We would like to thank the editor and all referees for their comments to improve our paper. Based on these comments the following main changes were applied:

- The abstract and discussion (Section 4.3) was edited to make it more concise as suggested by Referee #3.
- The introduction was changed such that the different altimetry based calibration strategies were introduced there and included in the hypothesis as suggested by Referee #1.
- In the method section (Section 3), a table was added to create an overview of the different calibration strategies (Table 4 in the manuscript) as suggested by Referee #1 and #2. With this table, we hope that it becomes clearer for the reader how the different calibration strategies build on each other and interact with each other.
- In the results and discussion section, several aspects were included, for example discussing the model performance with respect to the individual flow signatures (suggested by Referee #1), the influence of the number of virtual stations on the discharge estimation (suggested by Referee #3), GRACE uncertainties (suggested by Referee #1 and #3), and model performance metrics (suggested by Referee #1 and #2).
- A section was added to describe opportunities for future studies (Section 4.5) as suggested by Referee #1 and #3.

More details on the individual changes can be found in the responses to the reviewers and the marked-up revised manuscript. In the responses to the reviewers, a reference to the individual changes was included (page and line number) based on the marked-up revised manuscript.

Dear Anonymous Referee #1,

Thank you very much for your feedback on our paper on “Using altimetry observations combined with GRACE to select parameter sets of a hydrological model in data scarce regions”. Hereby we would like to respond to your comments:

Comment 1: I got lost in some of the technical detail around the various alternative calibration strategies tested for calibration. As the abstract seems to suggest insights relating to calibration strategy are the main contribution of this m/s, so I think this needs some more attention. For example, the research hypotheses (l. 109-11) do not address this aspect. In the introduction, can you provide some discussion around the rationale for the different experiments? In fact, to support that, it would be helpful if the authors could provide a table listing, for each variant, the objective function, any transformation of model or observation data (i.e. the observation model), the potential benefits of the variant (i.e., why was it tested), and the empirically-found pros and cons.

Response: This is an excellent suggestion - we agree, the different calibration strategies with respect to altimetry were only introduced in the methods section (Section 3.3.3), but not mentioned in the introduction nor the hypothesis. We changed this in the manuscript by adding a section in the introduction (p. 3, l. 91) and adjusting the hypothesis (p. 4, l. 120). In addition, we agree it would be helpful for the readers to include an overview of the different calibration strategies including their objective functions, discharge – water level conversion techniques and benefits/drawbacks. Therefore, the table shown below was included (Table 4 in the manuscript).

Comment 2: Please consult Domeneghetti (2016) and Oubanas et al. (2018) and consider whether they may be relevant to your discussion.

Response: Thank you for pointing out these interesting papers! We included them in the manuscript (p. 31, l. 761 and 763).

Comment 3: With the caveat that I did not understand all details, I seem to gather that one of the main conclusions of this m/s is that selecting parameters based on rank correlation between discharge and altimetry water level is not sufficient to constrain model parameters, and that altimetry levels need to be converted to actual discharge to provide an appropriate constraint. Is that correct? If so, then that would be expected when evaluating against a performance measure that is extremely bias-sensitive, like Nash-Sutcliffe efficiency (NSE). However, while I know NSE is religiously adhered to by some hydrologists, it is not a relevant performance indicator for all possible uses of river discharge modelling (and indeed many hydrologists have already found a new religion in the more information-rich components of Kling-Gupta Efficiency, KGE). For many practical applications, a high correlation may well be more important than a bias-free estimate, for example in flood and drought applications. Even if volumetric accuracy is more important (e.g. in water resources volume management) then, in this case, you have some gauged data, so provided correlation is high a post-model bias correction would be straightforward. (Although of course station gauge data always have some bias of their own against the unknown truth!). Furthermore, given the almost certainly large uncertainty and bias in the CHIRPS rainfall data for this region, it is likely that a parameter set minimising bias will compensate for the biases and errors I the rainfall data. (Perhaps there are some rain gauge data to test this). In summary, I would recommend *not relying on NSE nearly as much, and also considering correlation measures, perhaps by using the KGE breakdown. At the very least, more discussion is needed.*

Response: We agree the Nash-Sutcliffe efficiency has its limitations just as any other metric. Nevertheless, it still can provide us with valuable information. For many applications in water resources management, it is important to capture both the flow dynamics and volumes correctly; for instance for the management of a dam in the context of flood/drought protection. In that case, a bias-sensitive performance metric such as the Nash-Sutcliffe becomes quite useful.

The Spearman Rank Correlation function only accounts for the dynamical changes and not for the volume which indeed could be taken into account by using information available through gauged data as Referee #1 suggested. This would be possible for this study, but hypothetically, what if no gauged information would be available (which is the reality for the vast majority of river basins world-wide)? This was the assumption made in this study, to answer the question of how well can we do to reproduce river flow in a basin where no flow observations are available and only altimetry data are used for model calibration. Then this study illustrated the added value of converting the water level to discharge using the Strickler-Manning equation to capture the volume better. We agree that the bias in for example the rainfall data can then be compensated through the additional calibration parameters which therefore need to be constrained as much as possible. A section on the model performance metric was added in the discussion (p.30, l.720).

Comment 4: Please add some discussion about the performance of the different variants against the different flow signatures introduced in l. 276-280. Rather than referring to Euser et al., why not include the formula in a table and list the performance of each model variant? I note that most of the signatures are sensitive to bias (see below) and the runoff coefficients also to bias in rainfall. That means that the potential bias in the spatial rainfall estimates and station discharge records needs to be discussed.

Response: Thank you for pointing this out. The performance of the different variants with respect to the different flow signatures is visualized in Figure 7 in the original manuscript, but not discussed explicitly as the focus was on improving the over model performance with respect to the flow. We included this in the manuscript (p. 24, l. 519; p.25, l. 551, 566 and 580; p. 26, l. 600 and 610) together with a table summarizing the formulas for the different flow signatures (Table 5 in the manuscript). In addition, a detailed table summarizing the model performance for each calibration strategy with respect to each flow signatures (as shown in Figure 7) was added in the supplementary material for the interested reader (Table S4).

Table 1: Overview of the calibration strategies applied in this study

Calibration strategy name	Calibration data	Objective function	Nr. of calibration parameters	Comments	Discharge – water level conversion method	Benefits (+) & limitations (-)
Discharge (reference)	Discharge (at basin outlet)	D_{E}	17	Traditional model calibration on observed flow data Combination of 8 different flow signatures	-	-
Seasonal water storage	GRACE	$E_{NS,Stot}$	17	No discharge data used	-	-
Altimetry Strategy 1	Altimetry (at 18 virtual stations) & GRACE	Altimetry: $D_{E,R,WL}$ GRACE: $E_{NS,Stot}$	17	No discharge data used Combination of 18 virtual stations Combined with GRACE	-	+ No extra parameters or data needed + Assumption: monotonic relation between discharge and river water level - Focus on dynamics only, not volume
Altimetry Strategy 2	Altimetry (at 18 virtual stations) & GRACE	Altimetry: $D_{E,NS,RC}$ GRACE: $E_{NS,Stot}$	25	No discharge data used Combination of 18 virtual stations Combined with GRACE	Calibrated Rating curve	+ No extra data needed - Two extra parameters per cross-section
Altimetry Strategy 3	Altimetry (at 18 virtual stations) & GRACE	Altimetry: $D_{E,NS,SM}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combination of 18 virtual stations Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time
Water level Strategy 1	Water level (at basin outlet) & GRACE	Altimetry: $E_{NS,SM,GE}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time
Water level Strategy 2	Water level (at basin outlet) & GRACE	Altimetry: $E_{NS,SM,GE}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time

Comment 5: I would like to see some comparison of model vs remotely sensed GRACE and altimetry data, and the performance of the different calibrated variants against it.

Response: In the manuscript, we wanted to find out whether accurate discharge simulations can be obtained when calibrating to altimetry which is why supporting graphs visualizing the flow were mainly shown.

But with Figure 1, we would like to illustrate the difference between the following two strategies with respect to the water level: converting the simulated discharge to observed water levels using 1) calibrated rating curves and 2) the Strickler-Manning equation. Both strategies were applied to Virtual Station 4 (see Figure 2 for its location) as an example. This graph shows that the water level simulations improved significantly when applying the Strickler-Manning equation and including cross-section information. In addition, Figure 3 shows the model simulation results with respect to the total water storage compared to GRACE. This was added in the manuscript in the results section (p. 24, l. 513; p. 25, l. 558 and 577; Figure 9) and in the supplements (Figure S6).

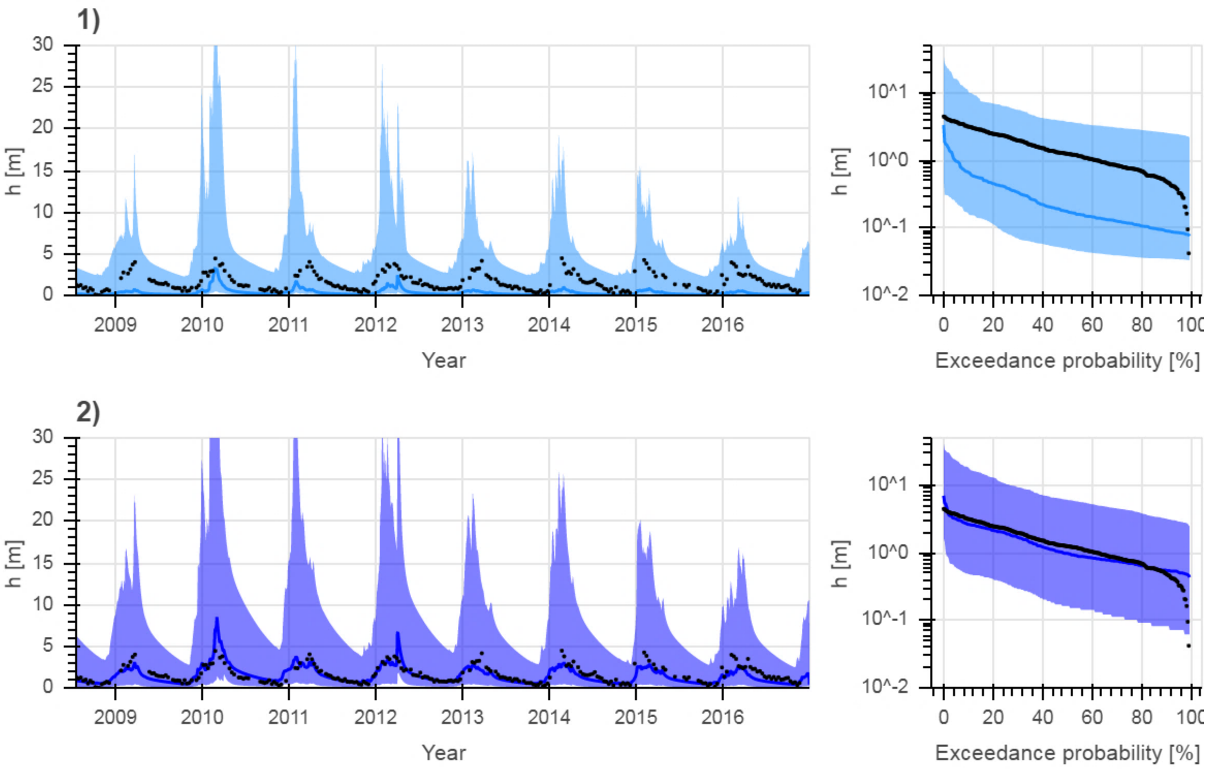

Figure 1: Range of model solutions for Virtual Station 4 (see Figure 2 for its location). The left panel shows the time series and the right panel the exceedance probability graph of the recorded (black) and modelled water level: the line indicates the solution with the highest calibration objective function and the shaded area the envelope of the solutions retained as feasible. Solutions retained as feasible based on altimetry observations using all virtual stations within the basin and 1) calibrated rating curves for the discharge – water level conversion or 2) the Strickler-Manning equation with cross-section information retrieved from Google Earth.

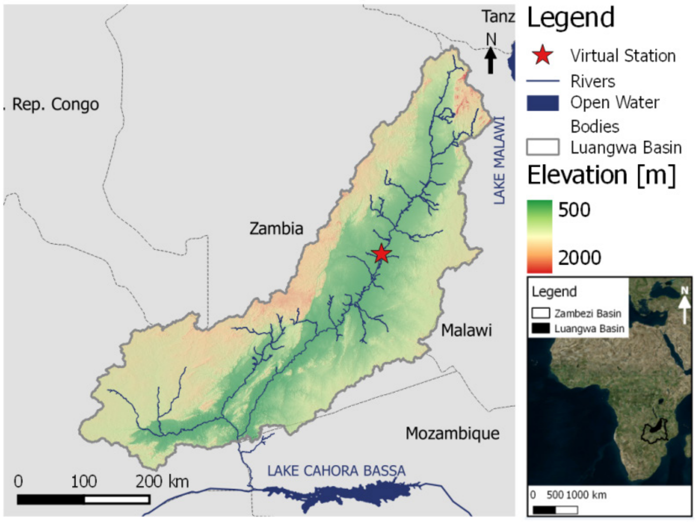

Figure 2: Map of the Luangwa River Basin illustrating the location of Virtual Station 4

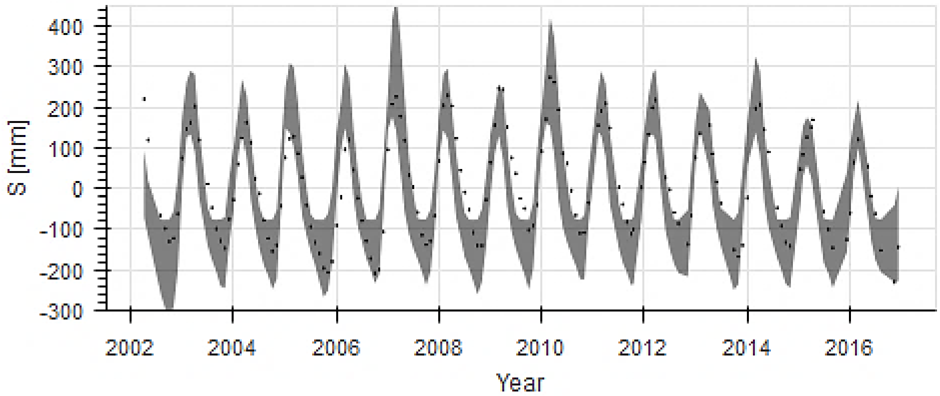

Figure 3: Range of random model realizations with respect to the total water storage (grey) including the observation according to GRACE (black).

Comment 6: GRACE observations are coarse and subject to various uncertainties. To better understand uncertainty relating to calibration to GRACE, can you discuss the contributions of the different storage terms to the temporal variation? This would help to understand where the main uncertainties might be, e.g., how important surface water storage variations are. Also, given the proximity of lakes, dams and wetlands (Cahora Bassa, Lake Malawi, Bangwelu wetlands), they may well have had an influence on GRACE water storage variations. There is no question they are sufficiently close to affect the signal, but perhaps their water level variations haven't been very large during the analysis period. Please discuss this and provide some evidence. For example, you could look at their water level changes (e.g. from altimetry) and you could map the temporal correlation of each GRACE pixel to the respective pixels over each of these 3 areas. Finally, please discuss the SEE between model and GRACE water storage in comparison to the random noise in the GRACE solutions.

Response: Thank you for this comment. There are indeed quite some uncertainties and random noise in the GRACE observations; this was included in the discussion as it was missing (p. 29, l. 679). Within the hydrological system, there are several components that contribute to the total water storage such as the water stored on the surface, in the shallow subsurface zone and in the groundwater. The temporal variation of the first two components is relatively high whereas groundwater levels change slowly. The temporal variation in the monthly total water storage is dominated by the slow variations in the groundwater level. In addition, there are strong seasonal variations in this region due to a very clear wet and dry season which is reflected in all storage components.

As pointed out by Referee #1, there are several lakes/reservoirs and wetlands in the area that could affect GRACE observations. For example the water level variations at Cahora Bassa are significantly larger than the variations in GRACE focusing on the pixel where the virtual station is located (Figure 4A). This influence decreases when focusing on a larger area for instance the area within a 300 km radius of the virtual station (Figure 4B) which is the same distance used to smooth the data and filter out noise. Similar results were found for the other open water bodies and swamps mentioned by Referee #1. In this study, the smallest distance between the basin and a large open water body or swamp was 51 km for Lake Malawi, 72 km for Kafue Flats, 74 km for Cahora Bassa, 135 km for Kariba, 173 for Bangweulu and 210 km for Tanganyika (Figure 5). Hence, large open water bodies and swamps can indeed affect GRACE observations considerably especially for small areas.

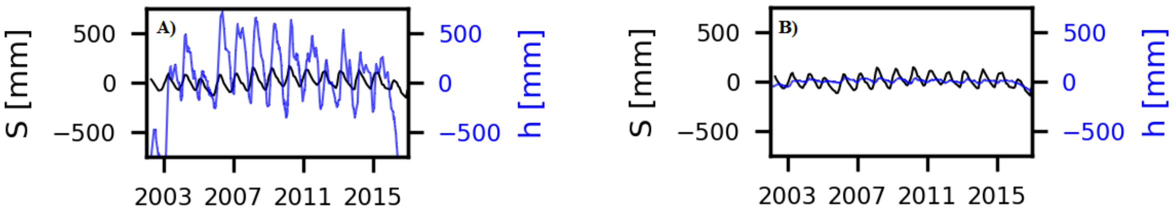

Figure 4: Altimetry observations at Cahora Bassa (blue) and average total water storage according to GRACE (black) for the following areas of interest: A) GRACE cell in which the virtual station is located, and B) area surrounding the virtual station with a radius of 3 degree (GRACE area of influence). The altimetry was multiplied with the area-weighted contribution of open water within the area of interest.

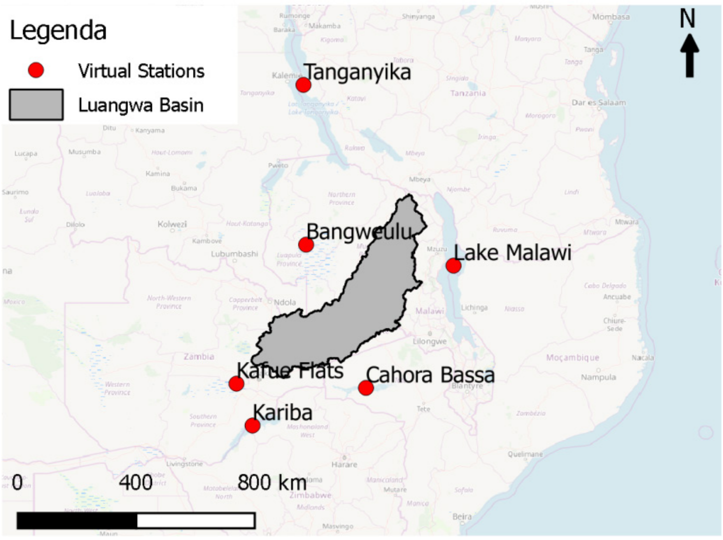

Figure 5: Map of virtual stations

The temporal correlation of each GRACE cell relative to a specific cell is illustrated in Figure 6. For this purpose, the GRACE observations for the cell in which the virtual station for Cahora Bassa is located is plotted against all cells within an area surrounding the virtual station with a radius of 3 degree (GRACE area of influence). This figure shows that there is a relatively strong temporal correlation between the GRACE cells which could be a result of for example the strong seasonality in this area. However, the temporal correlation between GRACE and the altimetry observation is significantly weaker for this example (blue dots in Figure 6). This indicates that the Cahora Bassa reservoir had a limited impact on the GRACE observations within its representative cell despite the large fluctuations.

