0.81)	0.56 (0.45 – 0.63)	0.45 (0.01 – 0.63)	0.23 (0.08 – 0.27)	0.63 (0.53 – 0.73)	0.09 (-0.10 – 0.13)	0.37 (0.15 – 0.38)

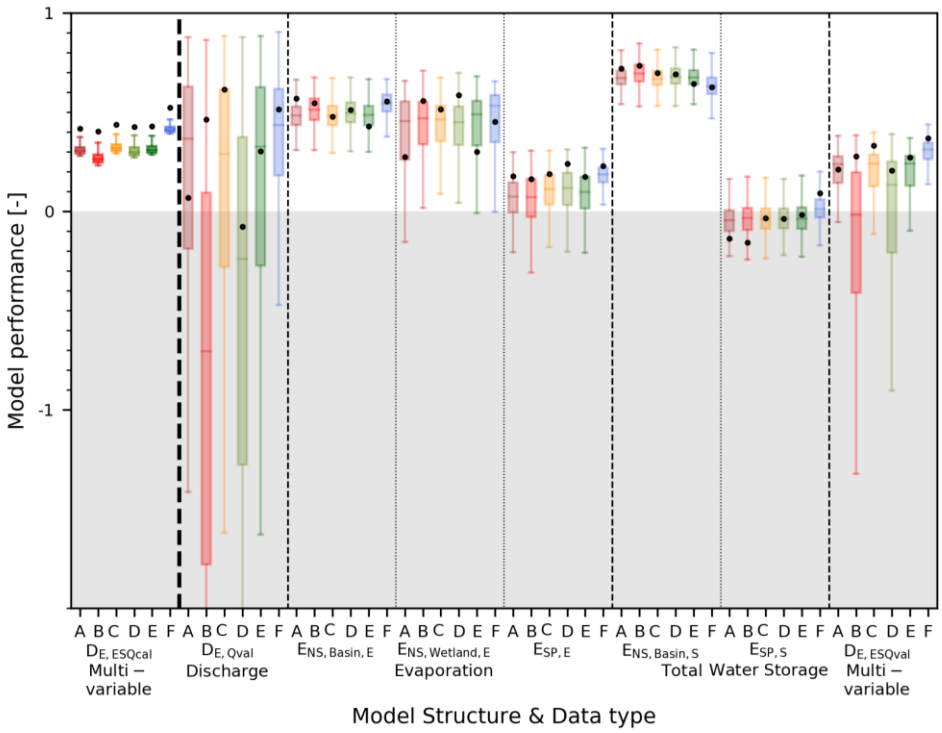

Figure 8: Model performance with respect to discharge, evaporation and storage for all models. The model is calibrated to multiple variables ~~all fluxes~~ simultaneously ($D_{E,ESQcal}$, darker boxplots in the first column) and evaluated with respect to each flux individually (lighter boxplots). The dots represent the model performance using the "optimal" parameter set and the boxplot the range of the best 5% solutions both according to $D_{E,ESQcal}$. The following performance metrics were used: 1) discharge using the overall model performance metric ($D_{E,Qval}$), 2) evaporation temporally basin-average ($E_{NS,Basin,E}$), 3) evaporation temporally wetland areas only ($E_{NS,Wetland,E}$), 4) evaporation spatially ($E_{SP,E}$), 5) storage temporally basin-average ($E_{NS,Basin,S}$), ~~6) storage temporally wetland areas only ($E_{NS,Wetland,S}$), 7~~6) storage spatially ($E_{SP,S}$), and ~~8~~7) the combination of evaporation, storage and discharge (combined metric $D_{E,ESQval}$).

