Black text: B. Guse's comments

Red text: S. Markstrom's response

I added numbers to the comments so I could more easily refer to them.

I apologize for misspelling Dr. Guse's name in a previous version of this response to his comments.

Major comments:

I encourage the authors to improve the readibility of the abstract to present the idea of this study in a clearer way.

Yes, I accept your specific comments below related to the abstract. In addition, I have rewritten much of the text.

1. Please think about the use of the notation "objective function“ for mean, CV,... . In my understanding, these are statistical values describing different model outputs without giving information of the model performance. The use of the term "objective function“ indicates an evaluation of the model performance according its common use in hydrological modelling. I propose to use "fundamental daily streamflow statistics (FDSS)“ as mentioned in the text instead of "objective function“.

Accepted. Yes, I agree that confusion may arise from the non-standard use of "objective function." I changed to the term "performance measure" as I want to emphasize that this is really a measure of how the model preforms in relation to the parameter values. Also, "performance measure" seems to make the text flow better.

2. A table with the model parameters and their corresponding processes is missing. I see that you refer to another article. However, this manuscript would be more readable, if the reader has an idea of the parameter used for this study. When stating that a certain number of parameters is required "to account for 90% of the parameter sensitivity“ is necessary to know how many parameters for this process are included in the model structure. For example, assuming that there are only two snow parameters, then it is not surprising when the number of required parameters is two. However, let's say that are eight parameters for the snow process then it is interesting to know that only two parameters are required.

Yes, I added a table (table 1) that lists all of the calibration parameters, description, and what I called "PRMS module type". This PRMS module type is what I believe you are asking for in your comment. I did not want to call this "process" because I did not want to confuse the reader with the sensitivity analysis based "process identification" the is performed on the PRMS output.

Now, table 2 does show the parameters and the corresponding identified processes, but this was determined by the sensitivity analysis. Processes identified here make no a priori assumptions about which parameters may affect any particular process. For instance, PRMS uses a potential evapotranspiration coefficient parameter. Clearly, this parameter can be directly associated with the "transpiration process", but to what degree is this parameter associated with the "snowmelt process"? PRMS does simulate snow sublimation, but a priori, should the potential ET coefficient be considered a "snow melt parameter"? Because of the unknown relationships in model structure, this must be determined with the global parameter sensitivity analysis, and that is the point of table 1.

3. Furthermore, in chapter 4.2, you should mention whether the parameters (accounting for 90%) are identical for a certain process or vary (P. 10, L.5-6).

That is the information I try to convey in table 2. The problem is that spatially (on an HRU-by-HRU basis), which specific parameters make up the 90% could vary. Table 2 summarizes this across all HRUs for the CONUS. The idea that I was trying to get across is that the number of parameters needed to characterize a process is some measure of the complexity of that process, and that complexity varies by process and spatially by region of the CONUS. Table 2 summarizes this in a general way so that PRMS modelers could have some idea about which parameters to actually use in their models.

To address this, I added he percent of the CONUS HRUs in which that parameter is part of the set that accounts for 90 percent of the cumulated sensitivity on an HRU-by-HRU basis to the parameter names listed in table 2. I hope this addresses comment 3 by showing which ones vary the most.

4. It is really interesting to see a systematic in the number of parameters as stated on P. 10, L.20-23. Could you explain it? At best in relation to the model structure? Are you expect a different result for different models (structures)?. While this result is reasonable for snowmelt, it is really surprising that you only need a small number of parameters to explain the soil moisture behaviour.

Yes, I added the sentence: "An analysis of theses parameter counts and how they relate to their respective process is beyond the scope of this article, but it could relate to the structure of PRMS and possibly indicate that some processes are over parameterized."

5. I think that the article would benefit if you could relate the results (e.g. P.10, L.24-30) to the process heterogenity in the different parts of the CONUS. There are certainly regions with very complex process patterns and other with a clear dominance of a single process. Are there other studies looking at process dominance or process heterogeneity in the CONUS? Maybe you can make a comparison with these studies?

I am unaware of studies which classify watersheds (regions, HRUs, etc.) necessarily by process (e.g. "snowmelt watersheds"). Some studies that I am aware of tend to classify space by mappings of soil, geology, vegetation, etc. or properties of driving climate data. These tend to use a principle components type analysis, so there are distinct classifications, but these classifications can not necessarily be related to a dominate process. Other studies tend to be based on streamflow statistics for dendritic grouping. This method seems to be effective for classification, but not necessarily classes that are associated with obviously identifiable processes.

6. It is certainly required to discuss the relationship of model parameters and the corresponding

processes. The stronger this relationship is, the more sensitive a parameter might be for this process. Could you mention how the parameter-process relationship affect your results?

Yes, the other reviewer suggested that I focus more on "parameter identification" and "process identification." I think this is related to your comment here. I rewrote the Introduction with this in mind.

7. By summing up the first-order partial variance and using this value as indicator to estimate the dominant process, you do not consider the parameter interactions (second and higher order sensitivities). However, the parameter interaction depends (among others) on the parameter selection. Could you explain how this aspect affect you results?

Yes, to section 3, I added: "An important caveat is that these higher order variances are not accounted for in the analysis. It is assumed that first-order partial variance is sufficient to identify sensitive parameters. This same assumption, as applied to process identification, may be more problematic. If there are sets of interactive sensitive parameters that have not been identified, then the associated process(es) will not be identified as such."

8. The interpretation of table 1 needs to be reworked. I do not agree at least with the sentence on P. 11, L.16-18 that a count of dominant parameters shows how important a parameter is. Assuming that a parameter is strongly related to a certain process, e.g. snowmelt, and is thus relevant for the three objective functions related to snowmelt, but not to the other processes (maybe except of runoff), it is still an important parameter for this specific process. This interpretation and also of the fig. 5 aggregates the results in my opinion in a strong way. It might be more interesting to look at the relationship of model parameters to the processes. To how many processes you can related a parameter? Are these results reasonable when looking at the model structure? An idea of how to relate model parameters and corresponding processes is given in the figures and tables in Pfannerstill et al. (2015).

Yes, I think the problem is my use of the word "important." This is not the right word. I have rewritten these sentences. Hopefully it is clearer. Figure 5 does show how many processes are identified (related to) a parameter. I hope that my rewritten description makes this issue clearer.

9. Concerning the discussion of the spatial heterogeneity in parameter sensitivity (subchapter 5.1), it might worth looking at the expert knowledge on dominant processes in the CONUS. It is not surprising when a HRU with a complex hydrological situation with relevant contributions from different runoff components provides a different results as a HRU with a strong dominance of one hydrological component. Here, I think that a general discussion of process dominance is missing and a discussion in the context of former studies on dominant processes in the CONUS (if existing).

See response to comment 5 about other studies.

10. Maybe you can think about presenting the results in Tab. 1 and Figs. 4 and 5 in a different way, so that the most important outputs are more emphasized. It is rather difficult to extract information of the relationship of parameter and processes from Tab. 1 and a counting how often a parameter occurs is also time-consuming. But in my opinion this information is required to make Fig. 5 more informative.

I'm not sure how to do this. The most important outputs, in my opinion, are to give the modeler versions of the table and figures exclusively for the area that he is modeling. And I have been doing this for the people that I work with. For this article, the problem is that I have to keep it general for all of CONUS.

Fig. 4: Is it maybe relevant thinking about the variability, e.g. in the snowmelt subplot? It is stated that on average 2.25 parameters are required to explain 90%. The map (subplot 4M) shows that in most of the HRUs only 2 or 3 parameters are required. However in the snow-dominated northern parts up to 10 parameters are required. It might be worth thinking about extracting additional information from this idea. One way would be to add an additional line in the subplots 4A-4H which is only related to HRUs which have certain relevance of this process (kind of threshold exceedance approach or something similar).

I believe that I have addressed this issue of HRU parameter variability in table 2 and the text I added in relation to figure 5.

11. Fig. 6: Could you explain why infiltration is the inferior process in many HRUs. I cannot imagine a hydrological situation in which the infiltration process is less relevant than total runoff, all runoff components, ETP, soil moisture.

It's not that infiltration is not important, it's just that the sensitivity analysis indicates that there are no parameters that can be changed to affect the model output. Also, there are often multiple processes that are pretty much at the same level of "inferiorness" and one has to be the most. In a very preliminary draft I had version of these maps that showed, for each HRU, the two most inferior process, the three most, etc. These maps really confused my co-authors and in the end, I dropped them.

12. It might be interesting to think about the following results of the Fig 4-5: According to Fig. 4 only 4.15 parameters are required to explain soil moisture, which is a relative low value keeping in mind that the soil moisture interacts with almost all other processes. Furthermore, there are 7.05 parameters needed for infiltration. Then, it is stated in Fig. 5 that soil_moist_max is overall the most important parameter. Do this mean that the relationship between soil_moist_max and soil moisture is extremely high so that only a few additional parameters (about 3) are needed to reproduce the soil moisture conditions?

Yes, I think this interpretation is correct. A source of confusion could be my use of the word “important.” In retrospect, that is a loaded word. See my response to your comments number 8 and 11.

Minor comments:

Abstract:

Page 2, Line 2: The first sentence of the abstract could be written more clearly. Why not only writing: "The Precipitation-Runoff Modeling System as a distributed-parameter hydrologic model has been applied to the conterminous United States.

Yes, accepted.

P. 2, L. 4-5: Whilst it is certainly clear that the number of parameters is an aspect of model complexity, this is not fully clear for the "interpretation of the model output“. Is this really an aspect of complexity? Do you assume that the model which provides a higher number of model outputs is more complex?

Yes, rewritten. I'm trying to establish the point that by identifying the dominate processes (with respect to PRMS), users can focus on the output variables related to those processes.

P. 2, L. 5-8: To make the abstract more readable, I would suggest to subdivide this sentence into two separate ones. There are too many aspects in this sentence (parameter sensitivity for simplification, parameter identification and its relationship to dominant processes, spatial patterns)

Yes, accepted.

P. 2, L. 9-10: I do not think that this sentence is understandable when reading the abstract at first before knowning the whole article. What do you mean with "processes correspond to variables“? Which type of variables?

Yes, changed this sentence.

P. 2, L. 11: The notation "categories“ is not clearly described in the abstract.

Yes, changed.

P. 2, L. 12-13: How do you estimate the "model performance“ by visualizing categories? This part needs to be improved.

Yes, changed.

P. 2, L. 16: The benefit of a reduction of the dimensionality of output variables or objective functions is not clear.

Yes. changed.

P. 2, L. 22: I would encourage the authors to add a final sentence to emphasise the general advantage of this study.

Yes, added.

Introduction:
P. 2, L. 28: The article would be benefit from a clear definition of "input parameters“. Is an input parameter related to a driver of the hydrologic cycle such as precipitation or solar radiation or more to a real model parameter? In all cases, it is better to avoid potential misunderstandings.

Yes, added.

P. 3, L. 1: References are missing such as for constraining parameter in models, e.g. Hrachowitz et al. (2014) and for stating that different parameter good have a comparable impacts on the model results.

Yes, added.