Unfortunately, we are not sure what Referee #1 is referring to when mentioning the abbreviation "SEE".

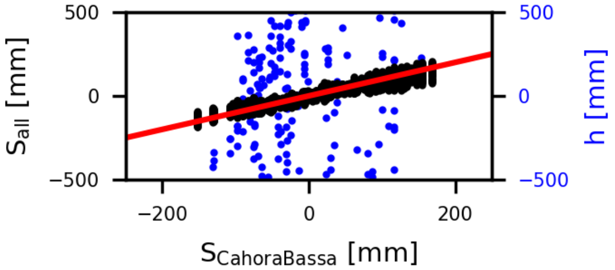

Figure 6: Temporal correlation of the GRACE observations for the cell in which the virtual station for Cahora Bassa is located (horizontal axis) and for A) all cells within an area surrounding the virtual station with a radius of 3 degree (GRACE area of influence, vertical axis, black), and B) the altimetry observation at Cahora Bassa (vertical axis, blue). The 1:1 line is visualised in red.

Comment 7: The apparent benefit of having accurate river cross-section data along with the altimetry data is an interesting one, and could be the most important contribution of this m/s. Can you explore opportunities to build on this insight a bit more please? For example, it is my understanding that profiles can be derived from the altimetry measurements. I am not a radar altimetry specialist and appreciate the authors are not either, but I am sure insights can be found in the literature. Secondly, given the importance of river geometry, can you discuss whether river width and pseudobathymetry from optical remote sensing might help you (see Sichangi et al., 2016; Hou et al., 2018), particularly now there are such data globally at Landsat resolution. In fact, a simple and useful addition would be to add a map of each virtual and actual gauge derived from the Global Surface Water Dataset which is a great resource (Pekel et al., 2016; https://global-surface-water.appspot.com/map). Finally, one of the other reviewers will probably already suggest you mention the SWOT mission. While not seeing inherent merit in arm-waving, in this case, it is interesting to discuss to what extent the SWOT observations might provide richer and/or more accurate data (e.g. on river cross-section and profile) than the current crop of altimeters.

Response: We agree, showing the benefit of detailed cross-section information when combining it with altimetry observations is the main major finding of this manuscript. This approach has a lot of potential. For example, it would be very interesting to combine altimetry observations with river width estimates derived from Landsat or Sentinel-1/2 (Huang et al., 2018). Alternatively, altimetry observations could be combined with CryoSat based altimetry observations which provide water level information at lower temporal resolution (every 369 days), but higher spatial resolution (equatorial inter-track distance of 7.5 km) providing valuable information to estimate the river slope (Schneider et al., 2017;Jiang et al., 2017). In addition, with the upcoming SWOT (Surface Water Ocean Topography) mission, more accurate altimetry observations should be available as also river slope observations and cross-sections; the repeat cycle will be 21 days and across-track resolution between 10 m and

60 m increasing the number of observation points available within a specific area (Biancamaria et al., 2016;Langhorst et al., 2019). Also, it would be very useful to improve cross-section estimates with respect to the submerged part as already explored in previous studies (Domeneghetti, 2016). Furthermore, drone observations could be used to obtain more accurate cross-section information and estimates of the river slope and roughness (Entwistle and Heritage, 2019). We added a more extensive discussion on these points in the revised manuscript (Section 4.5 was added).

Literature

Biancamaria, S., Lettenmaier, D. P., and Pavelsky, T. M.: The SWOT Mission and Its Capabilities for Land Hydrology, Surveys in Geophysics, 37, 307-337, 10.1007/s10712-015-9346-y, 2016.

Domeneghetti, A.: On the use of SRTM and altimetry data for flood modeling in data-sparse regions, Water Resources Research, 52, 2901-2918, 10.1002/2015WR017967, 2016.

Entwistle, N. S., and Heritage, G. L.: Small unmanned aerial model accuracy for photogrammetrical fluvial bathymetric survey, Journal of Applied Remote Sensing, 13, 1-19, 19, 2019.

Huang, Q., Long, D., Du, M., Zeng, C., Qiao, G., Li, X., Hou, A., and Hong, Y.: Discharge estimation in high-mountain regions with improved methods using multisource remote sensing: A case study of the Upper Brahmaputra River, Remote Sensing of Environment, 219, 115-134, https://doi.org/10.1016/j.rse.2018.10.008, 2018.

Jiang, L., Schneider, R., Andersen, O. B., and Bauer-Gottwein, P.: CryoSat-2 altimetry applications over rivers and lakes, Water (Switzerland), 9, 10.3390/w9030211, 2017.

Langhorst, T., Pavelsky, T. M., Frasson, R. P. d. M., Wei, R., Domeneghetti, A., Altenau, E. H., Durand, M. T., Minear, J. T., Wegmann, K. W., and Fuller, M. R.: Anticipated Improvements to River Surface Elevation Profiles From the Surface Water and Ocean Topography Mission, Frontiers in Earth Science, 7, 102, 2019.

Schneider, R., Godiksen, P. N., Villadsen, H., Madsen, H., and Bauer-Gottwein, P.: Application of CryoSat-2 altimetry data for river analysis and modelling, Hydrol. Earth Syst. Sci., 21, 751-764, 10.5194/hess-21-751-2017, 2017.

Dear Anonymous Referee #2,

Thank you very much for your feedback on our paper “Using altimetry observations combined with GRACE to select parameter sets of a hydrological model in data scarce regions”. To respond to your comments:

Comment 1: My main comment is that the general strategy followed for the model calibration lacks legibility. The 7 (?) calibration strategies tested are explained at various places in the manuscript (3.1, 3.3.1-4, again in 4.1.1-4) with a lot of redundancy and at the same time partial information here and there. We don’t really understand how the strategies interact (are they all independent from each other). For example it is not clear in section 3 whether the altimetry and water level strategies were applied after the GRACE strategy or independently. Is there a reference strategy to which all other strategies are compared? We lack also information about the objectives behind the technical setup of each strategy (what are the assumptions tested, why)? I think that a synthetic table presenting the strategies and how they are linked to each other would be very informative.

Response: This is an excellent suggestion - we agree that including a table presenting the strategies and their links would be very helpful; therefore Table 1, as shown below, was added (Table 4 in the revised manuscript). Each strategy was explained in detail in the methods section (Section 3), but we adjusted these descriptions and directly linked them to the new table. When explaining the results for each strategy, the individual strategies were briefly summarized in the results section to help the reader. However, this might not be necessary anymore when including the new table. We hope that with this table it becomes clearer how the different calibration strategies build on each other and interact with each other: the overall objective of this paper is to explore how well we can select parameter sets for hydrological models in catchments when *no* flow observations are available. The sequence of strategies is therefore meant to follow the potential thought process of a modeler in such an ungauged situation: first remove parameter sets that cannot reproduce the seasonal signal as indicated by GRACE. As this set of solutions still (at least in our case) contains many solutions that cannot reproduce river flow in a reasonable way, the set is subsequently further constrained by water level data from altimetry observations. This, in itself, has similarly little additional constraining power. Thus, water levels were converted to flow using different methods, including calibrated rating curves and the Strickler-Manning formula.

Comment 2: I have doubts on the interest of the “water level” strategies presented in the paper. They don’t correspond to the title of the paper that mentions only GRACE and altimetry data. If I understood correctly, these strategies correspond to using the water level time series of the gauging station instead of the discharge data. Since the discharge data are available, what is the interest of these strategies? Is it just about reconstructing a rating curve using Google Earth cross – sections? Why not, but there is really no need to involve a hydrological model in that case. I think that the authors should question the interest of presenting these strategies in the paper, and if yes explain how they relate to the other strategies and what they bring for the use of satellite altimetry data.

Response: Thank you for this comment. The “water level” strategies indeed used water level time series at the gauge station. The objective of including this strategy was to illustrate the importance of incorporating more accurate cross-section information. At the locations where altimetry observations were available, cross-section information was extracted from high-resolution terrain maps available on Google Earth. This, unfortunately, has a low accuracy, leaving us with inaccurate cross-section information at these locations. Unfortunately, accurate cross-section information from in-situ surveys was only available at the gauging station where, in turn, no altimetry observations are available. That is why water level time series were used to illustrate the importance of using more accurate cross-section information. We clarified that in the manuscript (p. 18, l. 413).

Comment 3: About water level based calibration : as shown by the results (Altimetry strategies 1 and 2) and discussed by the authors (p 25, l. 620-625; p26 l. 649-653), calibration of models directly on water level data generates additional uncertainties associated to the level – discharge transformation. Have the authors considered separating the problems by 1/ tackling the altimetry water level – discharge transformation issue (without hydrological model) 2/ considering the model multi-station calibration on discharge. It would bring a clearer theoretical framework, by separating the uncertainty sources (see for example Renard et al., 2010). Moreover, there is already a rich literature corpus on each subject, to which the authors could relate. I think this could be worth a discussion. Renard, B.; Kavetski, D.; Kuczera, G.; Thyer, M. & Franks, S. W. (2010), 'Understanding predictive uncertainty in hydrologic modeling: The challenge of identifying input and structural errors', Water Resources Research 46(5), W055521.

Response: It would indeed be interesting to separate the uncertainties related to the discharge – water level conversion from the hydrological model. For this conversion, there are several calibration parameters. So when disentangling this from the model, alternative information sources would be needed to estimate these parameters. Unfortunately, there was no further really useful information available at the virtual stations to estimate these parameters. This would be very interesting for a follow-up study doing exactly that in a more data rich region to look into these uncertainties more detailed. This aspect was added to the discussion section (p. 31, l. 764).

Comment 4: More information should be provided in the paper about GRACE, for the readers not familiar with satellite products. In particular, readers need to understand how the GRACE water storage anomalies (what is it exactly)? can be compared to total water storage in the model (not even speaking about calibration).

Response: Thank you for pointing this out. A section explaining GRACE more detailed for those not familiar with this product was indeed missing and was added to Section 2.1.2 (p. 5, l. 155).

Comment 5: Many performance indicators are used in the paper and not always explained / justified. The use of NSE on variables like water storage of flow duration curve seems a bit strange, as these variables behave very differently from discharge time series for which NSE is defined. Similarly, the general performance indicator for signatures combines NSE values and relative error values. Again, it is not clear to me how this indicator can be interpreted. What is the added value of using such complex indicators instead of more direct relative errors?

Response: In this paper we indeed used the Nash-Sutcliffe efficiency for the discharge time series, but also for other signatures such as the flow duration curve, and other variables such as total water storage or water level. Even though the Nash-Sutcliffe efficiency was originally defined for discharge time series as pointed out by Referee #2, it was assumed this performance metric can also provide valuable information for other signatures or variables. We agree additional study is required to confirm this assumption and to assess which performance metric would be most suitable, but this was beyond the scope of this study. We included this issue in the discussion (p. 30, l. 720). Furthermore, we wanted to incorporate multiple signatures of the discharge in the performance metric, instead of focusing on only part of the information available in the discharge time series. That is why these performance metrics for each signature were combined, in a similar way as in many earlier studies doing multi-objective calibration. However, we also agree that in the choice of objective functions there is always a strong subjective component and one error metric may be able to capture some aspects of the response better than another one. The reason we did not only show the individual performance indicators, but also decided to provide the combined ones is that we think that a good model should be able to reproduce all indicators simultaneously as well as possible. As there is quite some difference between the performance levels of different indicators, it is difficult to see the overall effect, when only analyzing their individual values.

Comment 6: In the model presentation it is not clear how the flow routing in the hydrographic network is computed – or is there any channel routing at all? This is quite important to know in the context of calibration with water level data (see also Comment 3).

Response: The flow routing scheme was indeed explained only briefly in the manuscript. For the flow routing, the mean flow length of each model gird cell to the outlet was derived based on the topography using a digital elevation map. In addition, it was assumed the flow velocity was constant in space and time; this velocity was calibrated. With this information on the flow path length and velocity, the accumulated flow in each grid cell was calculated at the end of each time step. This explained this in more detail in the manuscript (p. 9, l. 242).

Minor comments: - A table of presenting the parameters (+ how many parameters and which ones were calibrated for each strategy) would be useful in the main text, instead of the detail of all model equations - Provide a table with a clear list of signatures + associated performance criteria – the reader is left to guess what goes with what when it comes to presentation and interpretation of results. - p 11 l 253: what are type II errors? - p 13 l345-350: the authors present a Distance as performance criterion like Eq 3, but there are only water levels in this strategy? Were signatures calculated here as well? - Table 4 is confusing. Why are the criteria different for each strategy in the "model efficiency" column?

Response: We included a table to create an overview of the different calibration strategies and performance metrics (Table 5); we hope that this will also make it clearer why there are different performance metrics for each calibration strategy in Table 4 in the manuscript. A table of the parameters was presented in the supplements (Table S1). A type I error is the rejection of a true hypothesis (e.g. a good parameter set that was supposed to be accepted got rejected), while a type II error is the non-rejection of a false hypothesis (e.g. a bad parameter set that was supposed to be rejected got accepted); this was changed in the manuscript to avoid any confusion (p. 12, l. 276). When calculating the model performance with respect to altimetry, the Euclidian distance was used to combine the model performance of each individual virtual station into one error metric; we agree though the reference to Eq. 3 is confusing; that is why Eq. 5 was introduced.

Table 2: Overview of the calibration strategies applied in this study

Calibration strategy name	Calibration data	Objective function	Nr. of calibration parameters	Comments	Discharge – water level conversion method	Benefits (+) & limitations (-)
Discharge (reference)	Discharge (at basin outlet)	D_{E}	17	Traditional model calibration on observed flow data Combination of 8 different flow signatures	-	-
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Altimetry Strategy 2	Altimetry (at 18 virtual stations) & GRACE	Altimetry: $D_{E,NS,RC}$ GRACE: $E_{NS,Stot}$	25	No discharge data used Combination of 18 virtual stations Combined with GRACE	Calibrated Rating curve	+ No extra data needed - Two extra parameters per cross-section
Altimetry Strategy 3	Altimetry (at 18 virtual stations) & GRACE	Altimetry: $D_{E,NS,SM}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combination of 18 virtual stations Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time
Water level Strategy 1	Water level (at basin outlet) & GRACE	Altimetry: $E_{NS,SM,GE}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time
Water level Strategy 2	Water level (at basin outlet) & GRACE	Altimetry: $E_{NS,SM,GE}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time

Dear Anonymous Referee #3,

Thank you for your feedback on our paper "Using altimetry observations combined with GRACE to select parameter sets of a hydrological model in data scarce regions". We hereby would like to respond to your comments:

Comment 1: Using GRACE observation to constrain parameter space is definitely worthy to be evaluated. However, the uncertainty of GRACE observations in the model calibration process need to be considered. The parameter sets reproduce GRACE observation well may not be reasonably reflect hydrological process of the basin. It is in doubt whether it is reasonable to discard 75% of the parameter set only based on their poor ability to reproduce GRACE observations. It is recommended to calibrate the model based on radar altimetry firstly and then based on GRACE observation. The differences between the two cases may give some new insights about amount of information contained in the two types of satellite observations for hydrological model calibration.

Response: We agree there are quite some uncertainties related to the GRACE observations, especially when using it for a small river basin. This was included in the discussion as it was still missing (p. 29, l. 679). As Referee #3 suggested, we compared the following two calibration approaches: 1) calibrate based on GRACE first, then altimetry (done in the manuscript), 2) calibrate to altimetry first, then GRACE (new). This change of the order mostly affected the selection of the "best" parameter set, especially for Altimetry 1 and Water level 2 (Figure 1), but affected the selection of feasible parameter sets less when using altimetry data as can be seen by the similar ranges in the boxplots. This order had a larger effect when using water level time series at the gauge station. This was added in the manuscript (p. 24, l. 528 and Figure S9)

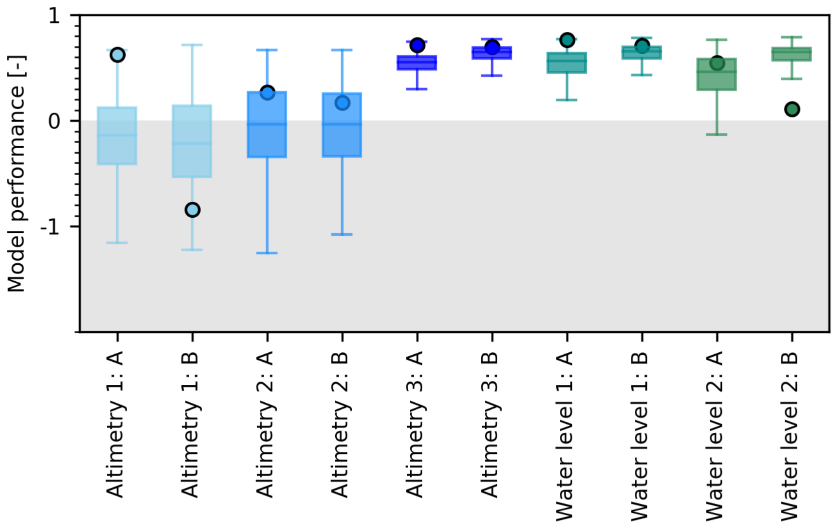

Figure 7: Model performance with respect to discharge for each calibration strategy. Parameter sets were selected based on A) first GRACE, then (satellite based) river water level, or B) first (satellite based) river water level, then GRACE.

Comment 2: Table 4 shows that the parameter set has the highest model efficiency in calibration based on satellite observation is not necessarily to perform best in simulating streamflow. To judge which strategy is more effective in model calibration, it is suggested to show the correlations between model efficiency in simulating the satellite observations and streamflow corresponding to each parameter set.

Response: Thank you for this interesting comment. As recommended by Referee #3, Figure 2 visualizes the correlation between the model efficiency with respect to (satellite based) river water levels and with respect to discharge. This figure shows that a high model performance with respect to the stream levels did not necessarily mean the model performance with respect to discharge was high. This was added in the manuscript (p. 25, l. 548, p. 26, l. 563 and Figure S8).