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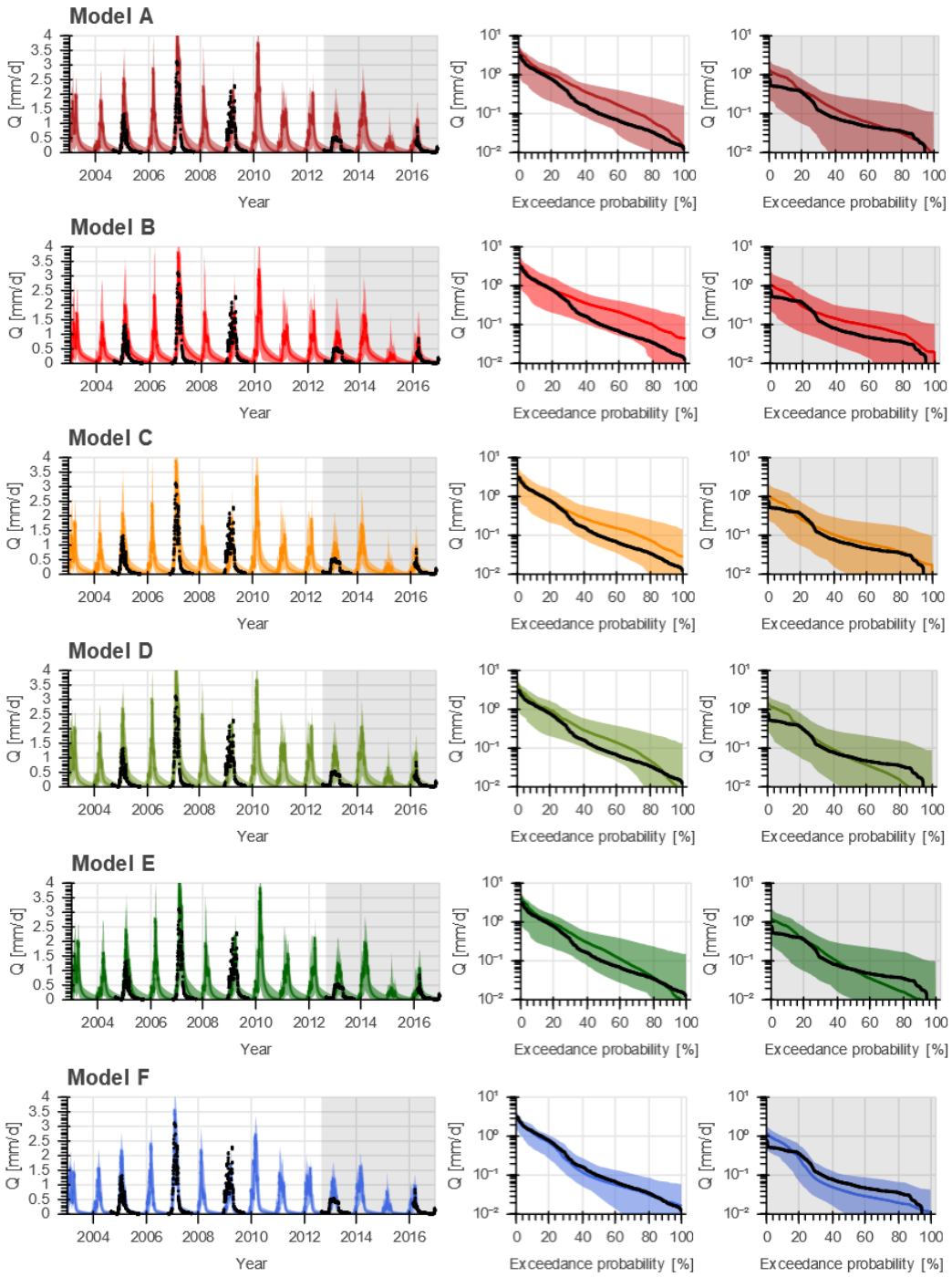

Figure 9: Range of model solutions for Models A to F. The left panel shows the hydrograph and the right panel the flow duration curve of the recorded (black) and modelled discharge: the line indicates the solution with the highest calibration objective function with respect to multiple variables ($D_{E,ESQcal}$) and the shaded area the envelope of the solutions retained as feasible. The data in the grey shaded area were used for validation.

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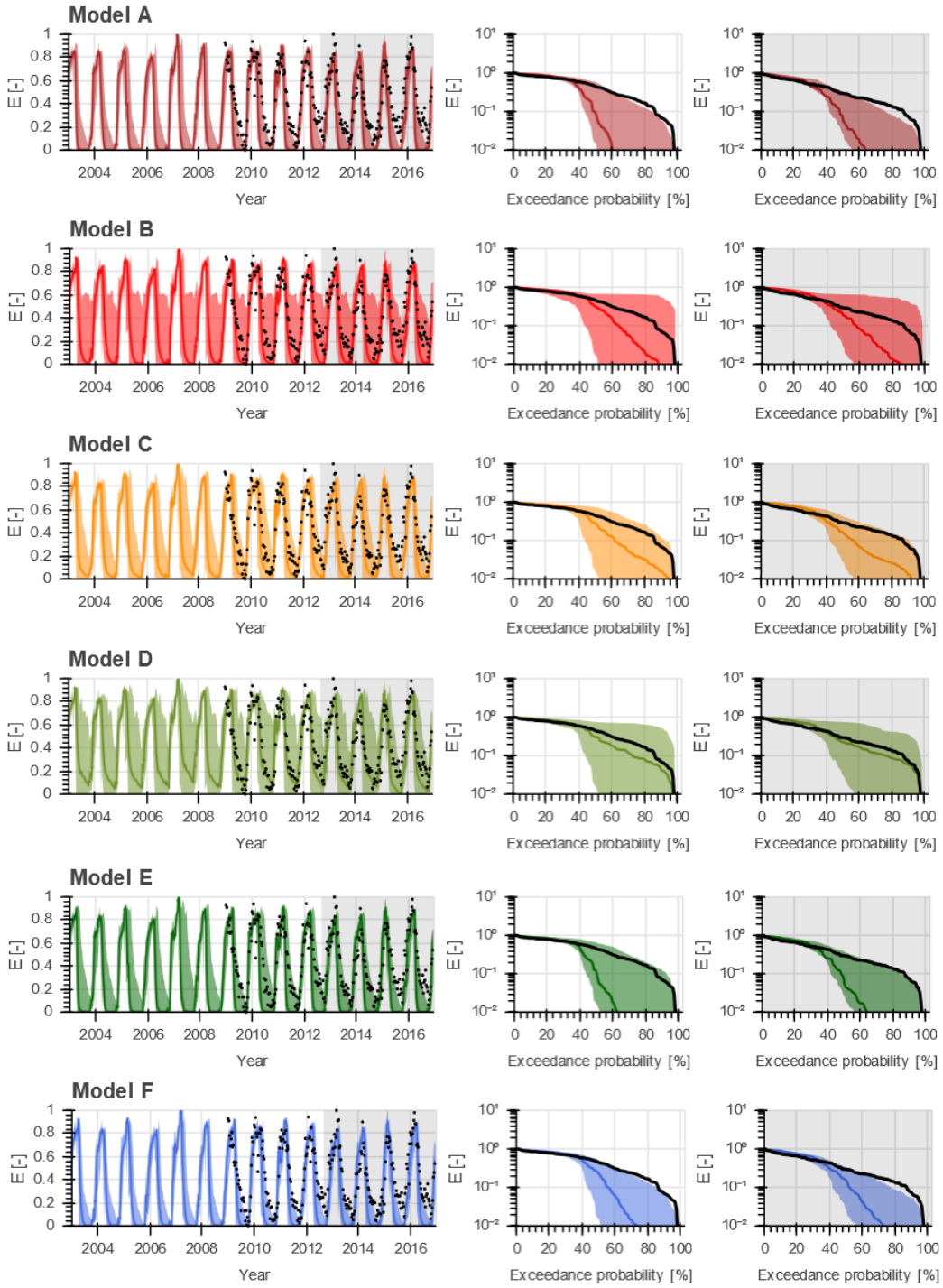