P. 3, L. 6: The three references are related to studies which investigate performance measures more precisely. It might be good to also have a reference to studies which are directly investigating the model output.

Yes, added.

P. 3, L. 11-12: Please also add the study from Reusser et al. (2009).

Yes, added.

P. 3, L. 14: Please indicate that you consider uncertainty in this study only on input parameter uncertainty and not on structural uncertainty in the model.

These lines were deleted in response to comments by another reviewer.

P. 3, L. 18-28: It might be good to mention here that it is at least at this scale impossible to support the results with adequate measurements in addition to the total discharge.

These lines were deleted in response to comments by another reviewer.

P. 4, L. 1: References are here missing, e.g. Wagener et al. (2003), Reusser et al. (2011), Guse et al. (2014).

Yes, added.

P. 4, L. 11: Reference of Reusser et al. (2011) is missing.

Yes, added.

P. 4, L. 20-22: As mentioned before, it is not clear why you aimed "to reduce the number of inputs and outputs". I think the overall aim should be a clearer characterization of the model parameters and to focus on the dominant processes.

Yes, I reworded this sentence.

Methods:

1. P. 4, L.29- P. 6, L.7: Please check carefully if you could reduce the subchapter 2.1 in length. Do you really need this information for this article?

Yes, this section has been reorganized.

P. 6, L.8-25: The selection of the eight output variables is reasonable and seems to be representative for hydrological studies with distributed models. Maybe you can emphasize this to give the article a more general character.

Yes, added.

P. 7., L. 18: Please also add the reference of Guse et al., 2014, since it is the initial study for Pfannerstill et al. 2015.

Yes, added.

Results:

1. P. 8, L. 17: Please think about a more precise title for the subchapter 4.1.

Yes, changed it to "Parameter sensitivity by process and performance measure"

2. P. 8, L. 20-23: This sentence is not understandable. It is understandable that you have calculated the sum of the first-order partial variance. However, it is not clear how you can estimate an average value (average of what?).

Yes, the meaning of the text here is not clear to you. I have added several sentences here to make this clearer.

3. P. 8, L. 23: The total sensitivity is one, is it? Why do you need to scale the sum of the sensitivities to the total sensitivity?

The sum of the individual sensitivities is not necessarily one. If none of the parameters are sensitive than the sum of the parameter sensitivities will be closer to zero.

4. P. 8, L. 23: "category of modeled process“instead of "category of process“.

Yes, accepted.

5. P. 8, L.28-30: I recommend to be more precisely here: You have calculated the sum of All partial sensitivities for a certain HRU for each process. Then, the process with the Highest sum of the first-order sensitivity is indicated as "dominant process“. To make This clear, you should add that the dominant process is the process with the largest sum Of all first-order partial variances (sensitivities). This is required since the sensitivity of A single parameter is not shown here.

Yes, reworded these sentences.

P. 9, L.17-18: Can you extract a systematic pattern in these results?

Yes, added “, and humid versus arid climates.” to the previous sentence.

P. 10, L.24-25: Please add that this statement is not valid (or only to a low extent) to fig 4J and 4N.

Yes, added this.

P. 11, L. 6-9: Do you see a general systematic why the spatial patterns of parameter Sensitivity are different for the different objective functions. It might be interesting to Give further statements on this.

There are certainly patterns here and I very much agree that they are interesting. I have not had time to investigate this properly and would prefer to leave statements about this out of this article rather than speculate.

There is clearly a swath of sensitivity that goes through the Great Plains. Many hydrologic modelers in the US have noted that this area is notoriously difficult to model with physical, statistical, etc. models – and no one is really sure why this is. Our group has a PhD student who is looking into this. Maybe a subsequent article can address this further.

P.11, L. 28-32: When stating that the parameter "soil_moist_max" is the most important and a model calibration should be focused on it, then it is required to know for which process this parameter is relevant. Assuming that a typical calibration uses discharge as target variable, a focus on "soil_moist_max" helpful in the case of a dominance of "soil_moist_max" on runoff. However, to include this information in a calibration in the case of a dominance on other process but not on runoff?

Yes, I rewrote this paragraph based on comments from the other reviewer. I believe my revision addresses this comment as well.

P. 12, L.2-8: The part on the least sensitive parameter can be removed since the reader does not receive any details about the parameters. Or could you extract some further information from the fact that these parameters have a low sensitivity?

Yes, I now say that modelers should leave them at default values because there is limited information to calibrated them.

P. 12, L. 9-14: I think that the authors should add here some more details. It is really helpful if a parameter can be precisely characterized by saying that it is only dominant in a very specific case (e.g. for one process). But this information cannot currently not be extracted from article.

This varies by HRU/geographic region, so it is difficult to provide specific calibration instructions for the whole of the CONUS. I do provide exactly this type of information on an application site by application site basis to the modelers that I work with. I'm uncertain how to put this information into this article.

P. 13, L.8-12: I like this part. Maybe you can in addition relate it to the concept of vertical water redistribution (Yilmaz et al., 2008, Pfannerstill et al., 2015).

Yes, I added a sentence about this.

P. 14, L. 22-23, Step 1: Summed in time?

Yes, added.

P. 14, L. 24-25, Step 2: How to you obtain a score for each process? Do you assign each parameter to a certain process? If yes, then you have to mention somewhere which parameter is related to which process.

Please see my response to your comments 2 and 3 (“Major” comments section), and 2 and 3 in the “Results” comments section.

P. 16, L. 31: Spelling error: Mishra (2009)

On recommendation of other reviewer, I removed this paragraph.

Figures:

Fig. 1: Could be removed. I do not see an advantage of it. Maybe you can transfer it to the supplementary material.

Yes, removed.

Fig. 2: Does the last row and column present the average values along the row/column? Do you maybe have to change "process average“ and "objective function average“?

Please see response to “Major” comments 2 and 3.

I recommend to show the figure 3 before the figure 2, since fig. 3 provide a general map of the USA whilst, fig. 2 already show the distributed results.

Yes, moved figure 3 to figure 1 (after deleting old figure 1).

Figure 4 would benefit from knowing which parameters are within the 90% and how variable the parameters belonging to this 90% are?

Yes, see my response to comment 10.

Fig. 4: The legend needs to be graphically improved.

Yes.

I do not really see a real benefit of fig. 5. Maybe you can extract the results in a better way. One point might be that the model parameters are not explained and even the related processes are not highlighted in Fig. 5. In particular, it is not clear which information you can derive from the last place occurrence.

Please see my response to your comment 8.

It is not fully clear which information you can derived from investigating the most inferior process. It seems to be that this is either clear such as snowmelt parameter for California or related to the model structure.

The idea here is that modelers should not calibrate parameters associated with inferior processes in their watershed. If there are 35 calibration parameters, make sure to include the ones associated with the more dominate processes, and exclude the ones associated with the more inferior ones. I hope this idea comes across in the article.

Reference list:

Guse, B., Reusser, D. E., and Fohrer, N.: How to improve the representation of hydrological processes in SWAT for a lowland catchment – Temporal analysis of parameter sensitivity and model performance, Hydrol. Process., 28, 2651–2670, doi:10.1002/hyp.9777, 2014.

Hrachowitz, M., O. Fovet, L. Ruiz, T. Euser, S. Gharari, R. Nijzink, J. Freer, H. H. G. Savenije, and C. Gascuel-Odoux: Process consistency in models: The importance of system signatures, expert knowledge, and process complexity, Water Resour. Res., 50, doi:10.1002/2014WR015484, 2014

Pfannerstill, M., Guse, B., Reusser, D., and Fohrer, N.: Process verification of a hydrological model using a temporal parameter sensitivity analysis. Hydrology and Earth System Sciences 19: 4365–4376, 2015.

Reusser, D. E., Blume, T., Schaefli, B., and Zehe, E.: Analysing the temporal dynamics of model performance for hydrological models, Hydrol. Earth Syst. Sci., 13, 999–1018, doi:10.5194/hess-13-999-2009, 2009.

Reusser, D.E., and Zehe, E.: Inferring model structural deficits by analyzing temporal dynamics of model performance and parameter sensitivity. Water Resources Research 47(7): W07550. DOI:10.1029/2010WR009946, 2011.

Wagener, T., McIntyre, N., Lees, M.J., Wheater, H.S., Gupta, H.V.: Towards reduced uncertainty in conceptual rainfall–runoff modelling: dynamic identifiability analysis. Hydrological Processes 17: 455–476, 2003.

Yilmaz, K. K., Gupta, H. V., and Wagener, T.: A process-based diagnostic approach to model evaluation: Application to the NWS distributed hydrologic model, Water Resour. Res., 44, W09417, doi:10.1029/2007WR006716, 2008.

Thank you for this reference list. I added citations to all of these references.

Black text: S. Hoellering's comments

Red text: S. Markstrom's response

General comments

The authors presented an interesting idea of a methodological framework wherein parameters of the HRU based Precipitation-Runoff Modeling System (PRMS) can be identified as influencial in terms of essential hydrological model based processes and statistical streamflow indices serving as objective functions. Parameter influence on model output was evaluated by parameter senstivity index values originating from global sensitivity analysis with the Fourier Amplitude Sensitivity Test (FAST). The approach aims at reducing the number of model input parameters to focus on conceptualised processes assumed as hydrologically relevant within the watersheds of the conterminous United States.

I generally agree with the concept of referencing model response functioning in form of derived objective functions with dependent partial parameter sensitivities for region specific model parameter identification. This is one of the aspects which would be really worth publishing.
Apart from that, fundamental assumptions underlying this study are not sufficiently clarified to address the discussed issues effectively, which are certainly topical and relevant for model based catchment hydrology. The paper is technically well-structured, exhibiting findings of the presented concept concisely but it lacks the required presentation quality at too many different points. However, I found some serious shortcomings and recommend to revise a number of major and minor specific and technical points before the manuscript can be reconsidered for publication.

Specific comments

1. What is the main purpose of your paper?

You mention a number of issues e.g. "parameter identification", "process identification", "calibration advise for modelers" or "identification of [model] structural inadequacies". A better focus on one or two of these issues, preferably on the first and second is advisable here.

Yes, the other review suggested that I discuss more the relationship between parameters and processes. I think this is related to your comment here. I rewrote the introduction, with a focus on parameter and process identification.

As uncertainty analysis is not the issue here, I furthermore suggest to remove the part starting from P16L29, which is also rather speculative.

Yes, that paragraph has been removed.

2. Please also name your assumptions more precisely!

The fundamental assumption of this study is, that the conceptualisation of PRMS is structurally adequate to reproduce all hydrological processes of the CONUS. It is however not adressed, whether this assumption is valid or not or if the study doesn't claim to be transferable to real world processes and consequently stays a pure virtual PRMS experiment. Conclusions on the dominant hydrological processes are only valid if it is shown that PRMS actually is a good representation of hydrological processes. Processes in the study purely originate from and are defined by the PRMS structure whereby a comparison with observational data might be helpful in this application to show potential deficiencies or justify the fundamental assumption.

Yes, I restructured the PRMS methods section to include more about the calibration parameters and assumption and less detail about how the application was set up.