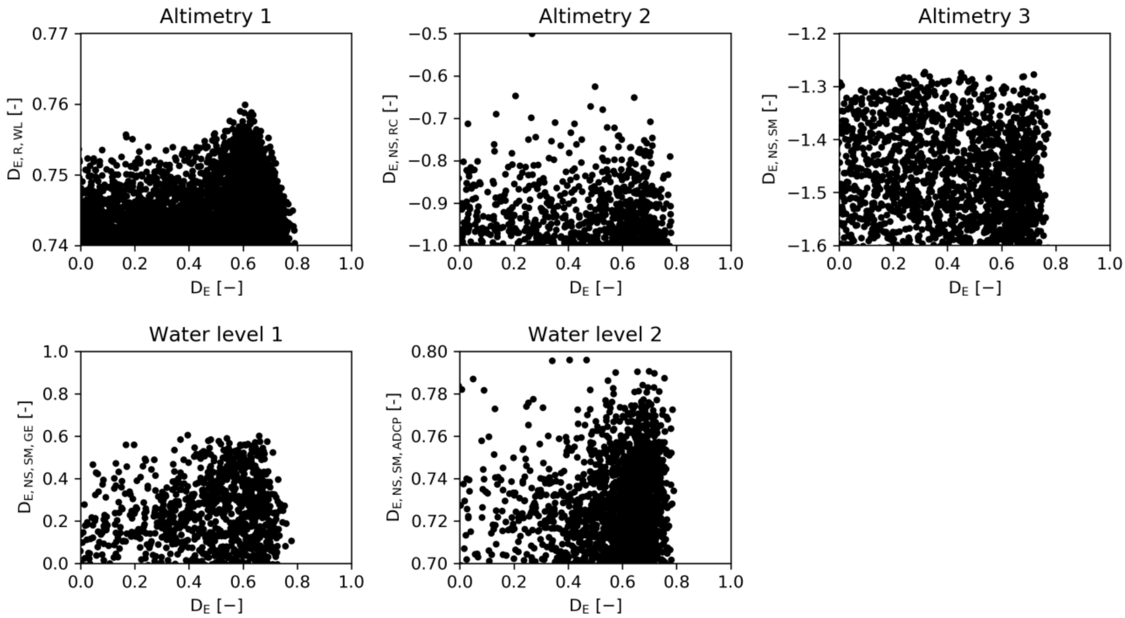

Figure 8: Model performance with respect to discharge (horizontal axes) vs. model performance with respect to (satellite based) river water level (vertical axes) for each calibration strategy

Comment 3: The discussions about the influences of number of virtual stations on model simulation should be extended to exam its influences on streamflow estimation.

Response: It is indeed a very interesting idea to extend the analysis such that the influence of the number of virtual stations on the streamflow simulation is included. As illustrated in Figure 3, the model performance with respect to discharge increased when using more virtual stations. However, at some point an optimum is reached where the model performance remained constant even when adding more virtual stations. The number of virtual stations where this optimum was reached varied per strategy. We added this point to the discussion of the results (p. 28, l. 644 and Figure S5).

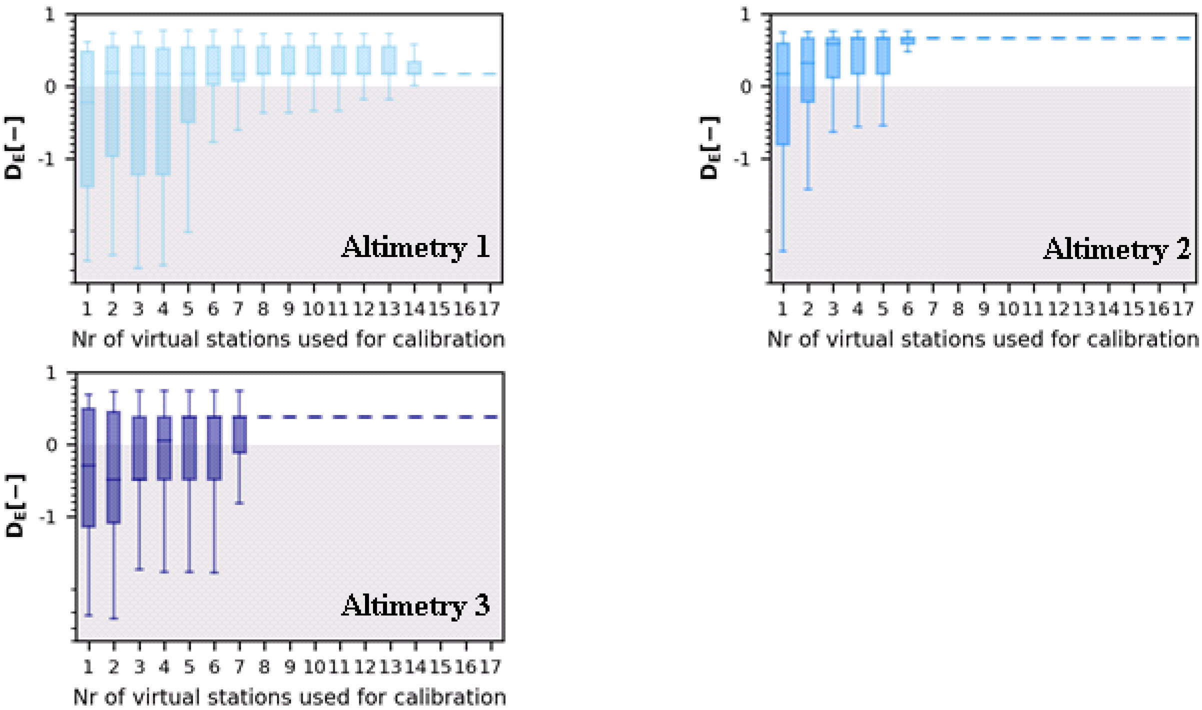

Figure 9: Model performance with respect to discharge (all signatures combined) using an increasing number of virtual stations for calibration

Comment 4: The spatial resolution of GRACE observations and hydrological simulation are different. How did you treat this difference in model calibration?

Response: We agree, in the manuscript it was not explained how we dealt with the differences in the spatial resolution. The gridded information was rescaled to the model resolution of 0.1°. If the resolution of the satellite product was higher than 0.1°, then the area weighted average was taken of all cells located within each model cell. Otherwise, each cell of the satellite product was divided into multiple cells such that the model resolution is obtained, retaining the original value. This was included in Section 2.1.2 (p. 5, l. 159).

Comment 5: In the results and discussion section, it is expected to get more understanding about the implications for the future studies in this research field from the findings of the current study, rather than limitation and comparison with previous studies, for which the relevance to the simulation results is not very high and therefore the content need to be reduced. Also the length of abstract need to be reduced.

Response: Thank you for this comment. There are indeed many interesting opportunities for future studies that could be included in the manuscript; this was done by including a new section in the discussion (Section 4.5). For example, it would be very interesting to combine altimetry observations with CryoSat based altimetry observations which provide water level information at lower temporal resolution (every 369 days), but higher spatial resolution (equatorial inter-track distance of 7.5 km) providing valuable information to estimate the river slope. Also, it would be very useful to improve cross-section estimates with respect to the submerged part as already explored in previous studies (Domeneghetti, 2016). We make the abstract and the section suggested by the reviewer more concise.

Literature

Domeneghetti, A.: On the use of SRTM and altimetry data for flood modeling in data-sparse regions, Water Resources Research, 52, 2901-2918, 10.1002/2015WR017967, 2016.

Marked up manuscript

Using altimetry observations combined with GRACE to select parameter sets of a hydrological model in data scarce regions

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Abstract. ~~To ensure reliable model understanding of water movement and distribution in terrestrial systems, sufficient and good quality hydro-meteorological data are required.~~ Limited availability of ground measurements in the vast majority of river basins world-wide ~~increase~~increases the value of alternative data sources such as satellite observations in ~~modelling. In the absence of directly observed river discharge data, other variables such as remotely sensed river water level may provide valuable information for the calibration and evaluation of~~ hydrological ~~models~~modelling. This study investigates the potential of ~~the use of~~using remotely sensed river water level, i.e. altimetry observations, from multiple satellite missions to identify parameter sets for a hydrological model in the semi-arid Luangwa River Basin in Zambia. A distributed process-based rainfall runoff model with sub-grid process heterogeneity was developed and run on a daily timescale for the time period 2002 to 2016. ~~Following a step-wise approach, various parameter identification strategies were tested to evaluate the potential of satellite altimetry data for model calibration.~~ As a benchmark, feasible model parameter sets were identified using traditional model calibration with observed river discharge data. For the parameter identification using remote sensing, data from the Gravity Recovery and Climate Experiment (GRACE) were used in a first step to restrict the feasible parameter sets based on the seasonal fluctuations in total water storage. ~~In a next step~~Next, three alternative ways of further restricting feasible model parameter sets ~~based on~~using satellite altimetry time-series from 18 different locations~~, i.e. virtual stations,~~ along the ~~Luangwa River and its tributaries~~river were compared. In the calibrated benchmark case, daily river flows were reproduced relatively well with an optimum Nash-Sutcliffe efficiency of $E_{NS,Q}$ = 0.78 (5/95th percentiles of all feasible solutions $E_{NS,Q,5/95}$ = 0.61 – 0.75). When using only GRACE observations to restrict the parameter space, assuming no discharge observations are available, an optimum of $E_{NS,Q}$ = -1.4 ($E_{NS,Q,5/95}$ = -2.3 – 0.38) with respect to discharge was obtained. ~~Depending on the parameter selection strategy, it could be shown that altimetry data can contain sufficient information to efficiently further constrain the feasible parameter space.~~ The direct use of altimetry based river levels frequently led to over-estimated ~~the~~ flows and poorly identified feasible parameter sets ~~due to the non-linear relationship between river water level and river discharge~~ ($E_{NS,Q,5/95}$ = -2.9 – 0.10~~); therefore, this strategy was of limited use to identify feasible model parameter sets.~~). Similarly, converting modelled discharge into water levels using rating curves in the form of power relationships with two additional free calibration parameters per virtual station resulted in an over-estimation of the discharge and poorly identified feasible parameter sets ($E_{NS,Q,5/95}$ = -2.6 – 0.25). However, accounting for river geometry proved to be highly effective; this included using river cross-section and gradient information extracted from global high-resolution terrain data available on Google Earth, and applying the Strickler-Manning equation ~~with effective~~

~~roughness as free calibration parameter~~ to convert modelled discharge into water levels. Many parameter sets identified with this method reproduced the hydrograph and multiple other signatures of discharge reasonably well with an optimum of $E_{NS,Q}$ = 0.60 ($E_{NS,Q,5/95}$ = -0.31 – 0.50). It was further shown that more accurate river cross-section data improved the water level simulations, modelled rating curve and discharge simulations during intermediate and low flows at the basin outlet ~~at which~~where detailed on-site cross-section information was available. ~~For this case, the Nash-Sutcliffe efficiency with respect to river water levels increased from $E_{NS,SM,GE}$ = -1.8 ($E_{NS,SM,GE,5/95}$ = -6.8 – -3.1) using river geometry information extracted from Google Earth to $E_{NS,SM,ADCP}$ = 0.79 ($E_{NS,SM,ADCP,5/95}$ = 0.6 – 0.74) using river geometry information obtained from a detailed survey in the field. It could also be shown that~~Also, increasing the number of virtual stations used for parameter selection in the calibration period ~~can~~ considerably ~~improve~~improved the model performance in a spatial split sample validation. The results provide robust evidence that in the absence of directly observed discharge data for larger rivers in data scarce regions, altimetry data from multiple virtual stations combined with GRACE observations have the potential to fill this gap when combined with readily available estimates of river geometry, thereby allowing a step towards more reliable hydrological modelling in poorly gauged or ungauged basins.

1 Introduction

Reliable models of water movement and distribution in terrestrial systems require sufficient good quality hydro-meteorological data throughout the modelling process. However, the development of robust models is challenged by the limited availability of ground measurements in the vast majority of river basins world-wide (Hrachowitz et al., 2013). Therefore, modellers increasingly resort to alternative data sources such as satellite data (Lakshmi, 2004;Winsemius et al., 2008;Sun et al., 2018;Pechlivanidis and Arheimer, 2015;Demirel et al., 2018;Zink et al., 2018;Rakovec et al., 2016;Nijzink et al., 2018;Dembélé et al., 2020).

In the absence of directly observed river discharge data, various types of remotely sensed variables provide valuable information for the calibration and evaluation of hydrological models. These include, for instance, remotely sensed time series of river width (Sun et al., 2012;Sun et al., 2015), flood extent (Montanari et al., 2009;Revilla-Romero et al., 2015), or river ~~or~~and lake water levels~~, i.e.~~ from altimetry (Getirana et al., 2009;Getirana, 2010;Sun et al., 2012;Garambois et al., 2017;Pereira-Cardenal et al., 2011;Velpuri et al., 2012).

Satellite altimetry observations provide estimates of the water level relative to a reference ellipsoid. For these observations, a radar signal is emitted from the satellite in the nadir direction and reflected back by the earth surface; the time difference between sending and receiving this signal is then used to estimate the distance between the satellite and the earth surface. As the position of the satellite is known at very high accuracy, this distance can then be used to infer the surface level relative to a reference ellipsoid (Łyszkowicz and Bernatowicz, 2017;Calmant et al., 2009). Satellite altimetry is sensed and recorded along the satellite's track. Altimetry based water levels can therefore only be observed where these tracks intersect with open-water surfaces; for rivers, these points are typically referred to as "virtual stations" (de Oliveira Campos et al., 2001;Birkett, 1998;Schneider et al., 2017;Jiang et al., 2017;Seyler et al., 2013). Depending on the satellite mission, the equatorial inter-track distance can vary between 75 km and 315 km, the along-track distance between 173 m and 374 m, and the temporal resolution between 10 days and 35 days (Schwatke et al., 2015;CNES, Accessed 2018;ESA, 2018;Łyszkowicz and Bernatowicz, 2017). Due to this rather coarse resolution, the application of remotely sensed altimetry data is at this moment limited to large lakes or rivers of more than approximately 200 m wide (Getirana et al., 2009;de Oliveira Campos et al., 2001;Biancamaria et al., 2017). Use of altimetry for hydrological models so far also remains rather rare due to the relatively low temporal resolution of the data, with applications typically limited to monthly or longer modelling time steps (Birkett, 1998).

In some previous studies, altimetry data were used to estimate river discharge at virtual stations in combination with routing models (Michailovsky and Bauer-Gottwein, 2014;Michailovsky et al., 2013) or stochastic models (Tourian et al., 2017). Other studies either directly related river altimetry to modelled discharge (Getirana et al., 2009;Getirana and Peters-Lidard, 2013;Leon et al., 2006;Paris et al., 2016) or they relied on rating curves developed with water level data from either in-situ measurements (Michailovsky et al., 2012;Tarpanelli et al., 2013;Papa et al., 2012;Tarpanelli et al., 2017) or, alternatively, from altimetry data (Kouraev et al., 2004). In typical applications, radar altimetry data from one single or only a few virtual stations were used for model calibration, validation or data assimilation; these data were mostly obtained from a single satellite mission, either ~~TOPES/Poseison~~ TOPEX/Poseidson or Envisat (Sun et al., 2012;Getirana, 2010;Liu et al., 2015;Pedinotti et al., 2012;Fleischmann et al., 2018;Michailovsky et al., 2013;Bauer-Gottwein et al., 2015). In previous studies, hydrological models have been calibrated or validated successfully with respect to (satellite based) river water levels for example by 1) applying the Spearman Rank Correlation coefficient (Seibert and Vis, 2016;Jian et al., 2017), or by converting modelled discharge to stream levels using 2) rating curves (Sun et al., 2012;Sikorska and Renard, 2017) or 3) the Strickler-Manning equation (Liu et al., 2015;Hulsman et al., 2018).

In the Zambezi river basin, altimetry data has been used in previous studies for hydrological modelling (Michailovsky and Bauer-Gottwein, 2014;Michailovsky et al., 2012). These studies used the altimetry data from the Envisat satellite in an assimilation procedure to update states in a Muskingum routing scheme. Including the altimetry data improved the model performance; especially when the model initially performed poorly due to high model complexity or input data uncertainties.

Despite these recent advances in using river altimetry in hydrological studies, exploitation of its potential is still limited. Various previous studies have argued and provided evidence based on observed discharge data that, in a special case of multi-criteria calibration, the simultaneous model calibration to flow in multiple sub-basins of a river basin, can be beneficial for a more robust selection of parameter sets and thus for a more reliable representation of hydrological processes and their spatial ~~pattern thereof~~patterns (e.g. Ajami et al., 2004;Clark et al., 2016;Hrachowitz and Clark, 2017;Hasan and Pradhanang, 2017;Santhi et al., 2008). Hence, there may be considerable value in simultaneously using altimetry data not only from one single satellite mission but in combining data from multiple missions, which has not yet been systematically explored. While promising calibration results using data from Envisat were found by Getirana (2010) in tropical and Liu et al. (2015) in snow-dominated regions, altimetry data from multiple sources has not yet been used to calibrate hydrological models in semi-arid regions.

Therefore, the overarching objective of this study is to explore the combined information content (cf. Beven, 2008) of river altimetry data from multiple satellite missions and ~~thus~~ its potential to identify feasible parameter sets for the calibration of hydrological models of large river systems in a semi-arid, data scarce region.

In a step-wise approach we compare three parameter identification strategies using altimetry data from multiple virtual stations ~~simultaneously~~ against a traditional calibration approach based on observed discharge at the outlet. The parameter identification strategies are 1) applying the Spearman Rank Correlation coefficient, or converting modelled discharge to stream levels using 2) rating curves or 3) the Strickler-Manning equation. These three strategies are tested on a distributed process-based rainfall-runoff model with sub-grid process heterogeneity for the Luangwa ~~River basin~~Basin. We test the following research hypotheses: 1) the use of altimetry data allows a meaningful selection of feasible model parameter sets to reproduce river discharge depending on the applied parameter identification strategy, and 2) the combined application of multiple virtual stations from multiple satellite missions improves the model's realism.

2 Site description

The study area is the Luangwa River in Zambia, a tributary of the Zambezi River (Figure 1). It has a basin area of 159,000 km^2 which is about 10% of the Zambezi River Basin. The Luangwa Basin is poorly gauged, mostly unregulated and sparsely populated with about 1.8 million inhabitants in 2005 (The World Bank, 2010). The mean annual precipitation is around 970 mm yr^{-1}, potential evaporation is around 1555 mm yr^{-1} and river runoff reaches about 100 mm yr^{-1} (The World Bank, 2010). The main land cover consists of broadleaf deciduous forest (55%), shrub land (25%) and savanna grassland (16%) (GlobCover, 2009). The irrigated area in the basin is limited to about 180 km^2, i.e. roughly 0.1% of the basin area with an annual water use of about 0.7 mm yr^{-1} which amounts to < 0.001% of the annual basin water balance (The World Bank, 2010). The landscape varies between low lying flat areas along the river to large escarpments mostly in the North West of the basin and highlands with an elevation difference up to 1850 m (see Figure 1B and Section 3.2 for more information on the landscape classification). During the dry season, the river meanders between sandy banks while during the wet season from November to May it can cover flood plains several kilometres wide.

The Luangwa drains into the Zambezi downstream of the Kariba Dam and upstream of the Cahora Bassa Dam. The operation of both dams is crucial for hydropower production, and flood and drought protection, but is very difficult due to the lack of information from poorly gauged tributaries such as the Luangwa (SADC, 2008;Schleiss and Matos, 2016;The World Bank, 2010). As a result, the local population has suffered from severe floods and droughts (ZAMCOM et al., 2015;Beilfuss and dos Santos, 2001;Hanlon, 2001;SADC, 2008;Schumann et al., 2016).

2.1 Data availability

2.1.1 In-situ discharge and water level observations

In the Luangwa basin, historical in-situ daily discharge and water level observations were available from the Zambian Water Resources Management Authority at the Great East Road Bridge gauging station, located at 30^o 13' E and 14^o 58' S (Figure 1) about 75 km upstream of the confluence with the Zambezi. In this study, all complete hydrological years of discharge data within the time period 2002 to 2016 were used; these are the years 2004, 2006 and 2008.