Figure 10: Range of model solutions for Models A to F. The left panel shows the time series and the right panel the duration curve of the recorded (black) and modelled normalised evaporation for wetland dominated areas: the line indicates the solution with the highest calibration objective function with respect to multiple variables ($D_{E,ESQcal}$) and the shaded area the envelope of the solutions retained as feasible. The data in the grey shaded area were used for validation.

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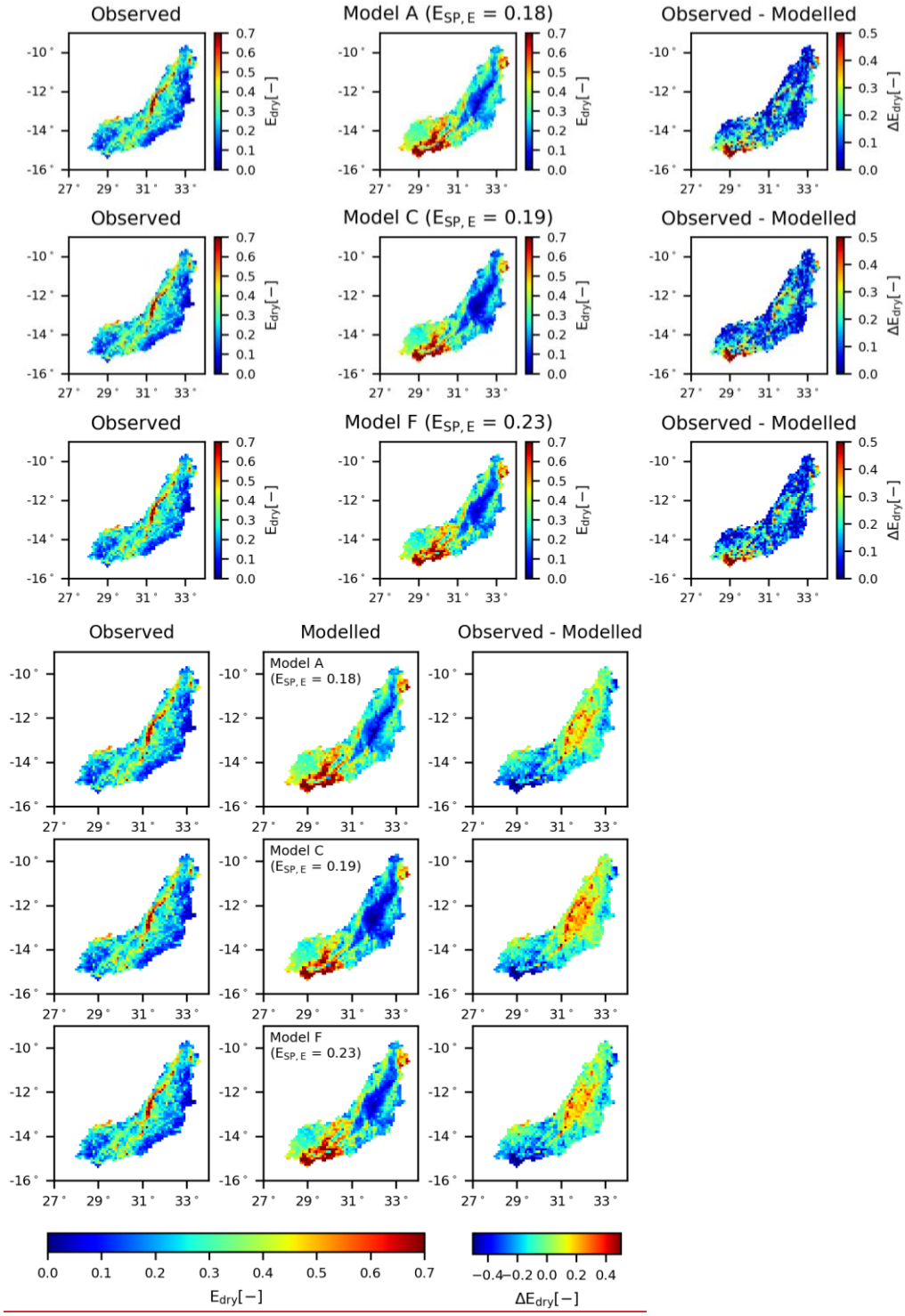

Figure 11: Spatial variability of the normalised total evaporation for Models A, C and F averaged over all days within the dry season. The left panel shows the observation according to WaPOR data, the middle panel the model result using the "optimal" parameter set with respect to multiple variables ($D_{E,ESQcal}$), and the right panel the difference between the observation and model.