3. P2L19/P10L20: As you similarly found out, more complex processes such as

the reproduction of streamflow and its components as well as mountainous regions require more calibration parameters. The general rather small remaining subset of sensitive parameters explaining the majority of the model output variance of processes might be predefined by the conceptual structure of PRMS and a hint to overparameterization.

Yes, I added a sentence essentially saying this.

The number of parameters required in a process is also predetermined by the model/process concept and its complexity. Maybe be a bit more specific and less general or sketchy in stating your findings i.e. in the sense of the influence a parameter exerts on a process which might not be purely predetermined by the concept of a model.

Yes. Based on the suggestion of another reviewer, I have added another table (table 1) that lists the parameters used in this study. In this table, I specify which "module type" each parameter is associated with in the source code. So, without bogging down this article with too many model structure issues, maybe this give the reader some idea of how the calibration parameters relate to the model structure.

4. P3L13: (How) do these two aspects of complexity correspond to the ones stated in the

abstract and explained directly above these lines? Maybe you should be more precise here!

Yes. I added some text about using sensitivity analysis to reduce the complexity to the model user. That is my point. Obviously, SA does nothing about model structure, but the model can appear less complex to the modeler by focusing on those parameters and processes in the model that can be affected.

5. P3L32: This issue has also been partly discussed e.g. by Reusser and Zehe (2011).

Yes, added this reference.

5. P5L8: HRUs are purely derived and defined by their geographic and topographic location. Process identification and catchment classification might be hampered by this definition e.g. by mingling of processes leading to a complex interplay and location specific response behaviour which cannot be always captured by one HRU. In addition to your discussed points a redefinition of HRUs based on dominant hydrologic processes instead of the applied discretisation based on geographic position might be a conceivable outcome and a consequence of your study maybe helpful for calibration.

Yes, added to discussion section.

6. P5L20: Here a more precise explanation might be helpful. Is simulated streamflow at locations with stream gauges evaluated differently from streamflow at sites without observations?

I removed this sentence/section. The other reviewer felt this was too much detail about this aspect.

7. P7L1: Here more attention to further studies with streamflow indices could be given (see e.g. Yadav et al. (2007)). Please discuss your choice in some more details.

8. P9L25: I suggest to start this chapter with the sentence “To identify the expected count of parameters ... (P9L28)” first the theory, then a specific example.

Yes, I moved the text preceeding “To identify…” down to a subsequent summary paragraph.

9. P10L23/P13L8: This view might be kind of model structure/concept specific (as stated above) and is not surprising as streamflow is a convolution of these individual processes. Isn’t total HRU runoff in PRMS the pure product or sum of the other streamflow processes (surface runoff, interflow and baseflow), hence involved process parameters add up to a larger number suggesting more complexity? Maybe you can be a bit more precise in the explanations (P13L13).

Yes, this is the point. Because process that happen “earlier” in the flow cycle affect the processes that happen later, there can be unexpected sensitivity of a process to a parameter that normally is not associated with that process. I added some text about this.

P15L25: To my knowledge PRMS offers different modules for PET calculations. (How) do sensitivity results and parameter identificaton change by replacing one module by another? This might be subject of future studies and worth mentioning.

Yes, added to “Further study” section.

P16L3: Someone who is interested in modelling the selected catchment is probably better advised to have a look at historical meteorological observations. From these it should be obvious that snowmelt might not be of any interest here.

Yes, that’s an obvious one.

Technical corrections

Typing errors:

The spelling and writing needs improvement and proofreading. To mention several of them:

Please be consistent in the writing and consider HESS manuscript preparation guidelines for authors e.g. Figure, Fig.

Yes, fixed Table, Fig., and Figure.

P2L15: indicate instead of indicates

Yes, fixed.

P4L3/P16L14: watershed**s**

Yes, fixed.

P8L15: Here poor comprehensibility can be better avoided by changing three to seven objective functions: “... 56 combinations of three objective functions and eight processes (plus totals).”

Yes, fixed.

P11L7: “...**is** surprising...”

Yes, fixed.

P15L12: “This is probably because it **is** a major component of the hydrologic cycle that is...”

Yes, fixed.

P15L21: tha**n**

Yes, fixed.

P16L7: use**d**

Yes, fixed.

P16L11: “...**is** defined...”

Yes, fixed.

P16L14: process**es**

Yes, fixed.

Reference/citation errors:
Citations in the manuscript are correct while the year 2014 in complete reference is not:
Markstrom, S. L., Regan, R. S., Hay, L. E., Viger, R. J., Webb, R. M. T., Payn, R. A., and LaFontaine, J. H.: PRMS-IV, the precipitation-runoff modeling system, version 4, U.S. Geological Survey Techniques and Methods, book 6, chap. B7, 158, http://dx.doi.org/10.3133/tm6B7, **2015**

Yes, fixed.

Figures:
General remarks:
Resolution and quality of the presented figures and maps seem to be generally not high enough or pixelated and need substantial improvement. Unfortunately, the labeling of latitudinal and longitudinal lines are not readable at all. Please improve the legibility or remove it or incorporate it in only one figure which might be enough to show it once.

Yes, I have removed the lat/long lines from all maps. My original figure are of very much higher quality than what is shown in the draft. MS Word seems to be importing them at a lower resolution than my originals. If this continues to be a problem, perhaps I can work with someone at HESS to ensure that the figures are high resolution.

Some of the shortcomings are listed here:

Figure 1: This map lacks both sufficient quality and a valuable information content. In my oppinion a different form of presentation such as histograms or kernel density estimates for selected attributes of HRUs could be beneficial.

Yes, this figure has been removed.

Figure 2: Please use consistent spelling or abbreveations for objective functions across tables and figures. Please explain the additional column “Process average” in the results section 4.1 and the meaning of the legend. The caption should also provide more information.

Yes, figure 2 has been remade with the same labels as table 2 (used to be table 1). I have also added a few sentences to explain “Process average” and how they are calculated.

Figure 3: Better use as Figure 1. It furthermore contains little information and poor legibility of region names.

Yes, this is now figure 1. I made the region labels larger.

Figure 4: “The plots A-**H** summarize...”

Yes, fixed.

Figure 5: Please clarify the connection to the ordered listing of Table 1.

Yes, added more to fig 4 (used to be figure 5) caption about this.

Figure 6: Please raise font sizes of titles above each map to be readable or remove them from the figure.

Yes, I removed them and remade the figures.

References

Reusser, D. E. and Zehe, E.: Inferring model structural deficits by analyzing temporal dynamics of model performance and parameter sensitivity, Water Resources Research, 47, doi:10.1029/2010WR009946, 2011.

Yadav, M., Wagener, T., and Gupta, H.: Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins, Advances in Water Resources, 30, 1756–1774, doi:10.1016/j.advwatres.2007.01.005, 2007.

Yes, thank you for these references. Citations to both have been added.

This list describes the major changes made to the manuscript in response to the reviewer's comments. This list is organized by the sections of the manuscript.

1. Rewrote the abstract to address: (1) Guse's comment 1 and that knowing the dominate process allows the modeler to focus on output that is related to those processes.
2. Introduction: (1) defined "distributed parameters"; (2) added reference to Hrachowitz et al., 2014; (3) rewrote the sections about "difficulty of interpreting model output" and complexity; (4) added references to Wagener et al., 2003; Reusser et al., 2011; Guse et al., 2014; (5) simplified last paragraph by cutting.
3. Methods: (1) added a paragraph stating limitations of PRMS, particularly within this study; (2) Added short paragraph with citations to previous applications of PRMS to similar studies; (3) removed the old figure 1;
4. Added a "Calibration parameters" section with a new table listing parameters and added text about how parameters associated with one process may end up effecting subsequent processes.
5. Change the words "objective functions" to "performance measures" throughout the document.
6. FAST analysis: added a few sentences about limitations of FAST with respect to higher order variances and parameter interaction.
7. Parameter sensitivity by process and performance measure: (1) added text to better describe figure 2; (2) added some text about limitations due to model structure; (3) added text to describe table 2 (formerly table 1) better.
8. Parameter count required to parameterize each process: (1) generally reorganized; (2) added more text about model structure; (3) improved description of figure 3; (4) improved discussion of table 2; (5) improved description of figure 4; (6) added a few sentences about "vertical routing order."

9. Further study: removed several of the more speculative paragraphs and added text about HRU definition and PRMS module selection.
10. Added the references suggested by the reviewers.
11. Tables: (1) added table describing the calibration parameters, (2) improved the captions on most tables.
12. Figures: (1) improved the captions to make them more descriptive; (2) increased the resolution of all map figures.

Towards simplification of hydrologic modeling: identification of dominant processes

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Abstract

The Precipitation-Runoff Modeling System, a distributed-parameter hydrologic model, has been applied to the conterminous United States.~~An application of the Precipitation-Runoff Modeling System, a distributed-parameter hydrologic model, has been developed for the conterminous United States.~~ In this study, two different aspects of the complexity in applying this model has been addressed: (1) the number of input parameters and (2) the interpretation of model output. Parameter sensitivity analysis was used to simplify the application of the hydrologic model. ~~through I~~identification of parameters related to dominant hydrologic processes (baseflow, evapotranspiration, runoff, infiltration, snowmelt, soil moisture, surface runoff, and interflow) at various geographic ~~scales~~locations. These processes mave been identified with ~~correspond to~~ model output variables for which ~~objective functions~~perfomance measures (mean, autoregressive lag 1, and coefficient of variation) are computed.

~~Categories of parameter~~ Parameter sensitivity values were ~~developed~~ computed in various ways, on the basis of geographic location, hydrologic process and model response. ~~Visualization of these categories~~Identified parameters and processes provide insight into model performance and useful information about how to structure the modeling application to take advantage of as much local information as possible. The results of this study indicate~~s~~ that (1) the choice of ~~objective function~~ performace measure and output variables have a strong influence on parameter sensitivity, (2) the dimensionality of distributed-parameter hydrology models can be reduced by removing input parameters, output variables and ~~objective functions~~performace measures from consideration on the basis of selection by hydrological process, (3) different hydrological processes require different numbers of parameters for simulation, and (4) some model sensitive parameters influence only one hydrologic process, while others may influence many. This article describes how this complexity can be addressed by focusing on parameter and hydrologic process identification through global parameter sensitivity analysis.

Commented [MSL1]: P. 2, L. 4-5: Whilst it is certainly clear that the number of parameters is an aspect of model complexity, this is not fully clear for the "interpretation of the model output". Is this really an aspect of complexity? Do you assume that the model which provides a higher number of model outputs is more complex?

rewrite this with respect to knowing dominate process allows the modeler to focus on output that is realted to those processes.