2.1.2 Gridded data products

Besides the above in-situ observations, several gridded data products were used in this study for topographic description, model forcing (precipitation and temperature), and model parameter selection/calibration (total water storage anomalies), as shown in Table 1. The temperature data was used to estimate the potential evaporation according to the Hargreaves method (Hargreaves and Samani, 1985;Hargreaves and Allen, 2003). The Gravity Recovery and Climate Experiment (GRACE) was used as proxy for the total water storage by measuring the variations in the Earth's gravity field to detect regional mass changes. These mass changes are dominated by variations in the terrestrial water storage after having accounted for atmospheric and oceanic effects (Landerer and Swenson, 2012;Swenson, 2012).

All gridded information was rescaled to the model resolution of 0.1°. The temperature and GRACE data were rescaled by dividing each cell of the satellite product into multiple cells such that the model resolution is obtained, retaining the original value. The precipitation was rescaled by taking the average of all cells located within each model cell.

Table 3: Gridded data products used in this study

	Time period	Time resolution	Spatial resolution	Product name	Source
Digital elevation map	NA	NA	0.02°	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)
Total water storage	2002 – 2016	Monthly	1°	GRACE	(Swenson, 2012;Swenson and Wahr, 2006;Landerer and Swenson, 2012)

2.1.3 Altimetry data

The altimetry data used in this study was obtained from the following sources: the Database for Hydrological Time Series of Inland Waters (DAHITI; https://dahiti.dgfi.tum.de/en/) (Schwatke et al., 2015), HydroSat (http://hydrosat.gis.uni-stuttgart.de/php/index.php) (Tourian et al., 2013), Laboratoire d'Etudes en Géophysique et Océanographie Spatiales (LEGOS; http://www.legos.obs-mip.fr/soa/hydrologie/hydroweb/; see supplements for more information), and the Earth and Planetary Remote Sensing Lab (EAPRS; http://www.cse.dmu.ac.uk/EAPRS/). In total, altimetry data was obtained for 18 virtual stations in the Luangwa basin (Figure 1A) for the time period 2002 – 2016 from the satellite missions Jason 1 – 3, Envisat and Saral (Table 2, Figure S2).

Table 4: Overview of the altimetry data in the Luangwa River Basin used in this study

Nr.	Longitude	Latitude	Time period	Nr. of days with data	Source	Mission	Space Agency	Temporal resolution	Equatorial inter-track distance	Along-track distance	Literature
1	30.2823°	-14.8664°	2008-2016	246	DAHITI	Jason 2, 3	NASA/CNES	10 days	315 km	294 m	(Schwatke et al., 2015;CNES, Accessed 2018)
2	30.0864°	-14.366°	2008-2015	92	DAHITI	Jason 2, 3					
3	32.1715°	-12.4123°	2008-2016	248	DAHITI	Jason 2, 3					
4	31.1868°	-13.5927°	2002-2016	104	DAHITI	Envisat, Saral	ESA (Envisat), ISRO/CNES (Saral)	35 days	80 km (Envisat), 75 km (Saral)	374 m (Envisat), 173 m (Saral)	(Schwatke et al., 2015;ESA, 2018;CNES, Accessed 2018)
5	31.6984°	-13.2039°	2002-2016	82	DAHITI	Envisat, Saral					
6	32.2998°	-12.2007°	2002-2016	100	DAHITI	Envisat, Saral					
7	32.2805°	-12.1157°	2002-2016	103	DAHITI	Envisat, Saral					
8	32.831°	-11.3674°	2002-2016	105	DAHITI	Envisat, Saral					
9	30.2704°	-14.8809°	2008-2015	247	HydroSat	Jason 2	NASA/CNES	10 days	315 km	294 m	(Tourian et al., 2016;Tourian et al., 2013)
10	31.78405°	-13.0995°	2002-2010	65	EAPRS	Envisat	ESA	35 days	80 km	374 m	(Michailovsky et al., 2012;ESA, 2018)
11	31.71099°	-13.1943°	2002-2010	93	EAPRS	Envisat					
12	30.2740°	-14.8763°	2008-2015	231	LEGOS	Jason 3	NASA/CNES	10 days	315 km	294 m	(Frappart et al., 2015;CNES, Accessed 2018)
13	32.15843°	-12.412°	2016-2016	28	LEGOS	Jason 3					
14	32.15989°	-12.4127°	2002-2009	137	LEGOS	Jason 1					
15	30.2740°	-14.8763°	2008-2016	271	LEGOS	Jason 2					
16	32.16056°	-12.4125°	2008-2016	283	LEGOS	Jason 2					
17	31.80001°	-13.0909°	2013-2016	35	LEGOS	Saral	ISRO/CNES	35 days	75 km	173 m	
18	30.61577°	-14.1852°	2013-2016	24	LEGOS	Saral					

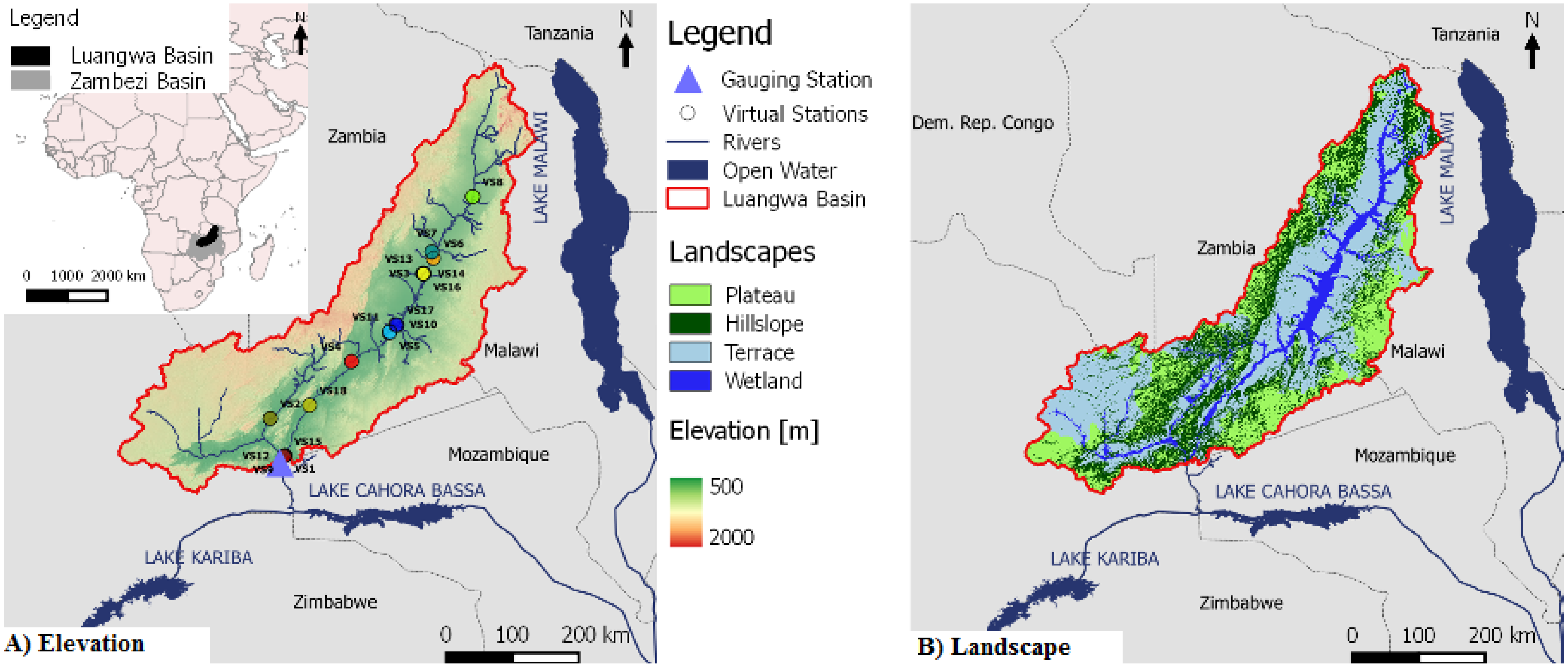

Figure 10: A) Elevation map of the Luangwa River Basin in Zambia including the Great East Road Bridges river gauging station and the locations of the 18 virtual stations (VS 1 – VS 18) with altimetry data used in this study; their colours correspond to those in Figure 3. B) Map of the Luangwa River Basin with the main landscape types (see Section 3.2).

2.1.4 River geometry information

In the Luangwa Basin, very limited detailed in-situ information was available on the river geometry such as cross-section and slope. For that reason, this information was extracted from global high-resolution terrain data available on Google Earth as done successfully in previous studies for other purposes (Pandya et al., 2017;Zhou and Wang, 2015). This was done for each virtual station and the basin outlet. Google Earth only provides river geometry information above the river water level. As the Luangwa is a perennial river, parts of the cross-section remain submerged throughout the year and thus unknown. To limit uncertainties arising from that, the cross-section geometry for each virtual station was therefore extracted from the Google Earth image with the lowest water levels at each individual virtual station. The dates of these images in general fall into the dry season, with flows at the Great East Road Bridges gauging station on the respective days ranging from 1% to 4% relative to the maximum discharge (see Supplementary Table S3 for the dates of the satellite images and the associated flows at the Great East Road Bridges gauging station). The database underlying the global terrain images in Google Earth originate from multiple, merged data sources with varying spatial resolutions. For the Luangwa Basin these include the Shuttle Radar Topography Mission (SRTM) with a spatial resolution of 30 m, the Landsat 8 with a spatial resolution of 15 m and the Satellite Pour l'Observation de la Terre 4/5 (SPOT) with a spatial resolution of 2.5 m to 20 m (Smith and Sandwell, 2003;Irons et al., 2012;Drusch et al., 2012).

In addition to Google Earth data, the submerged part of the channel cross-section was surveyed in the field on April 27th 2018 near the Great East Road Bridges river gauging station at the coordinates 30^{o} 13' E and 15^{o} 00' S (Abas, 2018) with an Acoustic Doppler Current Profiler (ADCP).

3 Hydrological model development

3.1 General approach

The potential of river altimetry for model calibration was tested with a process-based hydrological model for the Luangwa river basin. This model relied on distributed forcing allowing for spatially explicit distributed water storage calculations. The model was run on a daily time scale for the time period 2002 to 2016. To reach the objective of this study, the following distinct parameter identification strategies were compared in a stepwise approach: (1) traditional model calibration to observed river flow as benchmark; (2) identification of parameter sets reproducing the seasonal water storage anomalies based on GRACE data only; (3a) Altimetry Strategy 1: identification of parameter sets directly based on remotely sensed water levels combined with GRACE data; (3b) Altimetry Strategy 2: identification of parameter sets based on remotely sensed water levels by converting modelled discharges into water levels using calibrated rating curves combined with GRACE data; (3c) Altimetry Strategy 3: identification of parameter sets based on remotely sensed water levels by converting modelled discharges into water levels using the Strickler-Manning equation and including river geometry information (cross-section and gradient) extracted from Google Earth combined with GRACE data; (4a) Water level Strategy 1: identification of parameter sets based on daily river water level at the catchment outlet only using the Strickler-Manning equation and including river geometry information extracted from Google Earth combined with GRACE data; and (4b) Water level Strategy 2: identification of parameter sets based on daily river water level at the catchment outlet only using the Strickler-Manning equation and including river geometry information obtained from a detailed field survey with an Acoustic Doppler Current Profiler (ADCP) combined with GRACE data. Note that (1) is completely independent of (2) to (4) where no discharge data was used for the identification of parameter sets.

3.2 Hydrological model structure

In this study, a process-based rainfall-runoff with distributed water accounting and sub-grid process heterogeneity was developed (Ajami et al., 2004;Euser et al., 2015). The river basin was discretized into a grid with a spatial resolution of 10 x 10 km^2. Each model grid cell was characterized by the same model structure and parameter sets but forced by spatially distributed, gridded input data (Table 1). Runoff was then calculated in parallel for each cell separately. Subsequently, a routing scheme was applied to estimate the aggregated flow in each grid cell at each time step.

Adopting the FLEX-Topo modelling concept (Savenije, 2010) and extending it to a gridded implementation, each grid cell was further discretised into functionally distinct hydrological response classes as demonstrated by Nijzink et al. (2016). Each point within a grid cell was assigned to a response class based on its position in the landscape as defined by its local slope and “Height-above-the-nearest-drainage” (HAND; Rennó et al., 2008;Gharari et al., 2011). Similar to previous studies (e.g. Gao et al., 2016;Nijzink et al., 2016) here the response classes plateau, hillslope, terrace and wetlands were distinguished. Reflecting earlier work (e.g. Gharari et al., 2011), all locations with slope of > 4% were assumed to be hillslope. Locations with slopes lower than that were then either defined as wetland (HAND < 11m), terrace (11m ≤ HAND < 275m) or plateau (HAND ≥ 275m); see Figure 2. Following this classification wetlands make up 8%, terraces 41%, hillslopes 28% and plateaus 23% of the total Luangwa River Basin area as mapped in Figure 1B.

Each response class consisted of a series of storage components that are linked by fluxes. The flow generated from each grid cell at any given time step is then computed as the area-weighted flow from the individual response classes plus a contribution from the common groundwater component which connects the response classes (Figure 2). Finally, the outflow from each modelling cell was routed to downstream cells ~~following~~to obtain the accumulated flow in each grid cell at any given time step. For this purpose, the mean flow length of each model gird cell to the outlet was derived based on the flow direction ~~as~~ extracted from the digital elevation model. The flow velocity, which was assumed to be constant in space and ~~a~~time, was calibrated ~~effective~~. With this information on the flow path length and velocity ~~to obtain~~, the accumulated flow in each grid cell was calculated at ~~any given~~the end of each time step. The relevant model equations are given in Table 3. This concept was previously successfully applied in a wide range of environments (Gao et al., 2014;Gharari et al., 2014;Fovet et al., 2015;Nijzink et al., 2016;Prenner et al., 2018).

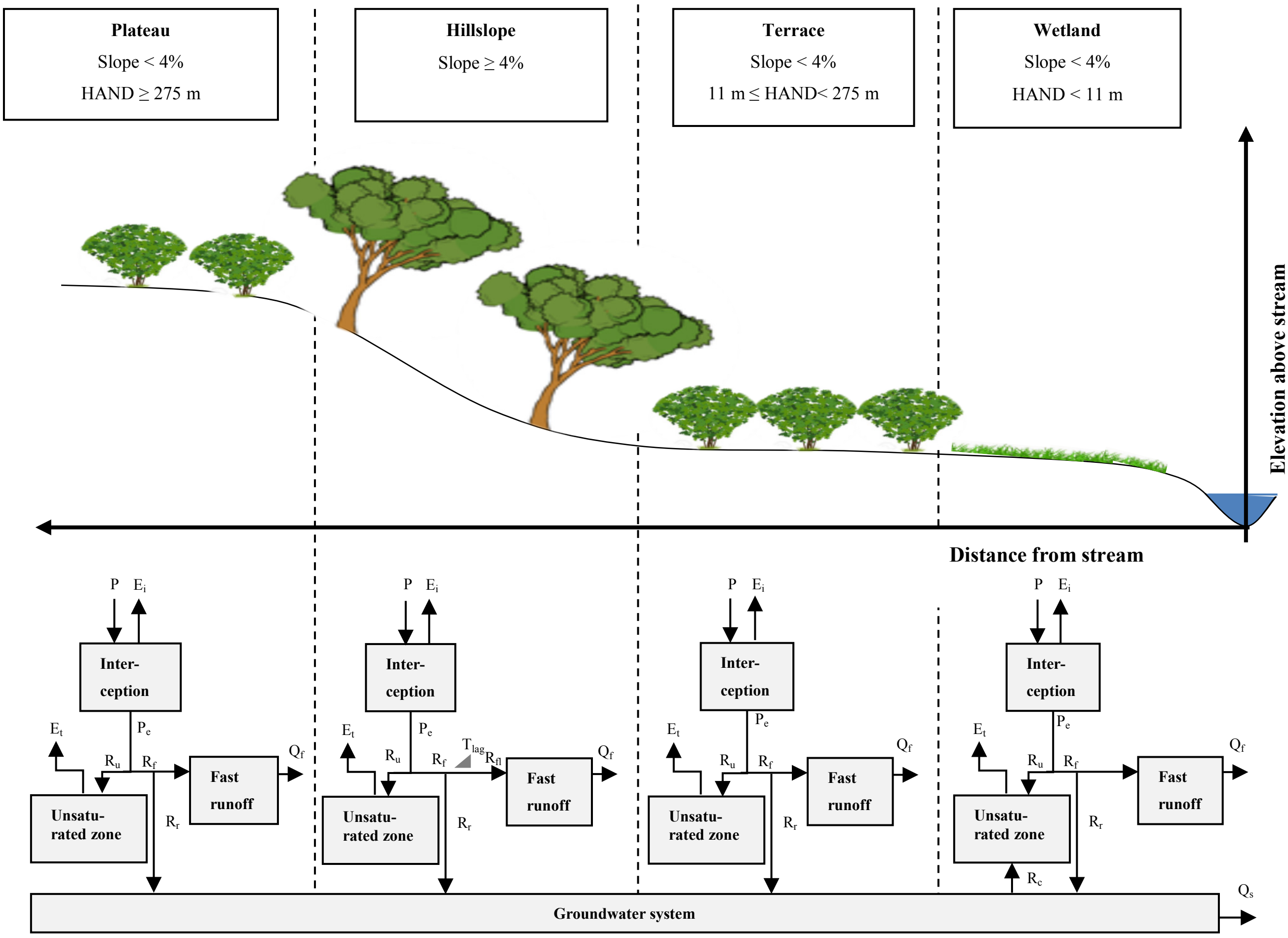

Figure 11: Sketch of the hydrological response classes including the thresholds used in this analysis for the slope and HAND (Height Above Nearest Drainage) and including their corresponding model structures. This spatial sub-grid discretization was applied to each grid cell. Symbol explanation: precipitation (*P*), effective precipitation (P_e), interception evaporation (E_i), plant transpiration (E_a), 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_c), fast runoff (Q_f), groundwater/slow runoff (Q_s).