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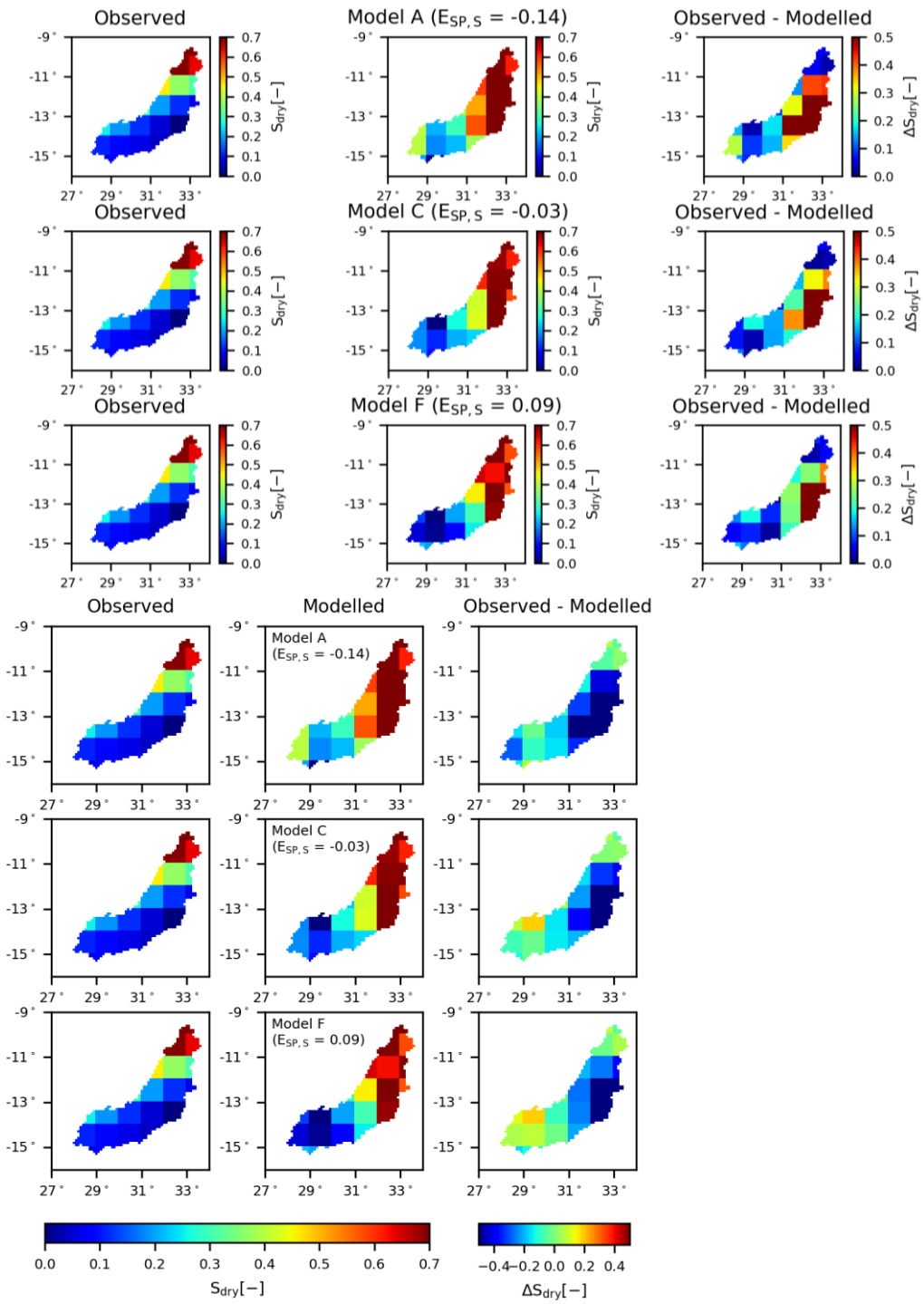

Figure 12: Spatial variability of the normalised total water storage anomalies for Models A, C and F averaged over all days within the dry season. The left panel shows the observation according to GRACE data, the middle panel the model result using the "optimal" parameter set with respect to multiple variables ($D_{E,ESQcal}$), and the right panel the difference between the observation and model.