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1 Introduction

It has long been recognized that distributed-parameter hydrology models (DPHMs) are complex because of the subtlety and diversity of the hydrologic cycle which they aim to simulate (Freeze and Harlan, 1969; Amorocho and Hart, 1964). In this study, two different aspects of this complexity are addressed:

(1) DPHMs have too many input parameters (Jakeman and Hornberger, 1993; Kirchner et al., 1996; Brun et al., 2001; Perrin et al., 2001; McDonnell et al., 2007). In this article, distributed parameters are defined as model inputs that remain constant through time, but can vary spatially across the landscape. Those who apply these models often have difficulty understanding what these parameters are and how they are used in the model. Regularly, there are several parameters that may have similar ~~effect~~ affect on the computations or may constrain the model in unintended ways (Hrachowitz et al., 2014). Despite the developer's claims that these DPHMs are more or less physically based, often there are not measurements or data sources available for reliable development of all of the input parameters. These unmeasured parameters, ostensibly tangible, are really empirical coefficients when it comes to application and calibration.

(2) The output produced by DPHMs is difficult to interpret (Schaefli and Gupta et al., 2008; Gupta et al., 2009; Gupta et al., 2012). Often, the meaning of output variables is not always intuitive and results sometimes can seem contradictory (e.g. when streamflow does not seem to correlate with climate information). ~~Consequently, development of objective measures of model performance (hereafter referred to as *objective functions*) is often a subjective exercise that can lead to different interpretation depending on the choices made (Krause et al., 2005; Mendoza et al., 2015b; Mendoza et al., 2015a).~~ The result of these complex issues has led to the study of parameter interaction (Clark and Vrugt, 2006) and equifinality (Beven, 2006).

Developing effective DPHM applications require that the modeler address these two aspects of complexity at the same time (i.e. the uncertainty problem: "If I am uncertain when estimating input parameters, due to either incomplete or inaccurate information, what affect does it have on the output?", and the calibration problem: "I know the output I want, which parameters should I change and how much should I change them?") (Cheney et al., 2015; Reusser and Zehe (2011). While, the user of a DPHM can do nothing about complexity associated with that model's internal structure, the apparent complexity to that user can be reduced by identifing those parameters and process that affect the DPHM in a particular application.

This article describes how this complexity can be addressed by focusing on parameter and hydrologic process identification through global parameter sensitivity analysis (SA). The

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P. 3, L. 6: The three references are related to studies which investigate performance
measures more precisely. It might be good to also have a reference to studies which
are directly investigating the model output.

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degree to which different values of model parameters can affect the simulation of certain model outputs can be identified (G). Furthermore, parameter sensitivity can be evaluated with respect to selected output variables, each representing different aspects of the hydrologic cycle (hereafter refered to as "processes"). Sensitivity analysis of this form can be used to both identify the input parmeters that are the most sensitive (i.e. the parameters that affect the simulation the most) and the dominate process(es) (i.e. those processes which are affected most, by the most sensitive parameters).

Results of SA can vary spatially and must be accounted for as such. Specifically, DPHM parameters can be more or less sensitive at different locations on the landscape. For example, parameters related to simulation of snow can become more sensitive at higher elevations, while parameters related to evaporation can become less sensitive at locations where capacity for soil water storage decreases. Consequently, this means that the dominate process(es), as identified by SA, will vary across the landscape as well. ~~These two issues are compounded as the spatial domain of the DPHM application expands. A common problem is that at large scale and with limited information, the effects of different hydrological processes can be indistinguishable from each other. For instance, groundwater recession and snowmelt from a receding snowpack can cause similar response in a streamflow hydrograph. If the prevailing hydrological process is not identified by the modeler, and subsequently parameterized in the model, the result can be "the right answer for the wrong reason" (Kirchner, 2006; McDonnell et al., 2007). This type of misunderstanding compounds both of the problems identified above as the modeler wastes resources working with insensitive input parameters and evaluating objective functions that do not relate with the real world physical processes. The result of these complex issues has led to study of parameter interaction (Clark and Vrugt, 2006) and equifinality (Beven, 2006).~~

Any particular DPHM must necessarily be complex because it must be able to simulate any and all hydrological process that may occur anywhere on the landscape. However, with the application of a DPHM to a specific site, it can become much less complex when the dominant hydrological process(es) are identified, as not all processes are active or at the same level of importance. The problem becomes less complex when hydrological processes not relevant to the modeled domain (or watershed) are removed from consideration (Wagener et al., 2003; Reusser et al., 2011; Guse et al., 2014; Bock et al., 2105; Bock et al., 2105). Dominant process concepts have been explored as a way to classify watersheds and natural hydrologic systems for simplifying DPHMs by several researchers (Sivakumar and Singh, 2012; Sivakumar et al., 2007). Some have suggested the approach for use as a possible classification framework (e.g. Woods, 2002; Sivakumar, 2004). Pfannerstill et al. (2015) developed a framework for identification and verification of hydrologic process in simulation models on the basis of temporal sensitivity analysis. McDonnell et al. (2007) discuss the possibility of simplifying hydrologic modeling by identifying “fundamental laws” so that over parameterized models are not needed. However, in our opinion we have not made much progress on that front and DPHMs are, in many ways and for many reasons, more complex than ever.

This article describes an SA for a modeling~~ DPHM~~ ~~approach~~ application~~ ~~ to ~~that has been applied to~~ the conterminous United States (CONUS, Fig 1.). ~~Specifically, by~~The large domain is simulated by an ~~aggregating~~ aggregated a ~~large~~ collection of many small ~~domain DPHMs~~ scale watershed applications.~~, the large domain can be simulated.~~ ~~This has the advantage of being able to use all local information and match local conditions. The disadvantage is that all of these DPHMs must be set up in a uniform way or the result is a “patchwork quilt” of parameter values.~~ Identification and simulation of these ~~small-scale catchments~~watersheds is determined by the resolution of the available information and how the DPHM responds to geophysical (e.g., topography, vegetation and soils) and climatological variation. Specifically, we propose to ~~reduce the complexity of the DPHM approach through identification of~~identify the sensitive parmaters and dominant hydrologic process(es), thereby identifying a reduced amount of~~ and reduce the number of~~ input~~s~~ and output~~s~~ to consider~~ed~~ (Chaney et al., 2015). ~~This is accomplished by relating a hydrologic process directly to parameters and objective functions. The questions addressed by this study are: (1) can DPHM application be simplified by reducing the dimensionality of the input, and (2) can geographic areas (regions, watersheds, HRUs, etc.) be categorized by hydrological process to aid identification of meaningful output?~~

2 Methods

~~2.1~~ Distributed-parameter hydrology model ~~Hydrologic model~~

The U.S. Geological Survey’s ~~(USGS)~~ Precipitation-Runoff Modeling System (PRMS) is the DPHM used in this study. PRMS is a modular, deterministic, distributed-parameter, physical-process watershed model used to simulate and evaluate the effects of various combinations of

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1. Coordinate with Guse Methods comment 1: P. 4, L.29- P. 6, L.7: Please check carefully if you could reduce the subchapter 2.1 in length. Do you really need this information for this article?

precipitation, climate, and land use on watershed response. Each hydrologic process simulated by the model is represented within PRMS by an algorithm that is based on a physical law (i.e. balance of energy required to melt the ice in a snowpack) or empirical relation with measured or estimated characteristics (i.e. a tank model used to simulate interflow). The reader is referred to Markstrom et al.~~,~~ (2015) for a complete description of PRMS.

A fundamental assumption of this study is that PRMS is able to simulate and differienate hydrologic signals from all the different processes at the scale of the CONUS. Two possible ways to evaluate this are: (1) an analysis of PRMS's internal structure, and (2) the history of PRMS applications. A detailed analysis of PRMS's structure is beyond the scope of this article (see Markstrom et al., 2015); however, PRMS is implemented in a very linear fashion. Each parameter is clearly identified with an equation that is related to simulation of a specific process. Equations are solved sequentially, generally in the order that is defined by water moving through the hydrologic cycle, starting from the atmosphere as precipitation and moving through the rivers as streamflow. The outputs of one equation maybe used as inputs to subquent equations. All of the inputs for a particular equation are required before that equation can be solved. This interdependancy in equations can lead to parameter interaction in the simulation of subsequent processes. For example, parameters related to distribution of temperature and solar radiation may show correlation with each other when evaluated with respect to simulation of evapotranspiration despite these parameters not being explicit terms in the evapotranspiration equations.

Past studies indicate that PRMS has been very useful useful in water resource and research studies across the CONUS (cite them) and is capable of matching measured data (cite them) in a variety of geophysical and climatological settings.

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To define the spatial domain for the CONUS application of PRMS, the locations of major river confluences, water bodies and stream gages have been ~~located as~~ georeferenced~~ points~~. ~~These~~ Approximately 56,000 stream segments are used to connect these ~~points~~locations~~ are mapped onto the natural river network of the entire CONUS, breaking the network into approximately 56,000 stream segments, which vary in length from approximately 1 meter to 175 kilometers, with 10 kilometers being typical~~. Using these stream segments, the left and right bank areas that contribute runoff directly to each segment have been identified, resulting in approximately 110,000 irregularly shaped hydrologic response units (HRUs) of various sizes (500 m^2 to 14,000 km^2) (Viger and Bock, 2014)~~ (fig. 1)~~. ~~These HRUs as defined by the real world points represent the conceptualization of areal space within the DPHM and vary in size from approximately 500 square meters to 14,000 square kilometers, with 100 square kilometers being typical. HRUs in PRMS are simulated as homogenous units and tend to be finer in areas that have more information (i.e. stream gages) and produce more streamflow (i.e. denser stream network). This topological network of stream segments and HRUs allows for evaluation of streamflow simulation at almost 60,000 specific locations on rivers, including nearly 8000 stream gages.~~ These stream segments and HRUs and derived by their geographic and topographic location, affecting their extent and resolution.

~~This~~ The CONUS application is forced with values of daily precipitation and daily maximum and minimum air temperature from the DAYMET data set (Thorton et al., 2014). ~~The one square kilometer gridded DAYMET data has been processed to provide mean daily HRU values on the basis of area weighted averaging using the USGS Geo Data Portal (Blodgett et al., 2011).~~ The climate information covers a time period from 1980-2013 on a daily time step, but a shorter period (1987 – 1989 used for warmup and 1990 – 2000 used for evaluation) was ~~selected~~ used ~~for~~ in this study.

2.1 Calibration Parameters

The version of PRMS used in this study has 108 input parameters. ~~For this study, a~~A parameter is defined as an input value that does not change over the course of a simulation run. Of these parameters, most would never be modified from their initial values (hereafter referred to as *non-calibration parameters*) because they are (1) computed directly from digital data sets through the use of a geographic information system (e.g. land-surface characterization parameters) (Viger, 2014), (2) boundary conditions (e.g. parameters to adjust daily precipitation and daily ~~min/max~~ air temperature forcings), or (3) model configuration options (e.g. unit conversions and model output options). This leaves 35 parameters under consideration for improved model performance, hereafter referred to as *calibration parameters* ~~(listed below in table 1 and described fully by Markstrom et al. (2015) in table 1-3).~~(Table 1). Each parameter is used within a PRMS code module that simulates a single hydrologic process in PRMS. The ouput variables of one module may be used as input variables to other modules. It is through these connections that calibration parameters associated with a PRMS module type may affect the results of other modules.