Table 5: 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), upwelling groundwater (R_c), fast runoff (Q_f), 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], splitter (W) [-], shape parameter (β) [-], transpiration coefficient (C_e) [-], time lag (T_{lag}) [d], reservoir time scales [d] of fast (K_f) and slow (K_s) reservoirs, areal weights (p_{HRU}) [-],time step (Δt) [d]. Model 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	Process functions
Interception	$\frac{\Delta S_i}{\boldsymbol{\Delta t}} = P - P_e - E_i \approx 0$	$E_i = \min\left(E_p, \min\left(P, \frac{\boldsymbol{I_{max}}}{\boldsymbol{\Delta t}}\right)\right)$ $P_e = P - E_i$
Unsaturated zone	Plateau/Hillslope/Terrace: $\frac{\Delta S_u}{\boldsymbol{\Delta t}} = R_u - E_t$ Wetland: $\frac{\Delta S_u}{\boldsymbol{\Delta t}} = R_u - E_t + R_c$	$E_t = \min((E_p - E_i), \min\left(\frac{S_u}{\boldsymbol{\Delta t}}, (E_p - E_i) \cdot \frac{S_u}{\boldsymbol{S_{u,max}}} \cdot \frac{1}{\boldsymbol{C_e}}\right))$ $R_c = \min\left(\left(1 - \frac{S_u}{\boldsymbol{S_{u,max}}}\right) \cdot \boldsymbol{C_{max}}, \frac{\frac{S_s}{\boldsymbol{\Delta t}}}{\boldsymbol{p_{HRU}}}\right)$ if $S_u + R_c \cdot \boldsymbol{\Delta t} > \boldsymbol{S_{u,max}} : R_c = \frac{\boldsymbol{S_{u,max}} - S_u}{\boldsymbol{\Delta t}}$ Plateau/Terrace/Wetland: $R_u = P_e$ Hillslope: $R_u = (1 - C) \cdot P_e$ $C = 1 - \left(1 - \frac{S_u}{\boldsymbol{S_{u,max}}}\right)^{\boldsymbol{\beta}}$
Fast runoff	$\frac{\Delta S_f}{\boldsymbol{\Delta t}} = R_{fl} - Q_f$	$Q_f = \frac{S_f}{\boldsymbol{K_f}}$ Terrace/Wetland: $R_f = \frac{\max(0, S_u - \boldsymbol{S_{umax}})}{\boldsymbol{\Delta t}}$ $R_{fl} = R_f$ Hillslope: $R_f = (1 - \boldsymbol{W}) \cdot C \cdot P_e$ $R_{fl} = R_f * f(T_{lag})$
Groundwater	$\frac{\Delta S_s}{\boldsymbol{\Delta t}} = R_{r_{tot}} - R_{c_{tot}} - Q_s$	$R_r = \boldsymbol{W} \cdot C \cdot P_e$ $R_{r_{tot}} = \sum_{HRU} \boldsymbol{p_{HRU}} \cdot R_r$ $R_{c_{tot}} = \sum_{HRU} \boldsymbol{p_{HRU}} \cdot R_c$ $Q_s = \frac{S_s}{\boldsymbol{K_s}}$
Total runoff	$Q_m = Q_s + Q_{f_{tot}}$	$Q_{f_{tot}} = \sum_{HRU} \boldsymbol{p_{HRU}} \cdot Q_f$
Supporting literature	(Gharari et al., 2014;Gao et al., 2014;Euser et al., 2015)	

3.3 Parameter selection procedures and model performance evaluation

To evaluate the information content and thus the utility of altimetry data for the selection of feasible model parameter sets, a step-wise procedure as specified in detail below was applied (Table 4). Note that given data scarcity and the related issues of epistemic uncertainties (Beven and Westerberg, 2011;McMillan and Westerberg, 2015) and equifinality (Beven, 2006;Savenije, 2001) we did not aim to identify the "optimal" parameter set in what is frequently considered a traditional calibration approach. In most hydrological applications the available data have limited strength for rigorous model tests (Clark et al., 2015;Gupta et al., 2008;Jakeman and Hornberger, 1993). Thus, to reduce ~~type II errors~~the risk of rejecting good parameters when they should have been accepted (Beven, 2010;Hrachowitz and Clark, 2017), we rather attempted to identify and discard the most implausible parameter sets (Freer et al., 1996) that violate our theoretical understanding of the system or that are inconsistent with the available data (Knutti, 2008). This allowed us to iteratively constrain the feasible parameter space and thus the uncertainty around the modelled hydrograph (Hrachowitz et al., 2014). To do so, a Monte-Carlo sampling strategy with uniform prior parameter distributions was applied to generate $5{\cdot}10^4$ model realizations. This random set of solutions was in the following steps used as baseline and iteratively constrained by identifying parameter sets that do not satisfy pre-specified criteria (see below), depending on the data type and source used.

3.3.1 Benchmark: Parameter selection and model performance based on observed discharge data

Model calibration

As benchmark, and following a traditional calibration procedure, the model was calibrated with observed daily discharge based on the Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970) using all complete hydrological years within the time period 2002 to 2016; these are the years starting in the fall of 2004, 2006 and 2008:

$$E_{\mathrm{NS,Q}} = 1 - \frac{\sum_t \left(Q_{\mathrm{mod}}(\mathrm{t}) - Q_{\mathrm{obs}}(t)\right)^2}{\sum_t (Q_{\mathrm{obs}}(\mathrm{t}) - \overline{Q_{\mathrm{obs}}})^2} \tag{1}$$

To limit the solutions to relatively robust representations of the system while allowing for data and model uncertainty (e.g. Beven, 2006;Beven and Westerberg, 2011) only parameter sets that resulted in $E_{\mathrm{NS,Q}} \geq 0.6$ were retained as feasible. The hydrological model consisted of 17 free calibration parameters (Table 4) whose uniform prior distributions are given in Table S1 in the supplementary material with associated parameter constrains as summarised in Table S2.

Table 6: Overview of the parameter identification strategies applied in this study

Calibration strategy name	Calibration data	Objective function	Nr. of calibration parameters	Comments	Discharge – water level conversion method	Benefits (+) & limitations (-)
Discharge (reference)	Discharge (at basin outlet)	$E_{NS,Q}$	17	Traditional model calibration on observed flow data Combination of 8 different flow signatures	-	-
Seasonal water storage	GRACE	$E_{NS,Stot}$	17	No discharge data used	-	-
Altimetry Strategy 1	Altimetry (at 18 virtual stations) & GRACE	Altimetry: $D_{E,R,WL}$ GRACE: $E_{NS,Stot}$	17	No discharge data used Combination of 18 virtual stations Combined with GRACE	-	+ No extra parameters or data needed + Assumption: monotonic relation between discharge and river water level - Focus on dynamics only, not volume
Altimetry Strategy 2	Altimetry (at 18 virtual stations) & GRACE	Altimetry: $D_{E,NS,RC}$ GRACE: $E_{NS,Stot}$	25	No discharge data used Combination of 18 virtual stations Combined with GRACE	Calibrated Rating curve	+ No extra data needed - Two extra parameters per cross-section
Altimetry Strategy 3	Altimetry (at 18 virtual stations) & GRACE	Altimetry: $D_{E,NS,SM}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combination of 18 virtual stations Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time
Water level Strategy 1	Water level (at basin outlet) & GRACE	Altimetry: $E_{NS,SM,GE}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time
Water level Strategy 2	Water level (at basin outlet) & GRACE	Altimetry: $E_{NS,SM,ADCP}$ GRACE: $E_{NS,Stot}$	18	No discharge data used Combined with GRACE	Strickler-Manning	+ Only 1 extra parameter - Cross-section data needed - Assumption: constant roughness in space and time

Model evaluation

The performance of all model realizations was evaluated post-calibration with respect to discharge using seven additional hydrological signatures (e.g. Sawicz et al., 2011;Euser et al., 2013) to assess the skill of the model to reproduce the overall response of the system and thus the robustness of the selected parameters (Hrachowitz et al., 2014). The signatures included the logarithm of the daily flow time series (hereafter referred to with the subscript logQ), the flow duration curve (FDC), its logarithm (logFDC), the mean seasonal runoff coefficient during dry periods (April - September; RCdry), the mean seasonal runoff coefficient during the wet periods (October - March; RCwet), the autocorrelation function of daily flow (AC) and the rising limb density of the hydrograph (RLD). ~~Detailed explanations~~An overview of these signatures can be found in Table 5, and more detailed explanations in Euser et al. (2013) and references therein. As performance measures for the model to reproduce the individual observed signatures the Nash-Sutcliffe efficiency ($E_{\mathrm{NS,logQ}}$, $E_{\mathrm{NS,FDC}}$, $E_{\mathrm{NS,logFDC}}$, $E_{\mathrm{NS,AC}}$; equivalent to Eq.1 and a metric based on the relative error ($E_{\mathrm{R,RCdry}}$, $E_{\mathrm{R,RCwet}}$, $E_{\mathrm{R,RLD}}$) were used (Euser et al., 2013):

$$E_{\mathrm{R},\theta} = 1 - \frac{|\theta_{\mathrm{mod}} - \theta_{\mathrm{obs}}|}{\theta_{\mathrm{obs}}} \quad (2)$$

Where θ is any of the three signatures evaluated with E_{R}. The signatures where combined, with equal weights, into one objective function, which was formulated based on the Euclidian distance D_{E} (Schoups et al., 2005) so that a value of 1 indicates a "perfect" model:

$$D_{\mathrm{E}} = 1 - \sqrt{\frac{1}{(N+M)}\left(\sum_{n}\left(1 - E_{\mathrm{NS},\theta_{\mathrm{n}}}\right)^2 + \sum_{m}\left(1 - E_{\mathrm{R},\theta_{\mathrm{m}}}\right)^2\right)} \quad (3)$$

Where θ is a signature, n indicates the signatures evaluated based on the Nash-Sutcliffe efficiency, m indicates the signatures evaluated based on the relative error and N and M are the respective number of signatures used.

Table 7: Overview of flow signatures used in this study

Flow signature	**Explanation**	**Function**	**Model performance equation**
Q	Daily flow time series	-	$E_{\mathrm{NS,Q}} = 1 - \frac{\sum_t (Q_{\mathrm{mod,t}} - Q_{\mathrm{obs,t}})^2}{\sum_t (Q_{\mathrm{obs,t}} - \overline{Q_{\mathrm{obs}}})^2}$
logQ	Logarithm of daily flow time series	-	$E_{\mathrm{NS,logQ}} = 1 - \frac{\sum_t (Q_{\mathrm{log,mod,t}} - Q_{\mathrm{log,obs,t}})^2}{\sum_t (Q_{\mathrm{log,obs,t}} - \overline{Q_{\mathrm{log,obs}}})^2}$
FDC	Flow duration curve	-	$E_{\mathrm{NS,FDC}} = 1 - \frac{\sum_t (Q_{\mathrm{sort,mod,t}} - Q_{\mathrm{sort,obs,t}})^2}{\sum_t (Q_{\mathrm{sort,obs,t}} - \overline{Q_{\mathrm{sort,obs}}})^2}$
logFDC	Logarithm of flow duration curve	-	$E_{\mathrm{NS,logFDC}} = 1 - \frac{\sum_t (Q_{\mathrm{log,sort,mod,t}} - Q_{\mathrm{log,sort,obs,t}})^2}{\sum_t (Q_{\mathrm{log,sort,obs,t}} - \overline{Q_{\mathrm{log,sort,obs}}})^2}$
RCdry	Runoff coefficient during dry periods	$RC_{\mathrm{dry}} = \frac{Q_{\mathrm{dry}}}{P_{\mathrm{dry}}}$	$E_{\mathrm{R,RCdry}} = 1 - \frac{\lvert RC_{\mathrm{dry,mod}} - RC_{\mathrm{dry,obs}} \rvert}{RC_{\mathrm{dry,obs}}}$
RCwet	Runoff coefficient during wet periods	$RC_{\mathrm{wet}} = \frac{Q_{\mathrm{wet}}}{P_{\mathrm{wet}}}$	$E_{\mathrm{R,RCwet}} = 1 - \frac{\lvert RC_{\mathrm{wet,mod}} - RC_{\mathrm{wet,obs}} \rvert}{RC_{\mathrm{wet,obs}}}$
AC	Autocorrelation function	$AC_{\mathrm{t}} = \frac{\sum_{\mathrm{i}} (Q_{\mathrm{i}} - \overline{Q}) * (Q_{\mathrm{i+t}} - \overline{Q})}{\sum (Q_{\mathrm{i}} - \overline{Q})^2}$	$E_{\mathrm{NS,AC}} = 1 - \frac{\sum_t (AC_{\mathrm{mod,t}} - AC_{\mathrm{obs,t}})^2}{\sum_t (AC_{\mathrm{obs,t}} - \overline{AC_{\mathrm{obs}}})^2}$
RLD	Rising limb density	$RLD = \frac{N_{\mathrm{peaks}}}{T_{\mathrm{r}}}$	$E_{\mathrm{R,RLD}} = 1 - \frac{\lvert RLD_{\mathrm{mod}} - RLD_{\mathrm{obs}} \rvert}{RLD_{\mathrm{obs}}}$

3.3.2 Parameter selection and model performance based on the seasonal water storage (GRACE)

In a next step we assumed that discharge records in the Luangwa Basin were absent. The starting assumption thus had to be that all model realizations, i.e. all sampled parameter sets, were equally likely to allow feasible representations of the hydrological system. In a stepwise approach, confronting these realizations with different types of data, we sequentially identified and discarded solutions that were least likely to provide meaningful system representations, thereby gradually narrowing down the feasible parameter space.

As altimetry data alone only contain limited information on the river flow volumes, we first identified and discarded solutions that were least likely to preserve observed the seasonal water storage (S_{tot}) fluctuations. To do so, the monthly modelled total water storage ($S_{\mathrm{tot,mod}} = S_{\mathrm{i}} + S_{\mathrm{u}} + S_{\mathrm{f}} + S_{\mathrm{s}}$) relative to the 2004-2009 time-mean baseline in each grid cell was compared to water storage anomalies as obtained from the GRACE data product (Tang et al., 2017;Fang et al., 2016;Forootan et al., 2019;Khaki and Awange, 2019). In the GRACE product, the same time period was used for the time-mean baseline (Swenson and Wahr, 2006;Swenson, 2012;Landerer and Swenson, 2012).

The model's skill to reproduce the seasonal water storage, i.e. S_{tot}, was assessed using the Nash-Sutcliffe efficiency $E_{\mathrm{NS,Stot}}$ (Eq. 1). Note that $E_{\mathrm{NS,Stot,j}}$ was computed at first from the time series of S_{tot} in each grid cell j which were then averaged to obtain $E_{\mathrm{NS,Stot}}$. If no additional data were available, a hypothetic modeller relying on $E_{\mathrm{NS,Stot}}$ to calibrate a model, may choose only the solution with the highest $E_{\mathrm{NS,Stot}}$ or allow for some uncertainty. To mimic this traditional approach but to balance it with a sufficient number of feasible solutions to be kept for the subsequent steps we here identified and discarded the poorest performing 75% of all solutions in terms of $E_{\mathrm{NS,Stot}}$ as unfeasible for the subsequent modelling steps.

3.3.3 Parameter selection and model performance based on satellite altimetry data

Next, the remaining feasible parameter sets were used to evaluate their potential to also reproduce time series of observed altimetry applying three distinct parameter selection and model evaluation strategies. Assuming again the situation of an ungauged basin (i.e. no time-series of river flow available), we kept for each strategy as feasible the respective 1% best performing parameter sets according to the specific performance metric associated to that strategy. In a final step, these solutions were then compared for their potential to reproduce actually observed river flow time series.

Altimetry Strategy 1: Direct comparison of altimetry data to modelled discharge

Hereafter referred to as with subscript WL, i.e. water level. In the simplest approach, we directly used altimetry data to correlate observed water levels with modelled discharge based on the Spearman rank correlation coefficient ($E_{\mathrm{R,WL}}$; Spearman, 1904):

$$E_{\mathrm{R,WL}} = \frac{\mathrm{cov}(r_{\mathrm{Q_{mod}}}, r_{\mathrm{WL_{obs}}})}{\sigma\left(r_{\mathrm{Q_{mod}}}\right) * \sigma(r_{\mathrm{WL_{obs}}})} \tag{4}$$

Where $r_{\mathrm{Q,mod}}$ and $r_{\mathrm{WL,obs}}$ are the ranks of the modelled discharge and the observed water levels, respectively. This method requires as assumption that the relationship between water level and discharge has to be monotonic. The Spearman rank correlation was applied successfully in previous studies to calibrate a rainfall-runoff model to water level time series (Seibert and Vis, 2016). As there were multiple virtual stations with water level data available in this study, the $E_{\mathrm{R,WL}}$ was computed at each location simultaneously. The individual values $E_{\mathrm{R,WL}}$ were weighted based on the record length of the corresponding virtual stations and then combined into the Euclidean distance as aggregate metric $D_{\mathrm{E,R,WL}}$, equivalent to Eq. 5.

$$D_{\mathrm{E},\beta,\gamma} = 1 - \sqrt{\left(\sum_i w_i * \left(1 - E_{\beta,\gamma}\right)^2\right)} \tag{5}$$

Where $E_{\beta,\gamma}$ is the individual model performance for each virtual station, β is the abbreviation for the model performance metric, γ the abbreviation for the parameter selection method and w_i the relative weight.

Altimetry Strategy 2: Rating curves

In the second strategy, as successfully applied in previous studies (Getirana and Peters-Lidard, 2013;Jian et al., 2017), model parameters were selected based on the models' ability to reproduce water levels by converting the modelled discharge to water levels, assuming these two are related through a rating curve in the form of a power function (Rantz, 1982):

$$Q = a * (h - h_0)^b \tag{6}$$

Where h is the water level, h_0 a reference water level, and a and b are two additional calibration parameters, determining the shape of the function and lumping the combined influences of different river cross-section characteristics, such as geometry or roughness. Note, that here for each virtual station h_0 is the elevation that corresponds to the water level of the Google Earth image with the lowest flow available. This strategy is hereafter referred to as with subscript RC, i.e. rating curve. As river-cross sections vary in space, each of the 18 virtual stations would require an individual set of these parameters a and b. To limit the number of additional calibration parameters, we here classified the river-cross sections of the 18 virtual stations into 4 classes (Figure 1A and Figure 3). For cross-sections within each class, i.e. geometrically similar, the same values for a and b were used, resulting in 4 sets of a and b and thus a total of 8 additional calibration parameters. The river cross-sections were extracted from global high-resolution terrain data available on Google Earth (see Section 2.1.4). The modelled river water levels were evaluated against the observed water levels at each virtual station using the Nash-Sutcliffe efficiency $E_{\mathrm{NS,RC}}$ (equivalent to Eq. 1), weighted based on the record length of the corresponding virtual stations and then combined into the Euclidean distance $D_{\mathrm{E,NS,RC}}$ as an aggregated performance metric (Eq. 5).

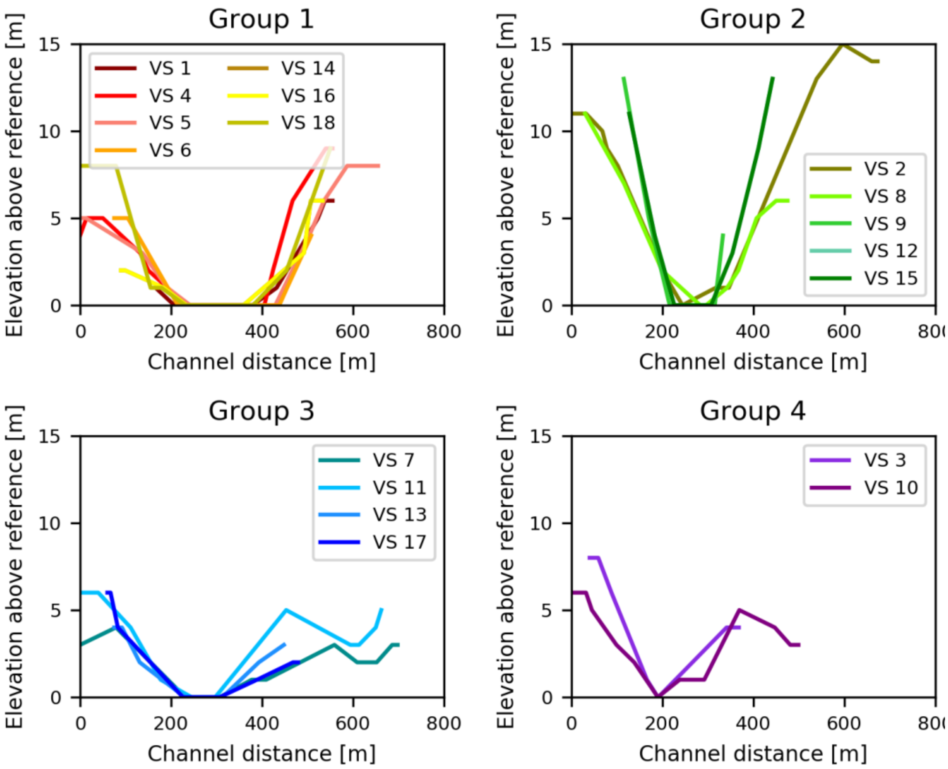

Figure 12: River profiles at 18 virtual stations (VS) divided into four groups. The reference level is equal to the lowest water level in the river profile for each location separately.