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4.1.3 Model deficiencies

Regardless of the calibration strategy, the benchmark model failed in particular to adequately reproduce evaporation dynamics in wetland dominated areas. During the dry seasons, the modelled evaporation decreased rapidly to zero in contrast to the observations (Figures 5 and 10). Partly as a consequence of that, the spatial pattern of evaporation was captured poorly as illustrated in Figures 6 and 11. Apart from the wetlands, the modelled average dry season evaporation was also extremely low in the centre of the basin which did not correspond with the satellite observations. At the same time, the evaporation was significantly overestimated in the southern part of the basin. Also the spatial pattern in total water storage anomalies were poorly represented since the model significantly overestimated storage anomalies in large parts of the basin (Figures 7 and 12). Note, overestimations in specific regions do not necessarily mean the actual (non-normalised) model values were also higher compared to the observation, but it does mean the model results in this cell/region were high relative to the remainder of the basin compared to observations. This was the case for the evaporation and total water storage even though it was negative during dry seasons (compare Figures S8 and S9 in the supplementary material).

4.2 First model adaptation: Adding groundwater upwelling (Models B, C and D)

In the benchmark model (Model A), there was no groundwater upwelling into the wetlands and floodplains around the river channels, similar to many distributed conceptual hydrological models (eg. Samaniego et al., 2010; Bieger et al., 2017). However, according to field and satellite-based observations, wetland areas remain moist at the end of the dry season while the remaining areas of the basin become very dry. Given the low elevation of these wetlands above rivers, it is plausible to assume that groundwater from higher parts of the catchment is pushed up into the unsaturated root zone of these wetlands. As a result, water deficits in the unsaturated zone are partly replenished by upwelling groundwater. It thereby can sustain relatively elevated levels of moisture, available for plant transpiration long into the dry season.

To improve the representation of evaporation in the model, the process of upwelling groundwater (R_{GW}) was added to the model. In principle, it was assumed that the upwelling groundwater is regulated by the head difference between upland groundwater and the groundwater in the wetland. As this information was not available, due to the lack of continuous gradients in the type of model used (Hrachowitz and Clark, 2017), this was done in a simplified way. In three alternative formulations of this hypothesis, the upwelling groundwater was made (1) a linear function of the water content in the unsaturated reservoir (Model B, Eq.9), (2) a linear function of the water content in the slow responding reservoir (Model C, Eq.10) and (3) a non-linear function of the water content in the slow responding reservoir (Model D, Eq.11). In other words, in Model B the groundwater upwelling was driven by the water deficit in the unsaturated zone, hence the lower the water content in the unsaturated zone, the higher the groundwater upwelling. In Models C and D, the groundwater upwelling was driven by the water content in the slow responding reservoir, the groundwater system, such that the higher the water content in the slow responding reservoir, the higher the groundwater upwelling. As a result of the non-linear relation between the groundwater upwelling and the water content in the slow responding reservoir in Model D, the groundwater upwelling increased the most under dry conditions and less under wet conditions. In Models B – D, the groundwater upwelling flowed into the unsaturated zone until it was saturated, hence until its maximum $S_{u,max}$ was reached (Eq.12). Model B required one additional calibration parameter, Model C two and Model D three (Tables 2 and 3).

4.2.1 Discharge based calibration

Following the first calibration strategy, the performances of Models B – D with respect to discharge did not improve significantly for the calibration period ($D_{E,Qcal}$ = 0.75 – 0.79) compared to Model A, regardless of the model (Table 6, Figures 3 and S2). For the validation period, Models B and D experienced a pronounced reduction of their ability to adequately reproduce the discharge signatures with $D_{E,Qval}$ = 0.08 and -1.7, respectively, since the flows were mostly underestimated

(Figure S2). On the other hand, Model C showed significant improvements with $D_{E,Qval}$ = 0.81. With respect to the evaporation from wetland dominated areas, the largest improvements were found for Model D ($E_{NS,Wetland,E}$ = 0.41) where the evaporation did not drop rapidly to zero anymore even though it was still significantly underestimated in the dry season (Figure S4). But this came at the cost of decreased simulations of all remaining variables (Table 6, Figure 3), hence the discharge, basin-average evaporation and total water storage and their spatial patterns (Figures S2 – S7). For example Figure S6 illustrates the poorly simulated temporally-averaged dry season evaporation for Model D which was higher in wetland areas (centre of the basin) compared to the surrounding areas which was not observed in the satellite based observations. For Models B and C, the model performances with respect to the remaining variables remained comparable to Model A or even decreased as can be seen in Table 6 and Figure 3. As a result, when considering all variables simultaneously, Model C performed the best with $D_{E,ESQval}$ = 0.32.

4.2.2 Multi-variable calibration

Following the second calibration strategy, Model C experienced the largest increases compared to Model A in its ability to describe features of discharge with $D_{E,Qval}$ = 0.61, while Model D decreased the most to $D_{E,Qval}$ = -0.08 with the high flows being overestimated and low flows underestimated (Table 7, Figures 8 and 9). With this calibration strategy, large improvements were observed in the reproduction of the evaporation from wetland dominated areas for all three Models B – D, especially for Model D with $E_{NS,Wetland,E}$ = 0.59 where the evaporation was simulated well even during the dry season as it did not decrease rapidly to zero in the dry season compared to Model A (Figure 10). For Models C and D, the spatial pattern in evaporation and total water storage anomalies improved, albeit moderately (Table 7) as large areas were still under- or overestimated (Figures ~~S10~~ S12 and ~~S11~~S13), whereas it decreased slightly for Model B. For all Models B – D, the basin-average temporal dynamics in evaporation and total water storage anomalies remained similar or decreased slightly (Table 7, Figures ~~S8~~ S10 and ~~S9~~S11). Overall, when considering the model performance with respect to all variables simultaneously, Model C showed the highest performances with $D_{E,ESQval}$ = 0.33.