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2.2 Hydrologic processes

PRMS produces more than 200 output variables that indicate the simulated hydrologic response ~~of the simulation~~ of a watershed through time (Markstrom et al., 2015, see ~~table~~ Table 1-5). In this study, eight of these output variables have been selected to represent the response of major hydrologic processes at the HRU resolution. These processes are: (1) baseflow (PRMS output variable *gwres_flow*) – the component of flow from the saturated zone to the connected stream segment; (2) evapotranspiration (*hru_actet*) – the total actual evapotranspitation lost from canopy interception, snow sublimation and soil and plant losses from the root zone; (3) runoff (*hru_outflow*) – the total flow from the HRU contributing to streamflow in the connected stream segment; (4) infiltration (*infil*) – the sum of rain and snowmelt that passes into the soil zone of the HRU; (5) snowmelt (*snowmelt*) – the amount of water that has changed from ice to liquid and becomes either surface runoff or infiltrates into the soil zone of the HRU; (6) soil moisture (*soil_moist*) – the storage state that represents the amount of soil water in the soil zone above wilting point and below total saturation in the HRU; (7) surface runoff (*sroff*) – water from a rainfall or snowmelt event that travels quickly over the land surface from the HRU to the connected stream segment; and (8) interflow (*ssres_flow*) – shallow lateral flow in the unsaturated zone to the connected stream segment. It is assumed that these eight output variables are representitive of hydrological studies with distributed models Details of how these processes are simulated by PRMS are described by Markstrom et al. (2015).

2.3 ~~Objective functions~~Performance measures

For DPHMs, there are many different ~~objective functions~~performance measures that have been developed for different purposes (Krause et al., 2005; Gupta et al., 2008; Gupta et al., 2009). Because this study is an analysis of model sensitivity, the ~~objective functions~~performace measures need only track changes in model output and do not necessarily need to include observed measurements. Consequently, ~~objective functions~~performance measures can be developed for processes that are not normally evaluated by ~~objective functions~~performance measures. Archfield et al. (2014) demonstrated that seven fundamental daily streamflow statistics (FDSS) can be used to group streams by similar hydrologic response and tend to provide non-redundant information. In this study, all seven FDSS were computed for each of the eight PRMS time series output variables corresponding to the processes. For the purpose of illustration, this ~~paper~~ article focuses on three of the FDSS: (1) mean; (2) coefficient of variation (CV); and (3) the autoregressive lag-one correlation coefficient (AR-1). In an intuitive sense, performance measures~~objective functions~~ based on these three statistics can be thought to represent changes in total volume, "spikiness" or "flashiness", and day-to-day timing, respectively. These performance measures~~objective functions~~ are computed on the daily time series of the process variables for the 10 year evaluation period.

3 FAST analysis

Global parameter sensitivity analysis measures the variability of model output given variability of calibration parameter values. This is determined by partitioning the total variability in the model output or change in performance measure~~objective function~~ values to individual calibration parameter (Reusser et al., 2011). The Fourier Amplitude Sensitivity Test (FAST) (Schaibly and Shuler, 1973; Cukier et al., 1973; Cukier et al., 1975; Saltelli et al., 2006) was selected for this study because it has been demonstrated that it can efficiently estimate non-linear hydrologic model parameter sensitivity (Guse et al., 2014; Pfannerstill et al. 2015; Reusser et al., 2011). FAST is a variance-based global sensitivity algorithm that estimates the first-order partial variance of model output explained by each calibration parameter (hereafter referred to as *parameter sensitivity*). Specifically, this first-order variance is the variability in the output that is directly attributable to variations in any one parameter and is distinguishable from higher order variances associated with parameter interactions~~.~~. An important caveat is that these higher order variances are not accounted for in the analysis. It is assumed that first-order partial variance is sufficient to identify sensitive parameters. This same assumption, as applied to process identification, may be more problematic. If there are sets of interactive sensitive parameters that have not been identified, then the associated process(es) will not be identified as such.

Selected parameters are varied within defined ranges at independent frequencies among different model runs. FAST identifies the variability of parameter sensitivities and their ranks, by means of their contribution to total power in the power spectrum. FAST has been implemented as the 'fast' library in the statistical software R (Reusser et al., 2011; R Core Team, 2015) in two parts. In the first part, the user identifies the calibration parameters and respective value ranges for the test, then FAST generates sets of test calibration parameter values (hereafter referred to as *trials*). Calibration parameter values are varied across the trials according to non-harmonic fundamental frequencies. The user then runs the DPHM for each trial and computes corresponding performance measures~~objective function values~~. Then the user runs the second part of the FAST package that performs a Fourier analysis of the performance measures~~objective function values~~ over the trial space looking for the frequency signatures associated with each calibration parameter~~.~~.

The FAST methodology results in a simple procedure for computing parameter sensitivities on an HRU basis for all the CONUS~~ (see fig. 1)~~. The steps in this process are as follows:

1. Assign appropriate ranges for the 35 calibration parameters (Markstrom et al., 2015; as in LaFontaine et al., 2013).
2. Run the first part of the FAST procedure (as described above) to develop over 9000 unique parameter sets, comprised of value combinations for the calibration parameters. These parameter sets in the trial space are independent of each other so they can run in parallel on a computer cluster.
3. Compute the FDSS based performance measure~~objective function~~ (mean, CV, and AR-1) values for each process.
4. Run the second part of the FAST procedure (as described above) using output from step 3, resulting in PRMS parameter sensitivities, at each HRU, for the 56 combinations of ~~three~~ seven performance measures~~objective functions~~ and eight processes (plus totals).

4 Results

4.1 Paramseter s~~S~~ensitivity by process and performance measure~~objective function~~

Figure 2 shows parameter sensitivity as a set of maps ordered by process and performance measure~~objective function~~. This illustrates the spatial variability in parameter sensitivity and the importance that choice of performance measure~~objective function~~ can make in terms of evaluation of hydrologic response. In these maps, the HRUs are colored according to the parameter sensitivity, which is computed by summing the first order sensitivity for all 35 parameters and then scaling (by average) each individual category of modeled process and performance measure~~objective function~~ to total sensitivity. Parameter sensitivity associated with process (column labeled "Process average" in Figure 2) are averaged across all of the parameter sensitivity values computed for the different performace measures; while parameter sensitivity associated the performance measues (last row labeled “Preformance measures” in Figure 2) are averaged across all of the parameter sensitivity values computed for the different processes. These categories are indicated by their position in the rows and columns in ~~figure~~ Figure 2. When looking at a single performance measure~~objective function~~ for a single process, the cumulative parameter sensitivity can vary from near 0.0 (white colored HRUs) to near 1.0 (black colored HRUs). Low values in these maps indicate that there are no parameters that can be changed in any way to affect the performance measure~~objective function value~~ (this situation is hereafter referred to as an *inferior process*). Likewise, each HRU has a cumulative sensitivity value (i.e. the sum of all of the parital sensitivities for each process). ~~which is highest for a particular~~The process with the largest sum~~,~~ on an HRU, is referred to as the *dominant process*~~.~~ for that HRU.

An example of an inferior process is clearly seen in the case of the mean of the snowmelt process in the southern CONUS HRUs. This is because the occurrence of snow in these areas is very infrequent. Also, there were HRUs for which the value of some performance measures~~objective functions~~ were mathematically undefined for certain processes (e.g. AR-1 and CV for the baseflow and snowmelt processes). These cases occur when the output variable representing the process does not change at all through time and are extreme examples of inferior processes. Likewise, a clear example of a dominant hydrologic process is the CV of interflow in the Intermountain West region of the CONUS (~~figs~~Figs. ~~2~~ 1 and ~~3~~2). This means that for these HRUs, there exist some calibration parameters that can be varied that affect this process to a very high degree.

Also apparent from ~~figure~~ Figure 2 is that there are clear spatial patterns in the parameter sensitivity on the basis of the geographical features of the CONUS. Generally, many of the maps show a sharp break in parameter sensitivity between mountain ranges and comparatively lower elevations, ~~and~~ northern contrasted with southern latitudes, and humid versus arid climates. Specific contrasts can be seen in several maps such as when examining the Humid Midwest as opposed to the Great Plains regions and the Pacific Coastal areas and the Desert Southwest region of the CONUS (~~fig~~Fig. ~~3~~1). Additionally, topographic features of the landscape are prominent (e.g. elevation for interflow), while in other maps, climate considerations seem to dominate (e.g. snowmelt). Another specific example is that the mean of each process, which indicates the ability of any particular parameter to change the total volume of water during a simulation, seems to have a low sensitivity band in the Great Plains region for all processes except for snowmelt (~~fig~~Fig. ~~3~~1). This band of low sensitivity has been noted in other modeling studies (Newman et al., 2015; Bock et al., 2015).

4.2 Parameter count required to parameterize each process

~~Figure 4 illustrates the extent to which it is possible to decompose the parameter estimation problem into a sub-set of independent problems, and hence reduce the dimensionality of the inference problem and avoid the troublesome nature of parameter interactions. It also illustrates that there is a strong spatial component to this decomposition.~~ To identify the expected count of parameters required to parameterize a particular process, cumulative parameter sensitivity across all HRUs of the CONUS has been computed and plotted (~~fig~~Fig. ~~4A~~3(a~~-)~~—~~H~~(h)). The sensitivity level accounted for by the most sensitive parameter, regardless of which parameter it is, for all HRUs across the CONUS is plotted in position 1 on the X axis of each of these plots (~~fig~~Fig. ~~4A~~3(a)— ~~H~~(h)). Then, cumulative sensitivity is plotted for the parameter in rank 2, and so on, until the cumulative sensitivity of all 35 calibration parameters is accounted for. The plots in ~~figure~~ Figure ~~4A~~3(a)—(h) ~~H~~ show that far fewer than the full 35 parameters, on average, are needed to account for most of the parameter sensitivity. In fact, to account for 90% of the parameter sensitivity, this count varies from an average low value of just over two for snowmelt to an average high value of over 9 for runoff in selected HRUs.

The actual count of calibration parameters required to account for 90% of the parameter sensitivity varies by process and region, as shown by the maps in ~~figure~~ Figure ~~4I~~3(i)—(p) ~~P~~. These maps were generated by counting the number of parameters required to obtain the 90% cumulative sensitivity level for each HRU. For example, ~~figure~~ Figure ~~4I~~ 3(i) indicates that for the baseflow process between three and nine parameters are needed in specific HRUs to account for 90% of the parameter sensitivity in the HRUs across the CONUS, with the higher count needed in mountainous, Great Lakes and New England regions. The maps also indicate that between four and six parameters are required for parameterization of evapotranspiration (~~fig~~Fig. ~~4J~~3(j)), five to 14 parameters are required for parameterization of runoff (~~fig~~Fig. ~~4K~~3(k)), four to 13 parameters are required for parameterization of infiltration (~~fig~~Fig. ~~4L~~3(l)), two to eight are required for parameterization of snowmelt (~~fig~~Fig. ~~4M~~3(m)), three to six parameters are required for parameterization of soil moisture (~~fig~~Fig. ~~4N~~3(n)), five to eight parameters are required for parameterization of surface runoff (~~fig~~Fig. ~~4O~~3(o)), and two to 13 parameters are required for parameterization of interflow (~~fig~~Fig. ~~4P~~3(p)). This analysis

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indicates that more parameters are needed to simulate the components of stream flow (e.g. baseflow, interflow, and groundwater flow) than processes that do not result directly in flow (e.g. snowmelt, evapotranspiration, and soil moisture). An analyis of theses parameter counts and how they relate to their respective process is beyond the scope of this article, but it could relate to the structure of PRMS and possibly indicate that some processes are overparameterized. In addition, simulated process that are identified as being sensitive to parameters with which they are not normally associated with, may indicate that these process are a convolution of other processes, consequently making parameters sensitive that are not normally sensitive.