Altimetry Strategy 3: Strickler-Manning equation

As third strategy, we converted the modelled discharge to river water levels using the Strickler-Manning equation (Manning, 1891):

$$Q = k * i^{\frac{1}{2}} * A * R^{\frac{2}{3}} \tag{7}$$

Where k is a roughness parameter, here treated as free calibration parameter and assumed constant for all virtual stations, i is the mean channel slope, here over a distance of 10 km, while A and R are the river cross-section area and hydraulic radius. Assuming trapezoidal cross-sections (see Figure 4 as illustrative example), A and R were calculated for each cross section according to:

$$A = B * d + \frac{1}{2} * d^2 * (i_1 + i_2) \tag{8}$$

$$R = \frac{A}{B + d * \left((1 + i_1^2)^{\frac{1}{2}} + (1 + i_2^2)^{\frac{1}{2}}\right)} \quad (9)$$

$$d = h - h_0 \quad (10)$$

Where B is the assumed river bed width, i_1 and i_2 are the river bank slopes, d the water depth, h the water level and h_0 the reference water level, here assumed to be the lowest observed river water level to limit the number of calibration parameters. In contrast to previous studies that use a similar approach but relied on locally observed river-cross sections (Michailovsky et al., 2012;Hulsman et al., 2018;Liu et al., 2015), here both, the river bed geometries (Figure 3) at and the channel slopes upstream of the 18 virtual stations were computed using high-resolution terrain data retrieved from Google Earth (see Section 2.1.4); similar data sources were already used in previous studies to extract the river geometry (e.g. Michailovsky et al., 2012;Pramanik et al., 2010;Gichamo et al., 2012). The reader is referred to Table S3 in the supplementary material for the values of the variables for each virtual station. This strategy is hereafter referred to as with subscript SM, i.e. Strickler-Manning.

Equivalent to above, the modelled river water levels were then evaluated against the observed water levels at each virtual station using the Nash-Sutcliffe efficiency $E_{NS,SM}$ (equivalent to Eq. 1), weighted based on the record length of the corresponding virtual stations and then combined into the Euclidean distance $D_{E,NS,SM}$ as an aggregated performance metric (Eq. ~~(3~~5).

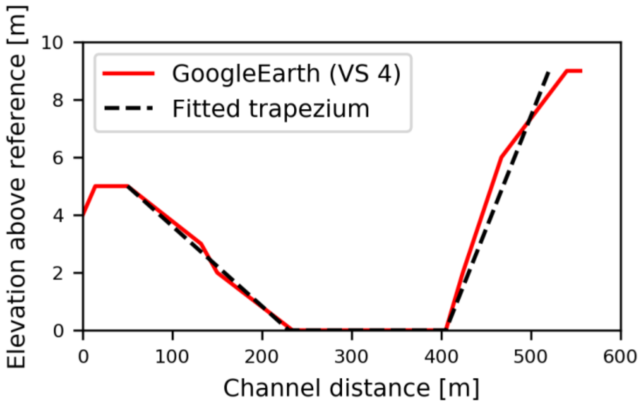

Figure 13: Example of approximating a trapezoidal cross-section (black) into the Google Earth based cross-section data (red) for virtual station "VS 4" (see also Figure 1A and Figure 3). The reference level is equal to the lowest water level in the river profile.

3.3.4 Parameter selection and model performance based on daily river water level at the basin outlet

~~In-situ measurements were available though at the Great East Road Bridge gauging station, the catchment outlet.~~ For the previous parameter identification strategy (Altimetry Strategy 3), river geometry information was extracted from high-resolution terrain data retrieved from Google Earth which have a low accuracy. Unfortunately, more accurate cross-section information from in-situ surveys was only available at the Great East Road Bridge gauging station, i.e. the basin outlet, where, in turn, no altimetry observations were available. That is why water level time series were used to illustrate the influence of the cross-section accuracy.

As shown in Figure 5, the Google Earth based above-water cross-section at the basin outlet corresponded in general well to the field survey considering that satellite images have limited spatial resolution. However, the in-situ measurement also illustrated the relevance of the submerged part of the channel cross-section at that location on the day the image was taken (June 2nd 2008). ~~To assess the influence of the cross-section accuracy, model~~

~~parameter sets were selected based on the models' ability to reproduce daily stream levels at the Great East Road Bridge gauging station, i.e. the basin outlet.~~

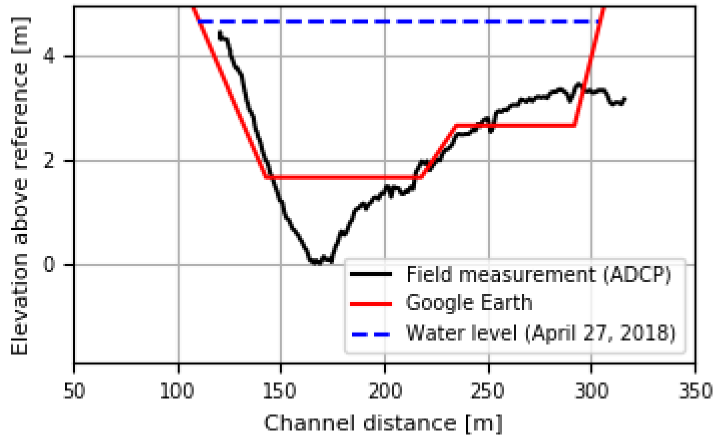

Figure 14: River cross-section at Luangwa Bridge obtained from Google Earth and detailed field survey including the river water level on June 2nd 2008. Field measurements were done with an Acoustic Doppler Current Profiler (ADCP) on April 27th 2018 at the coordinates 30° 13' E and 15° 00' S; the satellite image was taken on June 2nd 2008. The reference level is equal to the lowest elevation level measured with the ADCP.

Water level Strategy 1: River geometry information extracted from Google Earth

First, cross-section information was extracted from global high-resolution terrain data available on Google Earth (subscript GE) and used with the Strickler-Manning equation (Eq. 7) to convert the modelled discharge to water levels. This was combined with GRACE observations to restrict the parameter space in an equivalent way as in Section 3.3.3. The model performance with respect to river water levels was calculated with the Nash-Sutcliffe efficiency $E_{\mathrm{NS,SM,GE}}$ (Eq. 1).

Water level Strategy 2: River geometry information obtained from a detailed field survey

Second, cross-section information obtained from a detailed field survey with an ADCP (subscript ADCP) was used with the Strickler-Manning equation (Eq. 7) to convert the modelled discharge to water levels. This was combined with GRACE observations to restrict the parameter space in an equivalent way as in Section 3.3.3. The model performance with respect to river water levels was calculated with the Nash-Sutcliffe efficiency $E_{\mathrm{NS,SM,ADCP}}$ (Eq. 1).

4 Results and discussion

4.1 Parameter selection and model performance

The complete set of all model realizations unsurprisingly results in a wide range of model solutions (Figure 6A), with $E_{\mathrm{NS,Q}}$ ranging from -6.4 to 0.78 and with the combined performance metric of all signatures D_{E} ranging from -334 to 0.79 (Figure 7). With respect to the individual flow signatures, the model performance varied such that the largest range was found in $E_{\mathrm{NS,Q}}$ and smallest in $E_{\mathrm{NS,AC}}$ as visualised in Figure 7 and tabulated in Table S4. Although containing relatively good solutions, this full set of all realizations clearly also contained many parameter sets that considerably over- and/or underestimate flows.

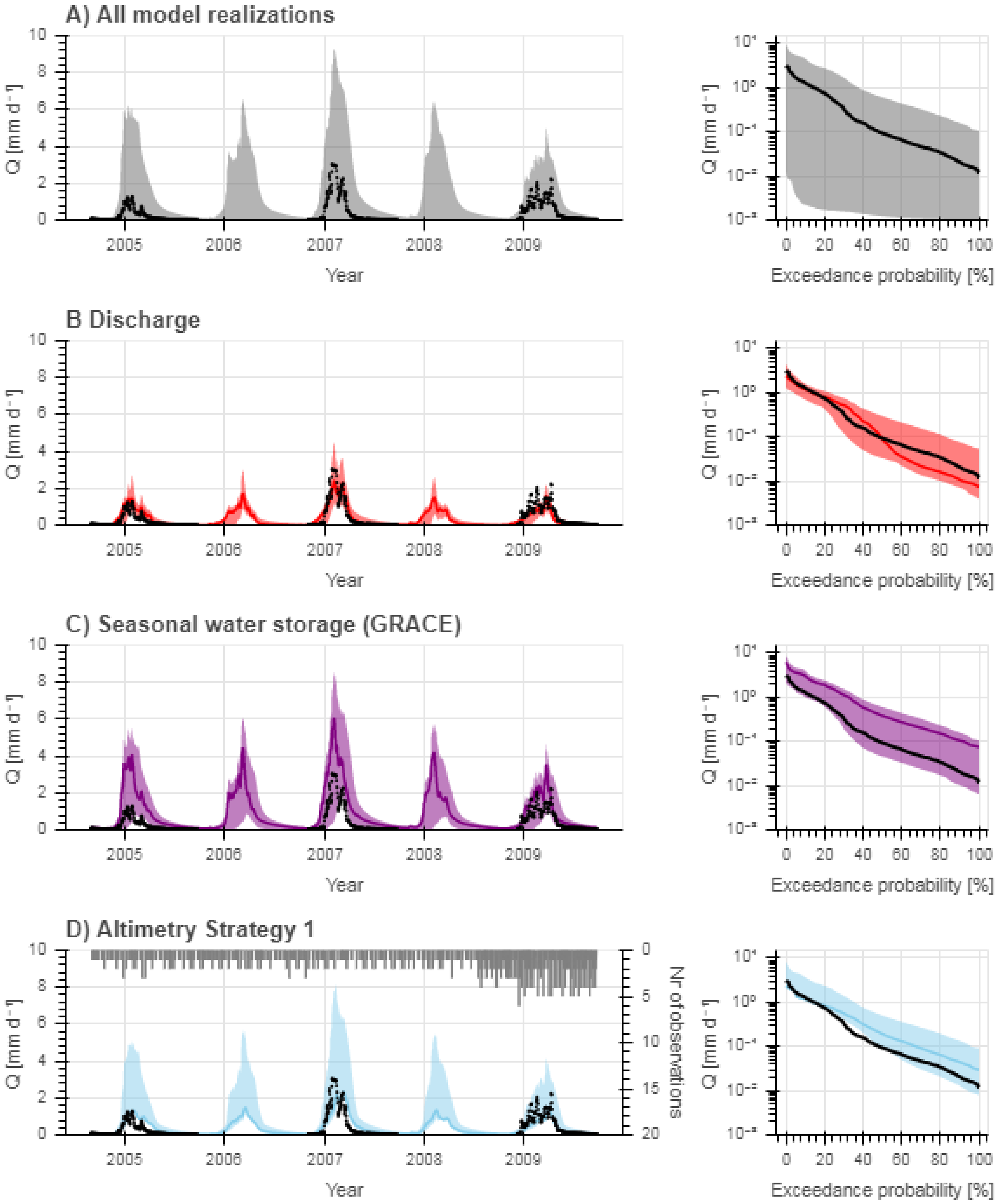

Figure 15: Range of model solutions. The left panel shows the hydrograph and the right panel the flow duration curve of the recorded (black) and modelled discharge: the line indicates the solution with the highest calibration objective function (E_{NS} or D_E) and the shaded area the envelope of the solutions retained as feasible. A) All model solutions included; solutions retained as feasible based on B) discharge (i.e. "traditional calibration"; $E_{NS,Q}$), C) GRACE ($E_{NS,Stot}$), and D) Altimetry Strategy 1 only ($D_{E,R,WL}$).The grey bars in the left subplot D indicate the number of altimetry observations available for each day.

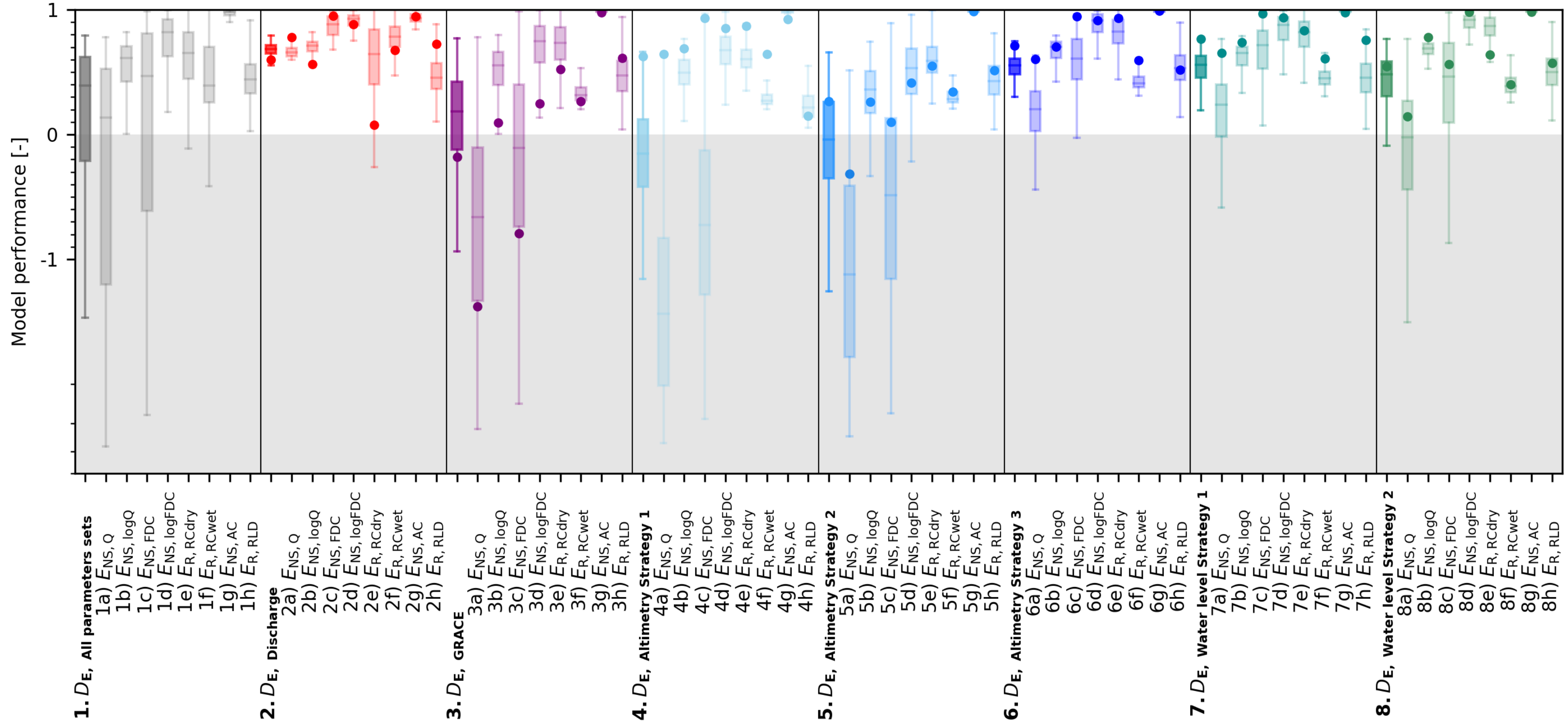

Figure 16: Comparison of different data sources to identify feasible parameter sets. Data sources applied: 1) All random parameters (no data), 2) Discharge, 3) GRACE, 4) Altimetry data combined with GRACE (Altimetry Strategy 1), 5) Altimetry data using the rating curves combined with GRACE (Altimetry Strategy 2), and 6) Altimetry data using the Strickler – Manning equation combined with GRACE (Altimetry Strategy 3), and 7) Daily river water level combined with GRACE using the Strickler – Manning equation and cross-section information retrieved from Google Earth (Water level Strategy 1), or 8) obtained from a detailed field survey with an Acoustic Doppler Current Profiler (ADCP, Water level Strategy 2). The boxplots visualise the spread in the overall model performance D_E with respect to discharge and the following individual signatures: a) daily discharge ($E_{NS,Q}$), b) its logarithm ($E_{NS,logQ}$), c) flow duration curve ($E_{NS,FDC}$), d) its logarithm ($E_{NS,logFDC}$), e) average runoff coefficient during the dry season ($E_{R,RCdry}$), f) average seasonal runoff coefficient during the wet season ($E_{R,RCwet}$), g) autocorrelation function ($E_{NS,AC}$), and h) rising limb density ($E_{R,RLD}$). The dots visualise the model performance when selecting the parameter set with the highest model efficiency according to each parameter identification strategy.