4.2.3 Model deficiencies

According to the results, the representation of evaporation strongly benefitted from including upwelling groundwater as function of the water content in the slow responding reservoir (Eq.10, Model C) especially for the second calibration strategy. The incorporation of this flux resulted in increased levels of water supply to the unsaturated zone of wetlands to sustain higher levels of transpiration throughout the dry periods (Figure 10). But even though the evaporation increased during dry periods, it was still underestimated especially towards the end of the dry season due to too large groundwater upwelling depleting the slow responding reservoir. The major weakness of the model remained its very limited ability to represent the spatial pattern in evaporation as there were several local clusters of considerable mismatches, both over- and underestimating observed evaporation. This was clearly visible for example in the centre and southern part of the basin (Figure 11). Also the spatial pattern in the total water storage anomalies remained poorly represented, in spite of some improvements compared to Model A, as they were considerably overestimated in the northern parts of the basin (Figure 12). This could be a result of deficiencies in the hydrological models or in the satellite-based observations.

4.3 Second model adaptation: Discretizing the groundwater system (Models E and F)

In all above models, the groundwater layer was simulated as a single lumped reservoir assuming equal groundwater availability throughout the entire basin. As groundwater processes can occur on relatively large spatial scales, this assumption may be valid for small- or mesoscale catchments, but not necessarily for larger basins such as the Luangwa basin. This may partly be responsible for the deficiency of all above models to meaningfully reproduce the spatial pattern of the total water storage. Taking Model C as a basis for further model adaptations, two more alternative model hypothesis were formulated. In both

models the slow responding reservoir, representing the groundwater, was spatially discretized. For Model E, the reservoir was split into four units with an area of 15,396 – 47,239 km^2 each containing four to six different GRACE cells (see Figure 1A). In contrast, Model F was formulated with a completely distributed slow reservoir at the resolution of the remaining parts of the model, i.e. 10 x 10 km^2. In Models E and F, the slow reservoir timescales K_s remained constant throughout the basin to limit the number of calibration parameters. Models E and F did not require additional calibration parameters. See Tables 2 and 3 for the corresponding model equations and calibration parameter ranges.

4.3.1 Discharge based calibration

Following the first calibration strategy, the calibrated and validated model performance with respect to discharge did not change significantly for Model E compared to Model C. For Model F on the other hand, the calibrated model performance increased to $D_{E,Qcal}$ = 0.91 (Table 6, Figures 3 and S2), but during validation it decreased to $D_{E,Qval}$ = 0.52 compared to Model C as a result of overestimated high flows (Figure S2). In other words, the discharge simulation was only affected when applying a fully distributed groundwater system (Model F). Also the simulated dynamics of the evaporation improved for Model F, especially for wetland dominated areas ($E_{NS,Wetland,E}$ = 0.56, Table 6) even though it remained significantly underestimated during the dry season (Figure S4). But for both models, no improvements in the spatial pattern of evaporation can be observed with $E_{SP,E}$ = 0.05 and -0.03 for Models E and F, respectively. As shown in Figure S6, for Model E and F the temporally-averaged dry season evaporation was very low in the centre of the basin compared to the remaining part of the basin in contrast to the satellite-based observations. The spatial pattern of total water storage anomalies were at least slightly better mimicked by Model F with $E_{SP,S}$ = 0.08 (Figure S7), which, in turn, came at the price of a poorer reproduction of the temporal dynamics of the basin-averaged total water storage anomalies ($E_{NS,Basin,S}$ = 0.66, Figure S5).

4.3.2 Multi-variable calibration

Including multiple variables in the calibration process did not improve the representation of the hydrological response with respect to discharge for Models E and F compared to Model C with $D_{E,Qval}$ = 0.30 and 0.51, respectively (Table 7, Figures 8 and 9). For both models, the flows were underestimated during low flows and overestimated during high flows (Figure 9). Also the evaporation from wetland dominated areas did not improve for both models as it decreased rapidly in the dry season (Figure 10). On the other hand, the spatial pattern in the evaporation was slightly better mimicked for Model F ($E_{SP,E}$ = 0.23), but still at low performance levels similar to Models A – D with large areas still being under- or overestimated (Figure S12~~0~~). Slight improvements could be observed though for the representation of spatial pattern in total water storage in Models F ($E_{SP,S}$ = 0.09, Figure S13~~1~~), albeit modestly. Overall, when considering the model performance with respect to all variables simultaneously, Model F showed the highest performances with $D_{E,ESQval}$ = 0.37.