Visually, these maps (~~fig~~Fig. ~~4I-P~~3(i)—(p)) indicate that HRU calibration parameter counts vary regionally. For most processes, higher parameter counts are seen in the more mountainous regions of the Cascade, Sierra, Rocky, Ozark, and Appalachian mountains, although this is true to a much lesser extent for the evapotranspiration and soil moisture processes (Figs. 3(j) and 3(n)). Higher values also seem prevalent in New England and Great Lake regions (~~fig~~Fig. ~~3~~1). This result seems to indicate that, no matter which part of the hydrologic cycle is simulated, more parameters are required in these regions. In contrast, low parameters counts seem prevalent in the Great Plains and Desert Southwest of the United States.

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Finally, Figure 3 illustrates the extent to which it is possible to decompose the parameter estimation problem into a sub-set of independent problems, and hence reduce the dimensionality of the inference problem and avoid the troublesome nature of parameter interactions. It also illustrates that there is a strong spatial component to this decomposition. In order to make the information presented in ~~figure~~ Figure ~~4~~ 3 more useful for DPHM application, the particular sensitive parameters have been determined for each HRU by ranking the calibration parameters by sensitivity for each category of process and performance measure~~objective function~~ for each individual HRU (not shown). A summary of this information is produced by counting the occurrence of each parameter across the HRUs and ranking them within their respective category of process and performance measure~~objective function~~ (~~table~~ Table ~~1~~2). To address the issue of the spatial variability of these parameters, the percentage of the total number of CONUS HRUs that would include the respective parameter as one of those that that account for 90% of the cumulative sensitivity. Higher values would indicate that the corresponding parameter is sensitive across more of the

CONUS. Refer to ~~Markstrom et al. (2015, table 1-3)~~Table 1 for a complete description of these parameters.

When looking at the categorical parameter lists of ~~table~~ Table ~~1~~2, it is expected that different parameters would associate with different processes (i.e. along a column), but it is surprising to see how different the parameter lists are for different performance measures~~objective functions~~ (moving across a row) for the same process. An example of this is the baseflow process: the baseflow coefficient (PRMS parameter *gwflow_coef*) is the most sensitive parameter for performance measures ~~objective functions~~ CV and AR1, but is not even in the list of sensitive parameters for the performance measure~~objective function~~ related to the mean of the process. This implies that this parameter is the most important for effecting the timing of baseflow, while it does not have any effect on the total volume of baseflow.

Further inspection of ~~table~~ Table ~~1~~ 2 indicates that some calibration parameters occur in many of the 24 categories (8 processes times 3 OFs), while some parameters do not occur at all. A count of how many times each parameter occurs provides insight into how ~~important~~ many process/performance measure combinations that particular parameter ~~is to the DPHM simulation~~influences. To investigate this for the CONUS application, another view of the information in ~~table~~ Table ~~1~~ 2 is shown in ~~figure~~ Figure ~~5~~4. The 25 sensitive calibration parameters ~~identified as sensitive in some category~~ from ~~table~~ Table ~~1~~ 2 are listed on the y-axis of ~~figure~~ Figure ~~5~~4, ranked by order of the number of times that they appear. Furthermore, each appearance is indicated by an adjacent circle~~,~~. Independent of the number of times a parameter occures withing a category (number of circles), the color of the circle indicates the proportion of the CONUS HRUs that are affected by that parameter. ~~with the color indicating the rank within the category in which it appeared.~~ Specifically, a red circle indicates ~~a first place appearance~~that more HRUs are affected, while blue indicates ~~a last place appearance, and shades of purple indicate something in between~~that fewer HRUs are affected.

Figure ~~5~~ 4 shows that three specific parameters affect 18 or more process~~/objective function~~ categories; seven parameters affect seven to 14 categories, and 15 specific parameters affect one to five categories. Finally, of the 35 parameters studied, 10 are never used for any combination of process~~/~~ and performance measure~~objective function~~ (~~table~~ Table ~~1~~ 2 and ~~fig~~Fig. ~~5~~4). It is apparent from ~~figure~~ Figure ~~5~~4, that for the CONUS application of PRMS, the ~~most important~~ parameters affecting the most process categories are *soil_moist_max*

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(maximum available water holding capacity), *jh_coef* (Jensen-Haise air temperature coefficient), and *dday_intcp* (intercept in degree-day equation).~~–~~Because these parameters affect so many process categoies, ~~Modelers~~ modelers would be wise to invest their resources in developing the best values possible for these parameters to avoid unintended parameter interaction. Ideally, these parameters could be estimated from reliable external data and set for the model and not calibrated. The ~~least important~~parameters that affect the least number of process categories ~~parameters~~ (aside from the parameters that are never sensitive) are *cecn_coef* (convection condensation energy coefficient), *ssr2gw_exp* (coefficient in equation used to route water from the soil to the groundwater reservoir), *emis_noppt* (emissivity of air on days without precipitation), *potet_sublim* (fraction of potential evapotranspiration that is sublimated), and *slowcoef_lin* (slow interflow routing coefficient). Ideally, these parameters could be set to default values since there is limited calibration information for them.~~ and only calibrated if necessary~~. Also apparent from ~~figure~~ Figure ~~5~~ 4 is that there are many parameters between these two extreme groups. Parameters like *smidx_coef* (soil moisture index for contributing area calculation) can appear in several process~~/objective function~~ categories, without any high rankings, while there are other parameters like *slowcoef_sq* (slow interflow routing coefficient) that appear in relatively few process~~/objective function~~ categories, but have high rankings. This behavior may be due to the vertical routing order (i.e. processes that occure nearer to the surface happen before the deeper ones) of the associated processes (Yilmaz et al., 2008; Pfannerstill et al., 2015). These parameters may be the best candidates for calibration because they are sensitive, while at the same time interaction across processes is perhaps limited.

5 Discussion

5.1 Causes of parameter sensitivity

There are regions where parameter sensitivity is typically high for a particular performance measure~~objective function~~ (e.g. New England region (~~fig~~Fig. ~~3~~1) for performance measure~~objective function~~ based on mean of processes) or typically low (e.g. Great Plains region (~~fig~~Fig. ~~3~~1) for mean of processes) regardless of the process (~~fig~~ Fig 2). Why do the HRUs of some regions exhibit parameter sensitivity to almost all processes, while others exhibit parameter sensitivity to almost none? All other things being equal, there can only be two sources of these spatial patterns:

1. The physiography that is used to define the non-calibration parameters (e.g. elevation, vegetation type, soil type) renders all calibration parameters insensitive. A theoretical example of this could be if an HRU is characterized as entirely impervious, resulting in the non-existence of any simulated soil water.

2. Patterns in the climate data used to drive the model (e.g. daily temperature and precipitation) could control model response. A theoretical example of this could be an HRU that receives no precipitation. The hydrologic response of the HRUs in either case would always remain unchanged, regardless of changes in any parameter value.

In either case, these sources of information are independent of the DPHM and could lead to the conclusion that the dominant processes identified by the methods outlined in this ~~paper~~ article could correspond to perceptible dominant processes in the physical world (i.e. how the "real world" works).

The number of unique calibration parameters for each process in ~~table~~ Table ~~1~~ 2 (i.e. counting the parameters across each row) may provide some insight into the complexity of each process. In theory, more "complicated" hydrologic processes would require more parameters for parameterization than the "simpler" ones. According to this view, runoff (17 calibration parameters) and infiltration (14 calibration parameters) are the most complex processes to simulate, with soil moisture (4) being the simplest. Interflow (12 calibration parameters), baseflow (11 calibration parameters), surface runoff, (10 calibration parameters), snowmelt (9 calibration parameters) and Evapotranspiration (8 calibration parameters) are in between. This reflects the fact that in PRMS, runoff is a much more complicated calculation with many of the other processes directly contributing information. Also apparent is that more parameters are needed to simulate the components of stream flow (e.g. baseflow, interflow, and surface runoff) than processes that do not result directly in flow (e.g. snowmelt, evapotranspiration, and soil moisture). The only process that does not follow this pattern is infiltration. Storm-event based infiltration is typically simulated with sub-daily time steps to account for the time/intensity variability of this process. It is possible that PRMS must compensate for this shortcoming in structure with a more complex parameterization of the process.

Table ~~1~~ 2 indicates that there are 10 calibration parameters that are never sensitive regardless of the process or performance measure~~objective function~~. This indicates that these parameters should always be set to default value, with minimal resources used to estimate them, and never be calibrated. Additional modeling studies could reveal situations where these parameters actually do exhibit some sensitivity, perhaps in situations with smaller geographical domains or over different time periods. It is also possible that these parameters are never sensitive, indicating some structural problem or unwarranted complexity in the DPHM and the removal of some algorithms from the source code of the DPHM is advised. Additional study is required of these 10 non-sensitive calibration parameters and upon further review of the PRMS source code, a structural problem (e.g. unintended constraint, non-differentiable behavior, or software bug) might be revealed. Alternatively, the problem could be related to invalid parameter ranges in the FAST analysis or problems with the climate data used to drive the model. Finally, it could be that alternative or improved performance measures~~objective functions~~ could resolve this issue.

5.2 Choice of performance measure~~objective function~~

The maps of ~~figure~~ Figure 2 clearly illustrate the importance that choice of performance measure~~objective function~~ can make in terms of evaluation of hydrologic response. When the maps of performance measures~~objective functions~~ within a single hydrologic process are compared (i.e. the maps across a single row), the spatial patterns and magnitude of the parameter sensitivity can be very different. This could indicate that the performance measures~~objective functions~~ based on the FDSS truly are non-redundant and are accounting for different aspects of the hydrological processes.

Table ~~1~~ 2 indicates that the baseflow coefficient (PRMS parameter *gwflow_coef*) (Markstrom et al., 2015) is the most sensitive parameter for performance measures~~objective functions~~ CV and AR1, but not sensitive to the mean of the baseflow process performance measures~~objective function~~. This indicates that despite knowledge of parameters being associated with the computations of simulation of a certain process, sensitivity analysis can reveal that the response of the simulation is completely different when the performance measure~~objective function~~ changes. It also indicates that sensitivity analysis might be an important step in selection of an appropriate performance measure~~objective function~~ and that uncritical application of performance measures~~objective functions~~ may be misleading.