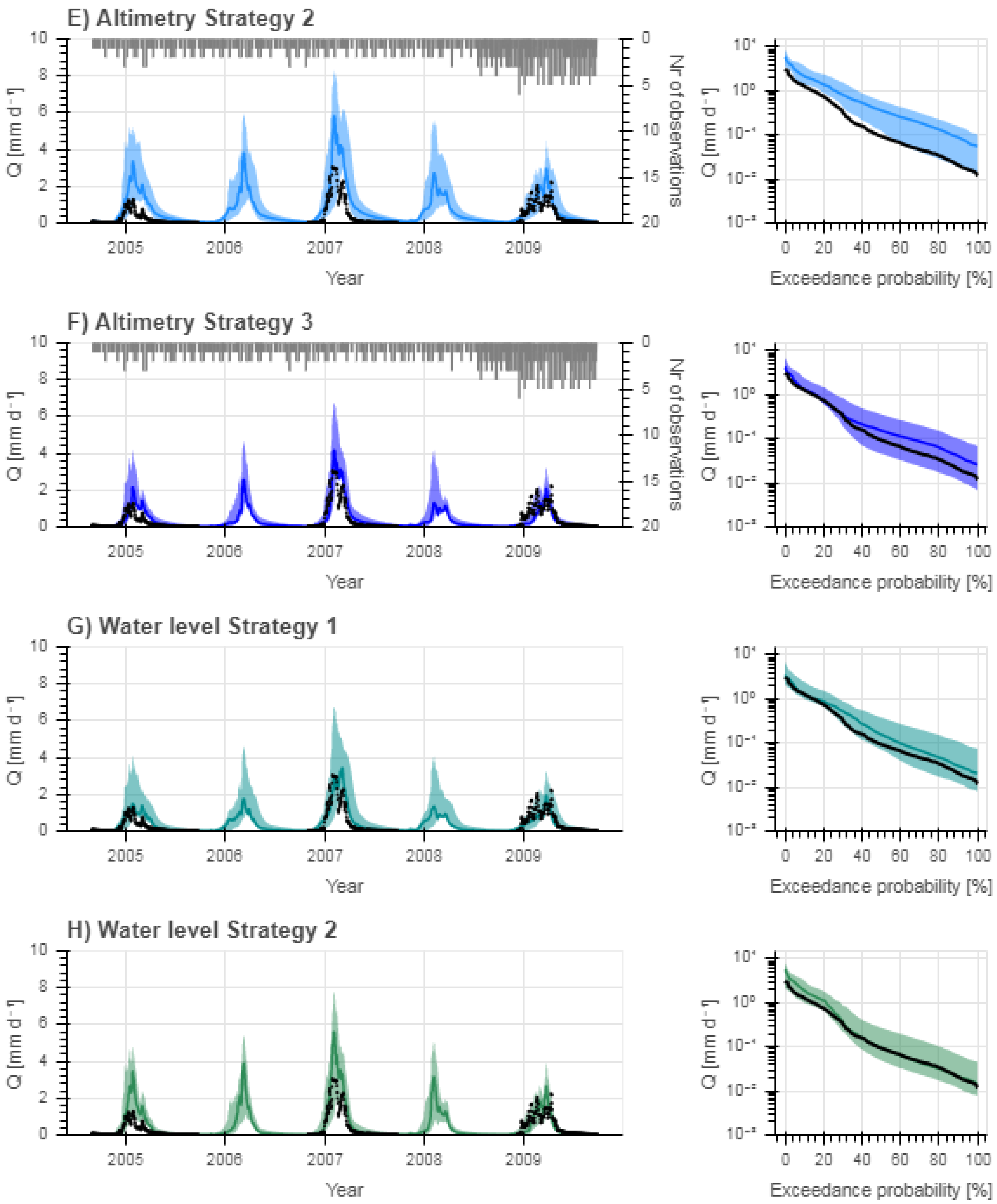

Figure 17: Range of model solutions. The left panel shows the hydrograph and the right panel the flow duration curve of the recorded (black) and modelled discharge: the line indicates the solution with the highest calibration objective function (E_{NS} or D_E) and the shaded area the envelope of the solutions retained as feasible. Solutions retained as feasible based on E) Altimetry Strategy 2 using rating curves for the discharge – water level conversion ($D_{E,NS,RC}$), F) Altimetry Strategy 3 using the Strickler-Manning equation for the discharge – water level conversion ($D_{E,NS,SM}$), and G) Daily in-situ water level using the Strickler Manning equation for the discharge – water level conversion with cross-section information retrieved from Google Earth (Water level strategy 1; $E_{NS,SM,GE}$) or H) obtained from a detailed field survey with an Acoustic Doppler Current Profiler (ADCP; Water level strategy 2; $E_{NS,SM,ADCP}$). The grey bars in the left subplots E and F indicate the number of altimetry observations available for each day.

4.1.1 Benchmark: Parameter selection and model performance based on observed discharge data

~~As~~For the benchmark~~, to assess which range of feasible parameter sets and solutions would have been obtained from a~~ case, applying the traditional model calibration approach~~, the model was calibrated with the available observed~~ using discharge data~~. In other words, only the sub-set of solutions from the above complete set of all model realizations that did satisfy the previously defined criterion (see Section 3.3.1), were retained as feasible. As shown in Figure 6B~~, this parameter selection and calibration strategy results in a reasonable model performance, in which the seasonal but also the daily flow dynamics and magnitudes are in general well captured as shown in Figure 6B. For some years, a number of solutions overestimate flows in the wet season and underestimate flows during the dry season, when the river becomes a small meandering stream with almost annual morphological changes which is difficult to meaningfully observe. The best performing solution has a calibration objective function $E_{\mathrm{NS,Q,opt}}$ = 0.78 (5/95th percentiles of all feasible solutions $E_{\mathrm{NS,Q,5/95}}$ = 0.61 – 0.75; Figure 7 and Table 6). For the post-calibration evaluation of all retained solutions, it was observed that most signatures are well reproduced by the majority of solutions, except for the dry season runoff coefficient (RC_{dry}; Figure 7 and Table S4). This resulted in aggregated model performances, combining all signatures, of $D_{\mathrm{E,5/95}}$ = 0.55 – 0.76 with the above identified best performing solution (i.e. $E_{\mathrm{NS,Q,opt}}$) reaching a value of $D_{\mathrm{E,opt}}$ = 0.60.

Table 8: Summary of the model results: elimination of unfeasible parameter sets and detection of optimal parameter set according to each parameter identification strategy including the corresponding model performance range ($E_{\mathrm{NS,Q}}$, D_{E}) indicating the model's skill to reproduce the discharge during the benchmark time period. For each strategy, the model efficiency for the optimal parameter set is summarised together with the corresponding performance metrics with respect to discharge ($E_{\mathrm{NS,Q,opt}}$, $D_{\mathrm{E,opt}}$); for all parameter sets retained as feasible, the maximum ($E_{\mathrm{NS,Q,max}}$, $D_{\mathrm{E,max}}$) and 5/95 percentiles ($E_{\mathrm{NS,Q,5/95}}$, $D_{\mathrm{E,5/95}}$) of all performance metrics with respect to discharge are summarised. Data sources used for the parameter set selection: 1) All parameter sets (no data), 2) Discharge, 3) GRACE, 4) Altimetry combined with GRACE (Altimetry Strategy 1), 5) Altimetry data using rating curves combined with GRACE (Altimetry Strategy 2), 6) Altimetry data using the Strickler – Manning equation combined with GRACE (Altimetry Strategy 3), and 7) Daily river water level combined with GRACE using the Strickler – Manning equation and cross-section information retrieved from Google Earth (Water level Strategy 1), or 8) obtained from a detailed field survey with an Acoustic Doppler Current Profiler (ADCP, Water level Strategy 2).

	Optimal parameter set		Feasible parameter sets	
	Model efficiency	**$E_{\mathrm{NS,Q,opt}}$ ($D_{\mathrm{E,opt}}$)**	**$E_{\mathrm{NS,Q,max}}$ ($E_{\mathrm{NS,Q,5/95}}$)**	**$D_{\mathrm{E,max}}$ ($D_{\mathrm{E,5/95}}$)**
1) All parameters sets	-	-	0.78 (-3.8 – 0.68)	0.79 (-1.4 – 0.71)
2) Discharge	$E_{\mathrm{NS,Q,opt}}$ = 0.78	0.78 (0.60)	0.78 (0.61 – 0.75)	0.79 (0.55 – 0.76)
3) Seasonal water storage (GRACE)	$E_{\mathrm{NS,Stot,opt}}$ = 0.56	-1.4 (-0.18)	0.78 (-2.3 – 0.38)	0.77 (-0.58 – 0.62)
4) Altimetry Strategy 1: Compare altimetry to discharge	$D_{\mathrm{E,R,WL,opt}}$ = 0.76	0.65 (0.63)	0.65 (-2.9 – 0.10)	0.66 (-0.83 – 0.50)
5) Altimetry Strategy 2: Rating curves	$D_{\mathrm{E,NS,RC,opt}}$ = -0.50	-0.31 (0.27)	0.51 (-2.6 – 0.25)	0.66 (-0.72 – 0.56)
6) Altimetry Strategy 3: Strickler-Manning equation	$D_{\mathrm{E,NS,SM,opt}}$ = -1.4	0.60 (0.71)	0.63 (-0.31 – 0.50)	0.75 (0.36 – 0.67)
7) Water level Strategy 1: satellite based cross-section	$E_{\mathrm{NS,SM,GE,opt}}$ = -1.8	0.65 (0.77)	0.77 (-0.48 – 0.60)	0.77 (0.28 – 0.70)
8) Water level Strategy 2: in-situ cross-section	$E_{\mathrm{NS,SM,ADCP,opt}}$ = 0.79	0.14 (0.55)	0.77 (-1.1 – 0.50)	0.77 (0.03 – 0.67)

4.1.2 Parameter selection and model performance based on the seasonal water storage (GRACE)

Starting from the set of all model realizations (Figures 6A and 7), and assuming no discharge observations are available, we then identified and discarded parameter sets as unfeasible when they did not meet the previously defined criteria to reproduce the seasonal water storage ($E_{NS,Stot}$; see Section 3.3.2). The range of random model realizations with respect to the total water storage is visualised in Figure 9. The sub-set of solutions retained as feasible resulted in a significant reduction in the uncertainty around the modelled variables, which is illustrated by the narrower 5/95th percentiles of the solutions compared to the set of all realizations, as shown in Figure 6C. The feasible solutions with respect to the GRACE reached $E_{NS,Stot,opt}$ = 0.56 ($E_{NS,Stot,5/95}$ = 0.45 – 0.52) (Figure 7, Table 6). These parameter sets were then used to evaluate the model for the years 2004, 2006, 2008 used in the benchmark case. While the flow dynamics are captured relatively well, many of the retained solutions considerably overestimated flows across all seasons (Figure 6C) resulting in a decreased performance with respect to the individual flow signatures, only the dry runoff coefficient ($E_{R,RCdry}$) improved significantly compared to the benchmark as shown in Table S4 and Figure 7. The parameter set associated with the best performing model with respect to GRACE ($E_{NS,Stot,opt}$) resulted for the benchmark period in a $E_{NS,Q}$ = -1.4 ($E_{NS,Q,5/95}$ = -2.3 – 0.38) and the corresponding $D_{E,opt}$ = -0.18 ($D_{E,5/95}$ = -0.58 – 0.62) with respect to discharge (Figure 7, Table 6). As illustrated in Figure 7 and Figure 6C, many parameter sets that resulted in implausible representations of the seasonal signals were eliminated. However, as also indicated by the rather modest values of $E_{NS,Q}$ and D_E with respect to discharge, the data source used here obviously contained only limited information to avoid the over predictions of flow during all wet seasons. The sequence of applying first GRACE and then altimetry, or the reverse, did not affect the identification of feasible parameter sets when using altimetry data as shown in Figure S9; however, it did affect the selection of the "best" parameter set.

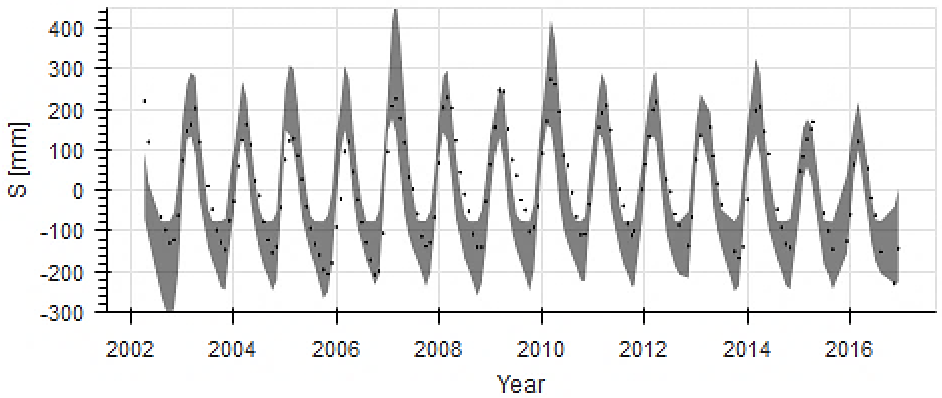

Figure 18: Range of random model realizations with respect to the total water storage (grey) including the observation according to GRACE (black)

4.1.3 Parameter selection and model performance based on satellite altimetry data

After having identified feasible parameter sets based on the seasonal water storage, additional unfeasible parameter sets were eliminated using altimetry data with three different strategies. In all three cases, the best 5% of all feasible parameter sets were selected; this resulted in 1% of all parameter sets.

Altimetry Strategy 1: Directly compare altimetry data to modelled discharge

~~In a~~The first approach, ~~the altimetry data were directly compared to the modelled discharge using the Spearman rank correlation coefficient. As shown in Figure 6D, this~~Altimetry Strategy 1, resulted in an overestimation of in particular intermediate and low flows as shown in Figure 6D. The feasible solutions reached an optimum of

$D_{E,R,WL,opt}$ = 0.76 ($D_{E,R,WL,5/95}$ = 0.74 – 0.75) with respect to altimetry observations. Focusing on the model's skill to reproduce the observed discharge using these feasible parameter sets for the benchmark period, the parameter set associated with the best performing model with respect to altimetry ($D_{E,R,WL,opt}$) resulted in a $E_{NS,Q}$ = 0.65 ($E_{NS,Q,5/95}$ = -2.9 – 0.10) and D_E = 0.63 ($D_{E,5/95}$ = -0.83 – 0.50) with respect to discharge (Figure 7, Table 6). Hence, the parameter set with the highest model performance with respect to altimetry, did not perform best with respect to discharge as shown in Table 6 and Figure S8. While the optimum model performance with respect to discharge was similar to the benchmark, the very wide range in the 5/95th percentiles of the solutions indicated that this strategy has only limited potential to identify implausible parameter sets. This was also the case with respect to the individual flow signatures as shown in Figure 7 and Table S4.

Altimetry Strategy 2: Rating curves

~~In a second approach, altimetry data were compared to the modelled stream water levels by converting the modelled discharge to water levels, based on rating curves. This~~The second approach, Altimetry Strategy 2, also resulted in an overestimation of the flows (Figure 8E). The feasible solutions reached an optimum of $D_{E,NS,RC,opt}$ = -0.50 ($D_{E,NS,RC,5/95}$ = -1.0 – -0.77) with respect to altimetry observations. As example, Figure S6A visualises the simulated and observed river water level at Virtual Station 4 where the model significantly underestimated the stream levels. Focusing on the model's skill to reproduce the discharge using these parameter sets for the benchmark period, the parameter set associated with the best performing model with respect to altimetry ($D_{E,NS,RC,opt}$) resulted in $E_{NS,Q}$ = -0.31 ($E_{NS,Q,5/95}$ = -2.6 – 0.25) and D_E = 0.27 ($D_{E,5/95}$ = -0.72 – 0.56) with respect to discharge (Figure 7, Table 6); hence similar to Altimetry Strategy 1, the best parameter set with respect to altimetry, did not perform best with respect to discharge (see Table 6 and Figure S8). The optimum model performance with respect to discharge was worse compared to the benchmark, and the wide range in the 5/95th percentiles of the solutions indicated this strategy poorly identified the feasible parameter sets. This was also the case with respect to the individual flow signatures as shown in Figure 7 and Table S4; only the dry runoff coefficient (E_{RCdry}) improved significantly compared to the benchmark.

Altimetry Strategy 3: Strickler-Manning equation

~~In a third approach, the altimetry data were compared to modelled stream water levels by converting the modelled discharge to water levels using the Strickler-Manning equation. This~~The third approach, Altimetry Strategy 3, resulted in improved flow predictions compared to the other two strategies using altimetry data (Figure 8F). Even though the feasible solutions exhibit a very poor ability to reproduce the altimetry data, with an optimum of $D_{E,NS,SM,opt}$ = -1.4 ($D_{E,NS,SM,5/95}$ = -3.8 – -1.8), the model's skill to reproduce the discharge for the benchmark period using these parameter sets, significantly increased compared to the two alternative strategies. As example, Figure S6B visualises the simulated and observed river water level at Virtual Station 4 where the model simulated the stream levels relatively well. The parameter set associated with the best performing model with respect to altimetry ($D_{E,NS,SM,opt}$) resulted in $E_{NS,Q}$ = 0.60 ($E_{NS,Q,5/95}$= -0.31 – 0.50) and D_E = 0.71 ($D_{E,5/95}$ = 0.36 – 0.67) with respect to discharge (Figure 7, Table 6). While the optimum model performance with respect to discharge was worse compared to the benchmark, the 5/95th percentiles of the solutions were significantly constrained by the removal of many implausible parameter sets; this was valid for the performance with respect to the individual flow signatures ($E_{NS,\theta}$ and $E_{R,\theta}$) and overall flow response (D_E) as shown in Figure 7 and Table

S4. This indicated that, although the model performance with respect to altimetry observations was low, this strategy contains valuable information to considerably constrain the feasible solution space.

4.1.4 Parameter selection and model performance based on daily river water level at the basin outlet

~~In this approach, daily river water level observations at the basin outlet only was compared to modelled stream levels by converting the modelled discharge to water levels with the Strickler-Manning equation using cross-section information 1) extracted from global high-resolution terrain data available on Google Earth (subscript GE) and 2) obtained from a detailed field survey (subscript ADCP).~~

Water level Strategy 1: River geometry information extracted from Google Earth

The parameter identification strategy "Water level Strategy 1", using cross-section information extracted from Google Earth

~~First, using cross-section information extracted from Google Earth,~~ resulted in a poor simulation of the river water level (Figure 10A) with an optimal objective function value with respect to river water levels of $E_{\mathrm{NS,SM,GE,opt}}$ = -1.8 ($E_{\mathrm{NS,SM,GE,5/95}}$ = -6.8 – -3.1). Focusing on the model's skill to reproduce the discharge using these feasible parameter sets for the benchmark period, the parameter set associated with the best performing model with respect to river water levels ($E_{\mathrm{NS,SM,GE,opt}}$) resulted in $E_{\mathrm{NS,Q,GE}}$ = 0.65 ($E_{\mathrm{NS,Q,5/95,GE}}$ = -0.48 – 0.60) and $D_{\mathrm{E,GE}}$ = 0.77 ($D_{\mathrm{E,GE,5/95}}$ = 0.28 – 0.70) with respect to discharge (Figure 7, Table 6); the model performance with respect to the remaining signatures as visualised in Figure 7 are tabulated in Table S4. As shown in Figure 8G, the discharge was overestimated in particular during intermediate and low flows.

Water level Strategy 2: River geometry information obtained from a detailed field survey

~~Second,~~The parameter identification strategy "Water level Strategy 2", using cross-section information obtained from a detailed field survey, resulted in improved river water level simulations (compare Figure 10A and B) with an optimal objective function value with respect to river water levels of $E_{\mathrm{NS,SM,ADCP,opt}}$ = 0.79 ($E_{\mathrm{NS,SM,ADCP,5/95}}$ = 0.60 – 0.74). The parameter set associated with the best performing model with respect to river water levels ($E_{\mathrm{NS,SM,ADCP,opt}}$) resulted in $E_{\mathrm{NS,Q,ADCP}}$ = 0.14 ($E_{\mathrm{NS,Q,5/95,ADCP}}$ = -1.1 – 0.50) and in $D_{\mathrm{E,ADCP}}$ = 0.55 ($D_{\mathrm{E,ADCP,5/95}}$ = 0.03 – 0.67) with respect to discharge (Figure 7, Table 6); the model performance with respect to the remaining signatures as visualised in Figure 7 are tabulated in Table S4.

Compared to using river geometry information extracted from Google Earth (Water level Strategy 1), the overall model performance with respect to discharge did not increase since the parameter space was already restricted using GRACE data. However, the modelled flow duration curve during intermediate and low flows (compare Figure 8G with H) and rating curve (Figure 11) improved significantly when using more accurate geometry information obtained from a detailed field survey covering the cross-section that is submerged most of the year which is thus unlikely to be captured by satellite based observations. Note, that the in-situ cross-section information was limited to the submerged part during the time of measurement; the remaining part (water levels > 5 m) was extrapolated which is likely to explain the larger discrepancies during high flows visible in the flow duration curve (Figure 8H).