4.3.3 Model deficiencies

Applying the second calibration strategy, Model F poorly reproduced the evaporation from wetlands (Figure 10) since the water availability for evaporation decreased rapidly in the dry season due to the limited water availability in the slow responding reservoir. This was a direct result of the limited connectivity in the distributed groundwater system within the basin and very likely points to the presence of contiguous groundwater systems extending beyond the modelling resolution that sustain dry season evaporation in wetlands. Strikingly, discretizing the groundwater basin only had limited effects on the spatial pattern in evaporation and total water storage anomalies. Despite their limited improvements, they remained poorly captured as several local clusters were over- and underestimated (Figures 11 and 12).

5. Discussion

As illustrated in the previous sections, satellite-based evaporation and storage anomaly data were used in an attempt to (1) iteratively improve a benchmark model structure and 2) identify parameter sets with which the model can simultaneously reproduce the temporal dynamics as well as the spatial patterns of multiple flux and storage variables.

The results suggested that among the tested models, Models C and F provided the overall best representation of the hydrological processes in the Luangwa basin, following the first and second calibration strategy respectively. The addition of upwelling groundwater alone (Model C) significantly improved the discharge simulations during validation regardless of the calibration strategy and the simulation of evaporation from wetland areas following the second calibration strategy. Discretizing the slow responding reservoir (Model F) reached reasonable overall performance levels, i.e. $D_{E,ESQval}$, when calibrating on discharge and its signatures only (Figure 3), with improved simulations of evaporation from wetland areas. But calibrating on multiple variables proved instrumental as it allowed to ~~significantly~~ improve the spatial pattern of the evaporation compared to calibrating with respect to discharge (Figures 11 and S12 in the supplementary material), while maintaining high levels for the other performance criteria (Figure 8). In general, it could also be observed that a further discretization of the model lead to a better representation of the system especially with respect to the spatial patterns. Nevertheless, while the model structure and calibration strategy did influence the spatial pattern in the evaporation (Figures S6 and S12 in the supplementary material) and total water storage anomalies (Figures S7 and S13 in the supplementary material), none of the tested models could adequately reproduce the observed spatial pattern ~~in evaporation and total water storage anomalies~~ which could be a result of model deficiencies or uncertainties in the satellite-based ~~observations of the~~ spatial patterns.

A potential reason for the models' problems to meaningfully describe the spatial pattern of the evaporation was in this study the use of the same parameters within a specific HRU in different model grid cells as also observed in previous studies (Stisen et al., 2018). As a result, the simulated spatial pattern was strongly influenced by the catchment classification method into distinct HRUs. In this study, the catchment was classified merely on the basis of topography into flat, sloped and wetland areas, whereas ecosystem diversity could also be considered as an additional layer in the classification. The poor representation of the spatial pattern in total water storage was also partly linked to that. Spatially distributing calibration parameters could improve the modelled spatial pattern assuming there is sufficient data available to meaningfully constrain the increased number of calibration parameters and thus to avoid elevated equifinality. In a preliminary test, the maximum interception storage (I_{max}) was spatially distributed using a linear transfer function with LAI (leaf area index) data similar to previous studies (Samaniego et al., 2010; Kumar et al., 2013) and using Model F as basis. This did not result in obvious improvements as shown in Figure S14 in the supplementary material. It was considered outside the scope of this study to analyse additional parameter distribution strategies with the limited data availability in this study region.

Another likely reason for the poorly modelled spatial pattern is the absence of lateral exchange of sub-surface water between model grid cells in the tested models, as contiguous groundwater bodies of varying but unknown spatial scale will shape water transfer through the landscape in the real world which remain unaccounted for in the model. Lateral exchange fluxes are as any flux driven by continuous gradients and resistances. However, conceptual-type models, such as the one used in this study, only mimic gradients within grid cells, but not between grid cells. As a result, the head difference between neighbouring cells remains unknown which entails that the direction and magnitude of lateral exchange between cells is unknown. Consequently, these fluxes can only be expressed on basis of free calibration parameters. However, in this data-scarce region it will not be possible to test whether the additional calibration parameters and the associated exchange fluxes are physically plausible. These unspecified boundary fluxes across grid cells are at the core of the closure problem (Beven, 2006a) and touch on the limits of what can be done in hydrology with our current observational technology and the available data. Therefore, adding lateral exchange flow to the model was considered outside the scope of this study.

In addition, each of the applied data sources have their own uncertainties and bias. These include uncertainties in observed discharge due to rating curve uncertainties (Westerberg et al., 2011; Domeneghetti et al., 2012; Tomkins, 2014) and limited data availability, in precipitation data, often as a result of poorly capturing mountainous regions or extreme events on small scales (Hrachowitz and Weiler, 2011; Kimani et al., 2017; Dinku et al., 2018; Le Coz and van de Giesen, 2019), in estimates of total water storage anomalies as a result of data (post-) processing including data smoothing using a radius of for example 300 km affecting the spatial variability on basin scale (Landerer and Swenson, 2012; Blazquez et al., 2018) and in evaporation data due to model, input data and parameter estimation uncertainties (Zhang et al., 2016). In general satellite products are a result of models that are prone to uncertainties related to the input data or model conceptualisation. Uncertainties in for example the spatial pattern of the precipitation affect the spatial pattern of the evaporation considerably as shown in Figure S15 in the supplementary material. In the ideal situation, the data would be validated with field measurements to assess the error magnitude. However, this was not possible due to data limitations. To compensate for bias errors in the satellite-based evaporation and to allow more reliable comparisons with model results, the satellite-based evaporation was adjusted with a correction factor of 1.08 (Section 2.1.2). Correcting the precipitation in a similar manner instead of the evaporation did not significantly affect the model results since normalised values were used for model calibration and evaluation (Figure S16 in the supplementary material).