5.3 Identification of dominant and inferior processes by geographic area

To identify the dominant and inferior process(es) by geographic area, the following procedure is done for each HRU:

1. The parameter sensitivity scores are summed for each parameter, resulting in a score for each parameter for each time series output variable and performance measure~~objective function~~.
2. The parameter scores are averaged by performance measures~~objective functions~~, resulting in a score for each process.
3. The process scores are ranked for each HRU.
4. The top (and bottom) ranked process determines the most dominant (and most inferior) single process as shown in ~~figure~~ Figure ~~6~~5.

When the sensitivities are computed this way, it is possible that certain parameters are included in both the most dominate and most inferior processes at the same time. This apparent contradiction is not necessarily a conflict but indicates that the calibration parameters must work in concert with the evaluation method. For example, there exist HRUs where the evapotranspiration process is dominant and at the same time the runoff or infiltration processes are inferior (~~fig~~Fig. ~~6A~~ 5(a) and ~~6B~~5(b)). The parameter *soil_moist_max* is indicated as being sensitive for all three of these processes (~~table~~ Table ~~1~~2). This parameter would demonstrate equifinality if evaluated within the context of the inferior processes (i.e. those output variables and performance measures~~objective functions~~) but would be a very effective calibration parameter resulting in optimal values when viewed within the context of the dominate process.

Generally, ~~figure~~ Figure ~~6A~~ 5(a) shows that evapotranspiration is the most prevalent dominant process for the CONUS. This is probably because it is a major component of the hydrologic cycle ~~that is important~~and sensitive parameters are available to affect it in every HRU. However, this is not universal, and the dominant process varies by geographic region, with snowmelt being the dominant process in the northern Great Planes and northern Rocky Mountains, total runoff being the most important in the Pacific Northwest, and with interflow important in bands across the Intermountain West (~~fig~~Fig. ~~3~~1). Each process is dominant somewhere depending on local conditions. Equally informative are the locations of the most inferior processes (~~fig~~Fig. ~~6B~~5(b)). This clearly shows that PRMS snowmelt parameters are not sensitive across the Central Valley of California, and in the Deep South and the Southwestern United States (~~fig~~Fig. ~~3~~1). Areas where runoff is more dominate ~~that~~ than evapotranspiration, as in the Cascade and coastal areas of the Pacific Northwest, are locations where the runoff is a substantially greater part of the water budget. Interestingly, infiltration and baseflow appear to be equally inferior across most of CONUS, with pockets of HRUs that are insensitive to soil moisture, surface runoff, and interflow, depending on local conditions. There are no HRUs that rank evapotranspiration as the most inferior process.

Dominant and inferior process can be identified for HRUs at the watershed scale as well. Figure ~~*6C*~~ 5(c) shows the most dominant process by HRU for the Apalachicola – Chattahoochee – Flint River watershed in the Southeastern United States. This watershed has been the subject of previous PRMS modeling studies (LaFontaine et al. 2013). When using this information at a finer resolution, it shows that evapotranspiration is the most dominant process watershed wide, but with pockets of HRUs in the northern part of the watershed where runoff is the most dominant and a pocket in the southern part of the watershed where infiltration is most dominant. Likewise, the most inferior process for each HRU is identified in ~~figure~~ Figure ~~*6D*~~5(d). This clearly indicates that parameters and performance measures~~objective functions~~ related to snowmelt, and to a lesser degree baseflow do not need to be considered when modeling this watershed. Figure ~~*6D*~~ 5(d) also indicates, that in the northern part of the watershed, infiltration and runoff are inferior processes as well, which could in part be due to impervious conditions around the Atlanta metropolitan area. This information could be used, in conjunction with ~~table~~ Table ~~1~~ 2 to develop the most effective parameter estimation and performance measure~~objective function~~ selection strategy when modeling this watershed.

This method of identification of inferior and dominate processes for a specific geographical location ~~are~~ is defined within the context of the application of the DPHM and may not have the same meaning within a different context. This method of using the PRMS watershed hydrology model as the context resolves problems that researchers have had classifying watersheds by dominate processes. Indicating that classification not only depends on the physiographic nature of the watershed, but also, the scale, resolution, and purpose for classification.

5.4 Further study

Providing modelers with reduced lists of calibration parameters on an HRU-by-HRU, watershed-by-watershed, or region-by-region basis is the first step in the path of this research. This approach could be developed into more sophisticated methods where orthogonal output variables and performance measures~~objective functions~~ could provide much more insight into methods of effective model calibration. Although assessment of parameter interactions is not possible with FAST, because the harmonic functions in a Fourier analysis are orthogonal, ~~A~~advancements in this approach may identify groups of parameters that effectively behave together, thus reducing the number of parameters and making specific model output respond more directly to a single or a few parameters, reducing parameter interaction. This suggests that model parameterization and calibration might benefit from a step-by-step strategy, using as much information as possible to set non-interactive parameters and remove them from consideration before the more interactive parameters are calibrated, reducing the dimensionality of the problem (Hay et al., 2006; Hay and Umemoto, 2006).

~~Another potential application is that it is possible that uncertainty maps related to the hydrological processes could be developed. A simple relation between the uncertainties of model output and input based on sensitivity can be described according to (Mishra, 2009):~~

$$\cancel{sens = \frac{\sigma_{input}}{\sigma_{output}},} \quad \cancel{(1)}$$

~~where *sens* is the parameter sensitivity,~~ $\cancel{\sigma_{input}}$ ~~is the uncertainty associated with the input parameters, and~~ $\cancel{\sigma_{output}}$ ~~is the uncertainty associated with the model output. If this equation is applied, process by process, using uncertainty estimates associated with the parameter groupings listed in table 1 and the spatially distributed objective function values shown in figure 2, it would be possible to develop maps of estimates of uncertainty by process and objective function. Developing estimates of spatially varying parameter uncertainty (~~$\cancel{\sigma_{input}}$~~) may be possible as more remotely sensed data sets become available. These maps of model output uncertainty, by process, could be an effective way to communicate DPHM uncertainty on the basis of geographic location and dominant process.~~

Another question for future research is does the classification of dominate hydrologic processes, both geographical and categorical, as described in this study apply to any other context? Comparable findings from other modeling studies, such as those by Newman et al.

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(2015) and Bock et al. (2015) might indicate that there could be a connection. These other studies use the same input information (i.e. being driven with the same climate data and using the same sources of information for parameter estimation) and thus simulation results and model sensitivity to this information might be similar. Also, can real world watersheds be classified by sensitivity analysis using DPHMs? Based on the findings of the work presented so far, the answer is inconclusive. Clearly there are some results that indicate that it might be possible. For example, the methods described here effectively identify "snowmelt watersheds" in the mountainous and northern latitudes, but, is all of this necessary to accomplish this? Might simpler methods (e.g. an isohyetal snowfall map) identify snowmelt watersheds just as effectively?

~~Questions remain about using parameter sensitivity for identification of structural inadequacies within the CONUS application and specifically, the PRMS model itself. In this application, certain hydrologic processes (e.g. depression storage, streamflow routing, flow through lakes, and strong groundwater/surface-water interaction) were not considered because of additional data requirements and parameterization complexity. Just as the spatial and temporal scope of any modeling project must be defined, the scope of the hydrologic processes, and the detail to which these processes are simulated must be likewise defined. Perhaps sensitivity analysis could help define this in a more objective way. Model development and application could perhaps proceed by first accounting for those processes that have the most effect.~~

Effect of HRU definition on results.

Effect of module selection on results.

6 Conclusion

Watersheds in the real world clearly exhibit hydrologic behavior determined by dominant processes based on geographic location (i.e. land surface conditions and climate forcings). A methodology has been developed to identify regions, watersheds and HRUs according to dominant process(es) on the basis of parameter sensitivity response with respect to a distributed-parameter hydrology model. The parameters in this model were divided into two groups – those that are used for model calibration and those that were not. A global parameter sensitivity analysis was performed on the calibration parameters for all HRUs of the conterminous United States. Categories of parameter sensitivity were developed in various ways, on the basis of geographic location, hydrologic process and model response.

Visualization of these categories provide insight into model performance and useful information about how to structure the modeling application should take advantage of as much local information as possible.

By definition, an insensitive parameter is one that does not affect the output. Ideally, a distributed-parameter hydrology model would have just a few calibration parameters, all of them meaningful, each controlling the algorithms related to the corresponding process. This would result in low parameter interaction and a clear mapping between input and output. However, this is not always the case, and despite the fact that parameter interaction is unavoidable in these types of models, this behavior is also seen in the real world. For instance, in watersheds where evaporation is very high, antecedent soil moisture is affected, which has a direct influence on infiltration. The real world process of evaporation has an effect on infiltration, just as evaporation parameters have an effect on simulation of infiltration in watershed hydrology models.

In conclusion, results of this study indicate that it is possible to identify the influence of different hydrologic processes when simulating with a distributed-parameter hydrology model on the basis of parameter sensitivity analysis. Factors influencing this analysis include geographic area, topography, land cover, soil, geology, climate, and other unidentified physical effects. Identification of these processes allow the modeler to focus on the more important aspects of the model input and output, which can simplify all facets of the hydrologic modeling application.

Data availability

The Precipitation-Runoff Modeling System software used in this study is developed, documented and distributed by the U.S. Geological Survey. It is in the public domain and freely available from their web site (http://wwwbrr.cr.usgs.gov/prms). Data analysis and plotting is done with the R software package (http://www.r-project.org), which is freely available, subject to the GNU General Public License.

The climate forcing data set used in this study came from the U.S. Geological Survey Geo Data Portal (http://cida.usgs.gov/climate/gdp). The HRU delineation and default parameterization came from the U.S. Geological Survey GeoSpatial Fabric (http://wwwbrr.cr.usgs.gov/projects/SW_MoWS/GeospatialFabric.html). Finally, the parameter sensitivity output values that were used to make the maps and tables in this article are available at ftp://brrftp.cr.usgs.gov/pub/markstro/hess.