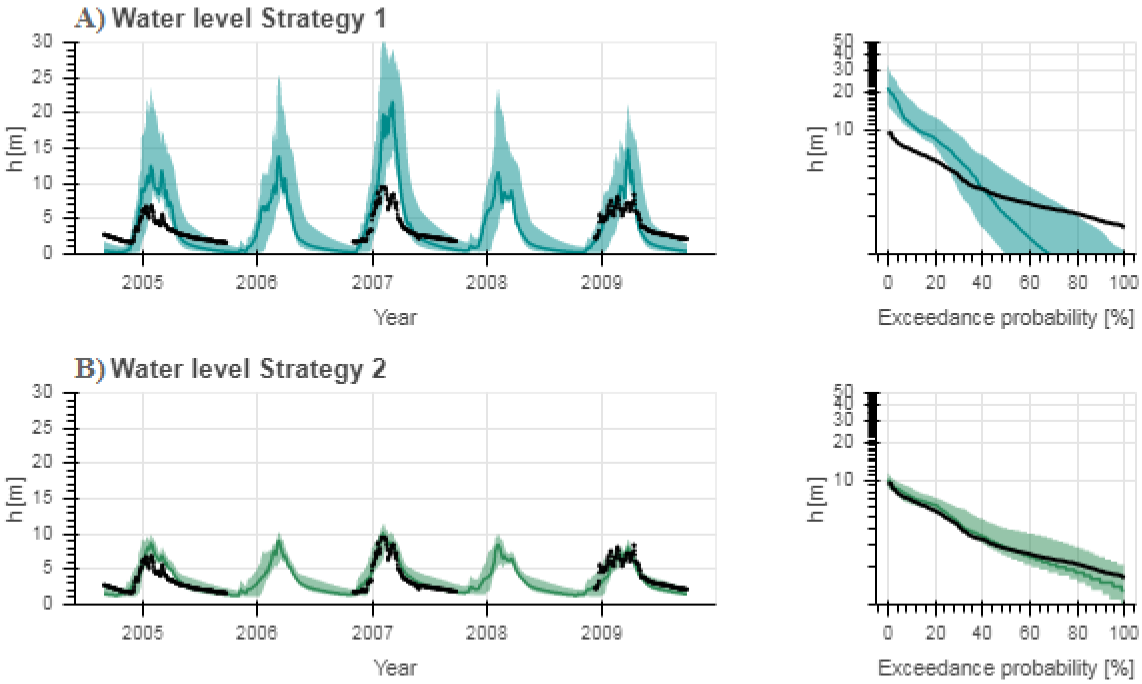

Figure 19: Range of model solutions. The left panel shows the hydrograph and the right panel the flow duration curve of the recorded (black) and modelled discharge: the line indicates the solution with the highest calibration objective function (E_{NS}) and the shaded area the envelope of the solutions retained as feasible. Solutions were retained as feasible based on daily water level time series at the basin outlet using the Strickler-Manning equation for the discharge – water level conversion; the cross-section was A) extracted from Google Earth (Water level Strategy 1), or B) obtained from a detailed field survey with an Acoustic Doppler Current Profiler (ADCP, Water level Strategy 2).

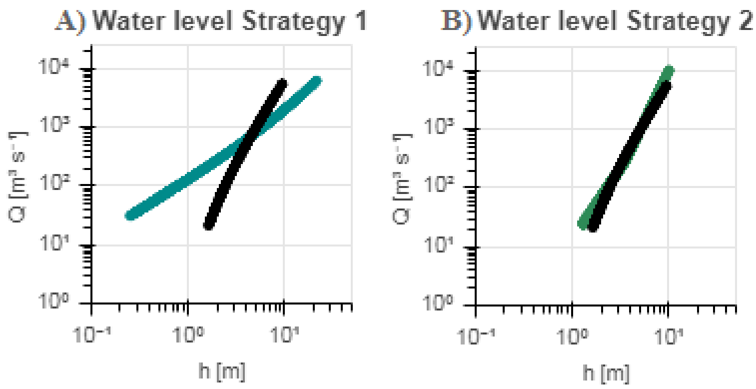

Figure 20: Discharge - water level graphs for the recorded (black) and modelled discharge and stream levels with the optimal model performance (E_{NS}) using the Strickler Manning equation for the discharge – stream level conversion with cross-section information A) extracted from Google Earth (Water level Strategy 1), or B) obtained from a detailed field survey with an Acoustic Doppler Current Profiler (ADCP, Water level Strategy 2).

4.2 Number of virtual stations used for model calibration and evaluation

In this study, altimetry data was available at 18 virtual stations. However, would the model performance change if more or less virtual stations were used? For this purpose, *n* random stations were selected for model calibration; the remaining stations were used for cross-validation (KlemeŠ, 1986;Gharari et al., 2013;Garavaglia et al., 2017). This was repeated to cover all combinations of *n* stations and for *n* = 1, 2 … 17. When applying Strategy 3 using altimetry data with the Strickler-Manning equation, this analysis revealed that when increasing the number of calibration stations, the model calibration performance $D_{E,NS,SM}$ gradually decreased, but the ability to meaningfully reproduce the remaining observations which were not used for calibration increased significantly (Figure 12). Similar results were obtained for Strategies 1 and 2 (compare Figure 12 with Supplementary Figures S3 and S4). Also the model performance with respect to discharge increased when using more virtual stations with an optimum at 7 – 15 stations depending on the calibration strategy (Figure S5). This provides evidence that in spite of reduced calibration performance, the simultaneous use of multiple virtual stations can contribute towards more plausible selections of model parameter sets and thus increase the model realism.

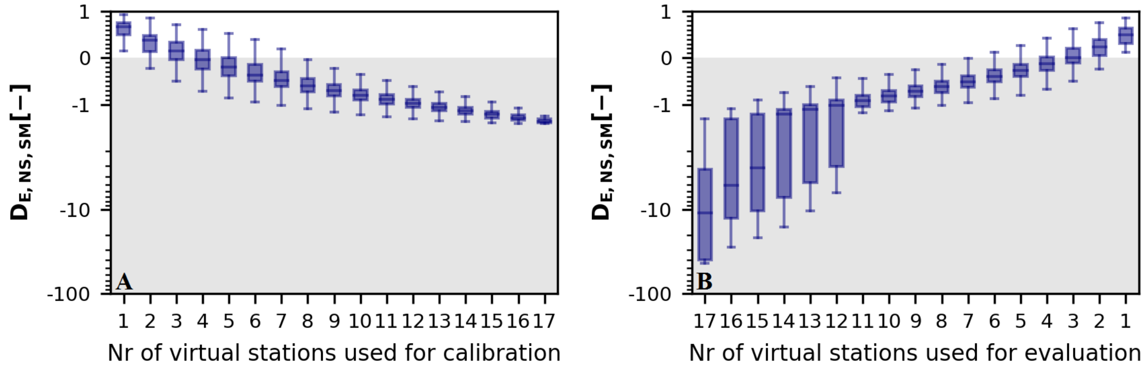

Figure 21: Influence of the number of virtual stations used for A) model calibration and B) evaluation on the model performance $D_{E,NS,SM}$ applying Altimetry Strategy 3.

4.3 Uncertainties and limitations

In the absence of discharge data for hydrological model calibration as commonly the case in poorly or ungauged regions, freely and globally available remotely sensed stream water levels could provide the opportunity to fill this gap as illustrated in this study, as well as in previous studies (e.g. Michailovsky and Bauer-Gottwein, 2014;Pereira-Cardenal et al., 2011;Sun et al., 2012). However, there are several limitations to the approach proposed in this study using altimetry for model calibration.

First, river altimetry data are prone to large uncertainties which increase for smaller river widths (Sulistioadi et al., 2015;Biancamaria et al., 2017). ~~For example, the RMSE of the altimetry data was about 0.6 m to 0.9 m in the Po river (Europe) using Envisat (Tarpanelli et al., 2013;Tourian et al., 2016); in the Ogooué river (Africa) about 0.2 m to 0.5 m using SARAL and Envisat (Bogning et al., 2018); and in the Mekong river (Asia) about 0.44 m to 0.65 m using Envisat (Birkinshaw et al., 2010).~~ Unfortunately, this uncertainty could not be estimated for the virtual stations used in this study due to data limitations. However, in previous studies in the Zambezi Basin, the RMSE relative to in-situ stream levels ranged between 0.32 m and 0.72 m using Envisat (Michailovsky et al., 2012) .

~~Besides altimetry, data uncertainties in the precipitation, temperature used to estimate the potential evaporation and GRACE based total storage anomalies should not be ignored. Large~~Second, large uncertainties in the forcing data (precipitation and temperature) with respect to the spatial-temporal variations~~,~~ should not be ignored. This could compromise comparison results between modelled river water levels and altimetry within the basin since it has a low temporal resolution (10 or 35 days). Also, bias in the ~~forcing~~precipitation data affects storage calculations and hence also the identification of feasible parameter sets based on GRACE~~; this could explain why the flows were frequently overestimated when using GRACE only. There are also data uncertainties in the cross-sections retrieved from~~ (Le Coz and van de Giesen, 2019); this could explain why the flows were frequently overestimated when using GRACE only. In addition, precipitation bias could be compensated through calibration parameters introduced for the discharge – water level conversion; therefore, such parameters should be constrained as much as possible. There are also data uncertainties in the cross-sections and river gradients extracted from high-resolution terrain data available on Google Earth due to its limited spatial resolution, but more importantly since no information is available below the water surface.

Further, GRACE observations are prone to uncertainties as a result of data (post-) processing including for example data smoothening (Landerer and Swenson, 2012;Blazquez et al., 2018). In addition, open water bodies or wetlands could affect GRACE observations if they are located in or near the basin, for example within a radius of about 300 km which is the distance often used for data smoothening. In this study, several open water bodies or wetlands were located ≤300 km of the Luangwa basin such as Lake Malawi, Kafue Flats, Cahora Bassa reservoir, Kariba reservoir, Bangweulu and Tanganyika. These open water bodies and wetlands had a limited impact on the GRACE observations due to limited fluctuations or different temporal variation as illustrated in Figure 13 for the Cahora Bassa reservoir.

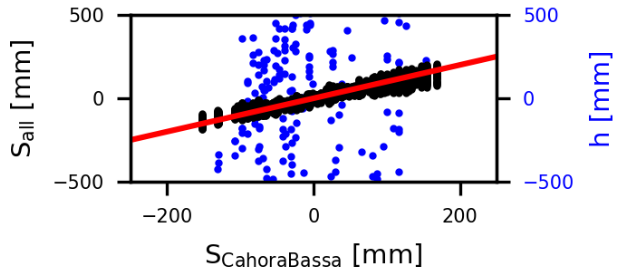

Figure 22: Temporal correlation of the GRACE observations for the cell in which the virtual station for Cahora Bassa is located (horizontal axis) and for A) all cells within an area surrounding the virtual station with a radius of 3 degree (GRACE area of influence, vertical axis, black), and B) the altimetry observation at Cahora Bassa (vertical axis, blue). The 1:1 line is visualised in red. The relatively strong temporal correlation between the GRACE cells could be a result of the strong seasonality in this area.

Uncertainties were not only introduced by the data, but also as a result of assumptions and simplifications. First, the reference level h_0 was assumed to be equal to the lowest river water level observed to limit the number of calibration parameters (Altimetry Strategy 2 and 3, Water level Strategy 1 and 2). ~~In reality however, this could be slightly different due to the increasing uncertainties during low flows when the river becomes more narrow and due to the low temporal resolution possibly missing the lowest water level.~~ Second, the roughness was assumed to be constant over the entire cross-section and for all virtual stations throughout the basin which affects the discharge - water level conversion and therefore also the model efficiency (Altimetry Strategy 3). Third, all 18 virtual stations were grouped based on their cross-section similarity to limit the number of calibration parameters (Altimetry Strategy 2), but differences within each group remain~~ which could influence the discharge-water level conversion and therefore also the model efficiency; hence, there is a trade-off in allowing differences between virtual stations and introducing more calibration parameters.~~. Fourth, the assumption of a constant flow velocity in space and time affects the timing of the flow influencing the comparison between model results and altimetry observations (all strategies).

Another limitation is the missing flow volume information when directly using (satellite based) river water levels for model calibration, using~~, for example,~~ the Spearman Rank Correlations as model performance metric (Altimetry Strategy 1; Seibert and Vis, 2016). This resulted here in an overestimation of intermediate and low flows due to the non-linear relation between stream levels and flows. In contrast, when converting the discharge to stream water levels, flow volume information was included at the cost of introducing additional ~~uncertainties. Converting modelled discharge to stream levels using rating curves introduced additional free~~ calibration parameters (Altimetry Strategy 2 and 3), thereby increasing the degrees-of-freedom and thus the potential for parameter equifinality in the model ~~(Beven, 2006). This is illustrated here by the eight calibration parameters introduced for Altimetry Strategy 2, which were poorly defined as also observed in previous studies (e.g. Sun et al., 2012;Sikorska and Renard, 2017).~~(Beven, 2006;Sikorska and Renard, 2017;Sun et al., 2012). ~~However, converting modelled discharge to stream water levels with the Strickler-Manning equation (Altimetry Strategy 3) required, besides the introduction of a single calibration parameter (roughness), the estimation of the channel cross-section and river gradient. Clearly, both of these variables are subject to uncertainties, which in this study include the limited spatial resolution of the satellite images available on Google Earth.~~Furthermore, it was assumed the Nash-Sutcliffe efficiency contained sufficient valuable information to describe the model performance with respect various flow signatures, river water level and total water storage. Additional study is recommended to confirm this assumption and to assess which performance metric would be most suitable.

4.4 Comparison with previous studies

Previous studies have successfully used river altimetry data to calibrate and evaluate rainfall-runoff models using a few virtual stations (Sun et al., 2012;Getirana, 2010;Getirana et al., 2010;Liu et al., 2015). In these studies, the modelled discharge was converted to stream levels by means of a hydraulic model or empirical relations. Our results support several previous findings and added a number of new ones.

Similar to previous studies, the rainfall-runoff model reproduced river flow relatively well when calibrating on remotely sensed stream water levels preferably at several virtual stations simultaneously, but discharge based calibration results performed significantly better (Getirana, 2010). Thus, while river altimetry data cannot fully substitute discharge observations, they at least provide an alternative data source that holds some informative value where no reliable discharge data are available. In addition, our results suggest that in spite of the typically limited temporal resolution of altimetry observations, these data, when using multiple virtual stations simultaneously, provide enough information to select meaningful model parameter sets (Seibert and Beven, 2009;Getirana, 2010). ~~Similar to previous studies we obtained comparably insensitive posterior parameter distributions when using rating curves to convert discharge to stream water levels for stream water level based calibrations. This indicated that the calibration parameters associated with the rating curves introduced with this method were not well-defined, thereby leading to increased model uncertainties (Sun et al., 2012;Sikorska and Renard, 2017).~~

In contrast to previous studies, altimetry data originated from five different satellite missions rather than a single one. As a result, altimetry data was available at 18 locations for the time period 2002 to 2016. This gave the opportunity to analyse the effect of combining different numbers of stations for calibration and evaluation. This study illustrated that better predictions can be achieved when using more virtual stations for calibration. Furthermore, this study demonstrated that in particular the combination of altimetry with information on river geometry (cross section, gradient) proved beneficial for the selection of feasible parameter sets within relatively narrow bounds comparable to the benchmark using discharge. When using more accurate cross-section information obtained from a detailed field survey rather than Google Earth based estimates, improved the water level simulations, modelled rating curve and discharge simulations during intermediate and low flows significantly for which on-site cross-section data was available. That is why it is recommended to acquire accurate cross-section information on locations concurring with altimetry overpasses (not done is this study).

4.5 Opportunities for future studies

For future studies, it would be very interesting to combine altimetry observations with river width estimates derived from Landsat or Sentinel-1/2 (Huang et al., 2018). Alternatively, the altimetry observations used here could be combined with CryoSat based altimetry observations which provide water level information at lower temporal resolution (every 369 days), but higher spatial resolution (equatorial inter-track distance of 7.5 km) providing valuable information to estimate the river slope (Schneider et al., 2017;Jiang et al., 2017). In addition, with the upcoming SWOT (Surface Water Ocean Topography) mission, more accurate altimetry observations should be available as well as river slope observations and width; the repeat cycle will be 21 days and across-track resolution between 10 m and 60 m increasing the number of observation points available within a specific area (Biancamaria et al., 2016;Langhorst et al., 2019;Oubanas et al., 2018). Also, it would be very useful to improve cross-section estimates with respect to the submerged part as already explored in previous studies (Domeneghetti, 2016). Furthermore, drone observations could be used to obtain more accurate cross-section information and estimates of the river slope and roughness (Entwistle and Heritage, 2019). Also, it would be interesting to assess and separate uncertainties related to the discharge – water level conversion from the hydrological model in a more data rich region.

~~In the Zambezi river basin, altimetry data has been used in previous studies for hydrological modelling (Michailovsky and Bauer-Gottwein, 2014;Michailovsky et al., 2012). These studies used the altimetry data from the Envisat satellite in an assimilation procedure to update states in a Muskingum routing scheme. Including the altimetry data improved the model performance; especially when the model initially performed poorly due to high model complexity or input data uncertainties.~~

5 Summary and conclusion

This study investigated the potential value of river altimetry observations from multiple satellite missions to identify feasible parameters for a hydrological model of the semi-arid and poorly gauged Luangwa River Basin. A distributed process-based rainfall-runoff model with sub-grid process heterogeneity was developed on a daily timescale for the time period 2002 to 2016. Various parameter identification strategies were implemented step-wise to assess the potential of satellite altimetry data for model calibration. As benchmark, when identifying parameter sets with the traditional model calibration strategy using discharge data, the model was able to simulate the flows relatively well ($E_{\mathrm{NS,Q}}$ = 0.78, $E_{\mathrm{NS,Q,5/95}}$ = 0.61 – 0.75). When assuming no discharge observations are available, the feasible parameter sets were restricted with GRACE data only resulting in an optimum of $E_{\mathrm{NS,Q}}$ = -1.4 ($E_{\mathrm{NS,Q,5/95}}$ = -2.3 – 0.38) with respect to discharge. Combining GRACE with altimetry data only from 18 virtual stations focusing on the water level dynamics resulted in frequently overestimated flows and poorly identified feasible parameter sets (Altimetry Strategy 1, $E_{\mathrm{NS,Q,5/95}}$ = -2.9 – 0.10). This was also the case when converting modelled discharge to water levels using rating curves (Altimetry Strategy 2, $E_{\mathrm{NS,Q,5/95}}$ = -2.6 – 0.25). The identification of the feasible parameter sets improved when including river geometry information, more specifically cross-section and river gradient extracted from Google Earth, in the discharge-water level conversion using the Strickler-Manning equation (Altimetry Strategy 3, $E_{\mathrm{NS,Q}} = 0.60$, $E_{\mathrm{NS,Q,5/95}} = -0.31 – 0.50$). Moreover, it was shown that more accurate cross-section data improved the water level simulations, modelled rating curve and discharge simulations during intermediate and low flows for which on-site cross-section information was available; the Nash-Sutcliffe efficiency with respect to river water levels increased from $E_{\mathrm{NS,SM,GE}} = -1.8$ ($E_{\mathrm{NS,SM,GE,5/95}} = -6.8 – -3.1$) using river geometry information extracted from Google Earth (Water level Strategy 1) to $E_{\mathrm{NS,SM,ADCP}} = 0.79$ ($E_{\mathrm{NS,SM,ADCP,5/95}} = 0.6 – 0.74$) using river geometry information obtained from a detailed field survey (Water level Strategy 2). The model performance also improved when increasing the number of virtual stations used for parameter selection. Therefore, in the absence of reliable discharge data as commonly the case in poorly or ungauged basins, altimetry data from multiple virtual stations combined with GRACE observations have the potential to fill this gap if combined with river geometry estimates.

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