The results in this study were sensitive to the choice of performance metrics with respect to the individual variables (discharge, evaporation and total water storage) and all variables combined. For instance, the overall model performance measure $D_{\mathrm{E,ESQval}}$ (Eq.32) was strongly influenced by the validated discharge model performance $D_{\mathrm{E,Qval}}$ due to its large range and variation between models compared to the remaining variables where the range was smaller and similar for all models (Figure 8). As a result, the overall model performance measure might not reflect each variable equally well which affected the choice of best performing model. However, this did not cause the poorly reproduced spatial pattern in the evaporation as it remained poorly modelled also when calibrating only with respect to that variable ($E_{\mathrm{SP,E}}$, Figure S17 in the supplementary material). In addition, the histogram component (γ) in the Spatial efficiency metric (E_{SP}, Eq.30) becomes less meaningful for very coarse resolutions when the river basin consists of only a few grid cells as was the case for GRACE. It would be interesting to examine the different components in E_{SP} more detailed in future studies to assess the overall suitability of this metric to identify feasible parameter sets across different spatial scales.

Reflecting the results of previous studies, this study found that calibrating to multiple variables including the spatial patterns improved the simulation of the evaporation and storage with some trade-off in the discharge simulation depending on the model structure (Stisen et al., 2011; Rientjes et al., 2013; Demirel et al., 2018; Herman et al., 2018; 2018; Dembélé et al., 2020). But in contrast and additional to previous studies, this study also provided an example, illustrating that spatial data, here evaporation and total water storage, can contain relevant information to diagnose model deficiencies and to therefore enable step-wise model structural improvement. Previous studies have largely relied on discharge observations to improve model structures (Hrachowitz et al., 2014; Fenicia et al., 2016) and only few studies used satellite data (Roy et al., 2017) even though it provides valuable information on the internal processes temporally and spatially which is not available with discharge data alone (Daggupati et al., 2015; Rakovec et al., 2016). Roy et al. (2017) observed that the simulated evaporation according to the spatially lumped model HYMOD (HYdrological MODel) rapidly dropped to zero in contrast to the satellite product GLEAM (Global Land Evaporation Amsterdam Model) in the Nyangores river basin in Kenya. They improved this simulated evaporation while maintaining good discharge performances by modifying the corresponding equation in HYMOD such that it was a function of the soil moisture.

While here we focussed on upwelling groundwater and spatial discretization, a promising avenue for future studies may be to evaluate the incorporation of simple formulations of subsurface exchange fluxes between model grid cells. Similarly, a further discretization of HRUs into different land cover and ecosystem types may be worthwhile. In addition, a systematic sensitivity

analysis is recommended to explore the influence of individual factors such as model structure and parameters on the spatial and temporal variability of different variables and to further improve the representation of the hydrological processes.

6. Conclusion

The objective of this paper was to explore the added value of satellite-based evaporation and total water storage anomaly data to increase the understanding of hydrological processes through step-wise model structure improvement and model calibration for large river systems in a semi-arid, data scarce region. For this purpose, a distributed process-based hydrological model with sub-grid process heterogeneity for the Luangwa River basin was developed and iteratively adjusted. The results suggested that (1) the benchmark model (Model A) calibrated with respect to discharge reproduced ~~simulated the~~ observed discharge ~~well, and~~ but also ~~the~~ basin-average evaporation and total water storage anomalies rather well, while ~~but~~ poorly capturing~~ed~~ the evaporation for wetland dominated areas as well as ~~and~~ the spatial pattern of evaporation and total water storage anomalies. ~~(2)~~ Testing five further alternative model structures (Models B – F), it was found that (2) among the tested model hypotheses Model F, allowing for upwelling groundwater from a distributed representation of the groundwater reservoir and (3) simultaneously calibrating this~~e~~ model with respect to multiple variables, i.e. discharge, evaporation and total water storage anomalies, resulted in marked improvements of the model performance, providing~~ed~~ the best simultaneous representation of all these variables with respect to their temporal dynamics and spatial pattern~~, except for the basin-average temporal dynamics in the total water storage anomalies~~. Overall, ~~I~~it was shown that satellite-based evaporation and total water storage anomaly data are not only valuable for multi-criteria calibration, but can play an important role in improving our understanding of hydrological processes through diagnosing model deficiencies and step-wise model structural improvement.

Abbreviations

CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
CMRSET	CSIRO MODIS Reflectance Scaling EvapoTranspiration
CRU	Climatic Research Unit
CSIRO	Commonwealth Scientific and Industrial Research Organisation
FAO	Food and Agriculture Organization
GEOS	Goddard Earth Observing System Model
GMTED	Global Multi-resolution Terrain Elevation Data
GRACE	Gravity Recovery and Climate Experiment
HRU	Hydrological Response Unit
MERRA	Modern-Era Retrospective analysis for Research and Applications
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
SSEBop	operational Simplified Surface Energy Balance
WaPOR	Water Productivity Open Access Portal

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