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Tables

Table ~~1~~2. Ordered list of most sensitive Precipitation-Runoff Modeling System calibration parameters by process and performance measure~~objective function~~. The parameters listed in each cell of the table are those that are required to account for 90 percent of the cumulative sensitivity across all hydrologic response units (HRUs). The number in parentheses following the parameter name is the percent of the CONUS HRUs in which that parameter is part of the set that accounts for 90 percent of the cumulated sensitivity on an HRU-by-HRU basis. These parameters are described ~~by Markstrom et al. (2015, table 1-3)~~ in Table 1. ~~.~~

Process	~~Objective Function~~Performance Measure		
	Mean ~~(i.e. total volume)~~	CV ~~(i.e. "flashiness")~~	AR 1 ~~(i.e. day-to-day timing)~~
Baseflow	jh_coef (100), soil_moist_max (91), dday_intcp (81), soil2gw_max (74), radmax (64), carea_max (37, jh_coef_hru (36)	gwflow_coef (48), soil_moist_max (40), jh_coef (28), soil2gw_max (28), smidx_coef(20), carea_max(16), tmax_allsnow(13), dday_intcp(12), smidx_exp (8)	gwflow_coef (48), soil_moist_max (44), soil2gw_max (22), carea_max (18)
Evapo-transpiration	jh_coef (100), soil_moist_max (96), dday_intcp (96), radmax (92), jh_coef_hru (62), smidx_coef (37), dday_slope (25)	radmax(100), jh_coef (100), soil_moist_max (95), dday_intcp (73), dday_slope (67), soil_rechr_max (34)	jh_coef(100), radmax(100), dday_slope(75), soil_moist_max(74), dday_intcp(67), soil_rechr_max(49)
Runoff	jh_coef(100), dday_intcp(96), soil_moist_max(96), radmax(93), jh_coef_hru(62), smidx_coef(37), dday_slope(26)	gwflow_coef(97), soil_moist_max(81), fastcoef_lin(76), pref_flow_den(71), carea_max(58), jh_coef(54), smidx_exp(49), smidx_coef(42), soil2gw_max(36), tmax_allsnow(15)	slowcoef_sq(90), soil2gw_max(90), gwflow_coef(82), carea_max(81), soil_moist_max(78), smidx_exp(72), smidx_coef(60), fastcoef_lin(36), pref_flow_den(35), jh_coef(30), slowcoef_lin(22)
Infiltration	smidx_exp(99), soil_moist_max(99), carea_max(99), smidx_coef(95), jh_coef(64), srain_intcp(50)	carea_max(80), tmax_allsnow(69), jh_coef, smidx_exp(63), srain_intcp(62), smidx_coef(54), tmax_allrain(48), radmax(37),	carea_max(72), soil_moist_max(64), smidx_exp(61), tmax_allsnow(60), srain_intcp(60), tmax_allrain(42), jh_coef(35),

		freeh2o_cap(36), soil_moist_max(35), dday_intcp(31), rad_trncf(18)	smidx_coef(24), freeh2o_cap(16), dday_intcp(16)
Snowmelt	tmax_allsnow(96), tmax_allrain(92)	tmax_allsnow(39), tmax_allrain(38), rad_trncf(9), freeh2o_cap(8), dday_intcp(7)	tmax_allsnow(34), dday_intcp(29), rad_trncf(28), radmax(24), tmax_allrain(17), jh_coef(15), freeh2o_cap(14), cecn_coef(14), emis_noppt(13), jh_coef_hru(13), potet_sublim(10)
Soil moisture	soil_moist_max(100), jh_coef(99), dday_intcp(94), radmax(82)	jh_coef(98), radmax(98), soil_moist_max(97), dday_intcp(94)	soil_moist_max(99), jh_coef(98), dday_intcp(89), radmax(35)
Surface runoff	smidx_exp(98), carea_max(98), soil_moist_max(98), smidx_coef(96), jh_coef(90), dday_intcp(33)	carea_max(93), smidx_exp(82), jh_coef(64), tmax_allsnow(55), smidx_coef(52), srain_intcp(33), soil_moist_max(23), tmax_allrain(22)	soil_moist_max(92), carea_max(83), jh_coef(65), smidx_exp(64), smidx_coef(42), tmax_allsnow(39), dday_intcp(25), srain_intcp(23), tmax_allrain(16), radmax(15)
Interflow	soil_moist_max(99), soil2gw_max(94), pref_flow_den(90), jh_coef(84), carea_max(65), smidx_exp(45), dday_intcp(31), smidx_coef(19)	fastcoef_lin(100), soil_moist_max(87), pref_flow_den(71), jh_coef(61), carea_max(49), soil2gw_max(29), smidx_exp(25), tmax_allsnow(17), dday_intcp(16)	soil_moist_max(96), fastcoef_lin(89), slowcoef_sq(83), carea_max(72), jh_coef(61), pref_flow_den(47), smidx_exp(47), ssr2gw_exp(40), soil2gw_max(26), dday_intcp(18), tmax_allsnow(16)
Parameters not sensitive			
adjmix_rain, fastcoef_sq, ppt_rad_adj, radj_sppt, radj_wppt, sat_threshold, ssr2gw_rate, tmax_index, transp_tmax, wrain_intcp			

Figures

~~Figure 1. The Hydrologic Response Units defined for the conterminous United States. Each Hydrologic Response Unit is drawn in a different color to distinguish it from its neighbors.~~

Figure 1. Location Map of the conterminous United States showing the different geographic regions referred to this study.

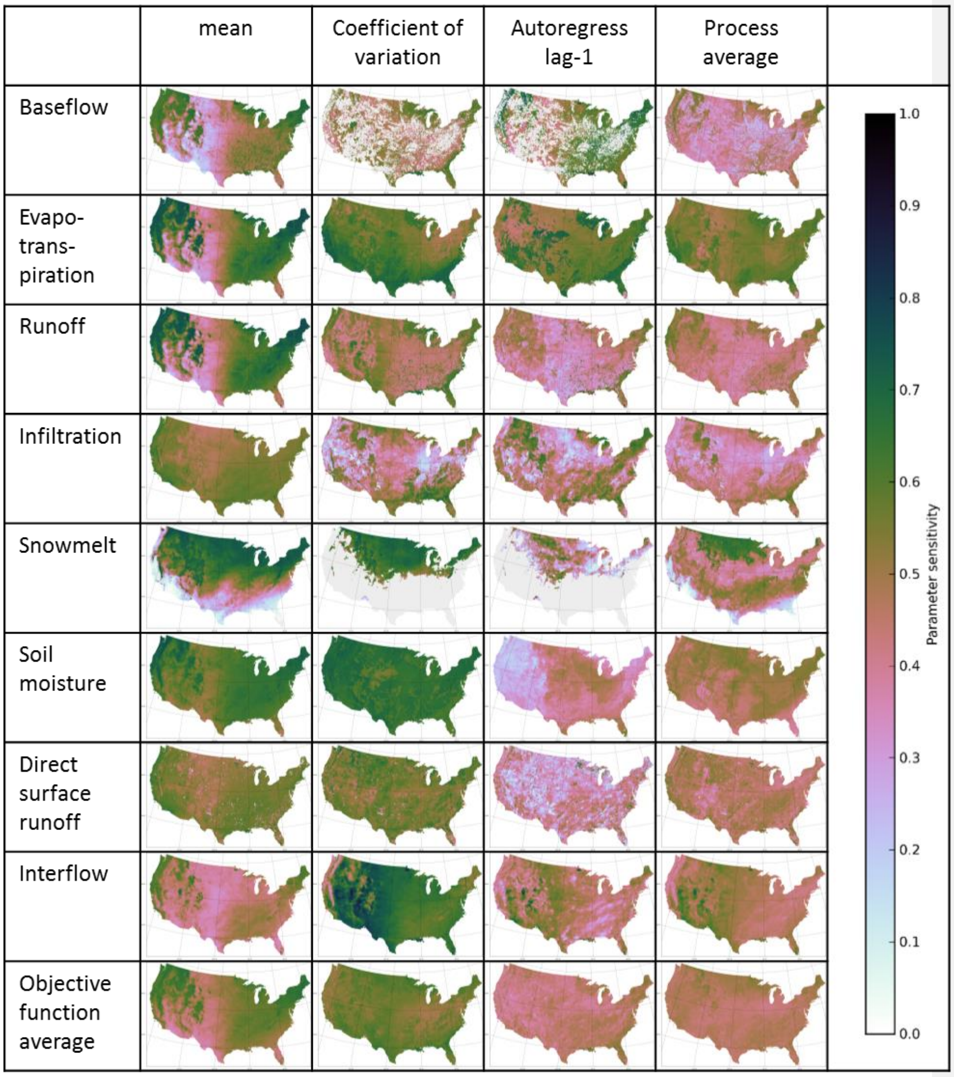

Figure 2. Maps of the conterminous United States showing Precipitation-Runoff Modeling System parameter sensitivity by Hydrologic Response Unit by process and selected performance measure~~objective function~~.

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~~Figure 3. Location Map of the conterminous United States showing the different geographic regions referred to this study.~~

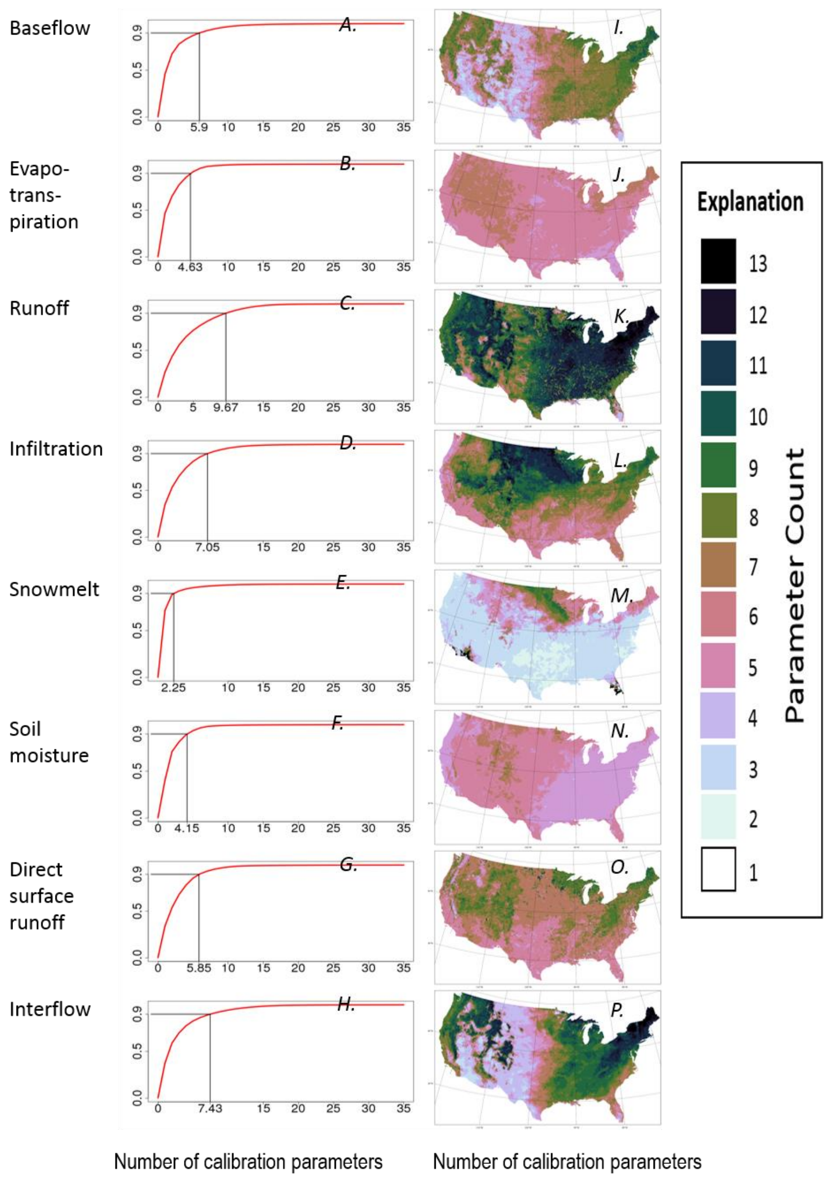
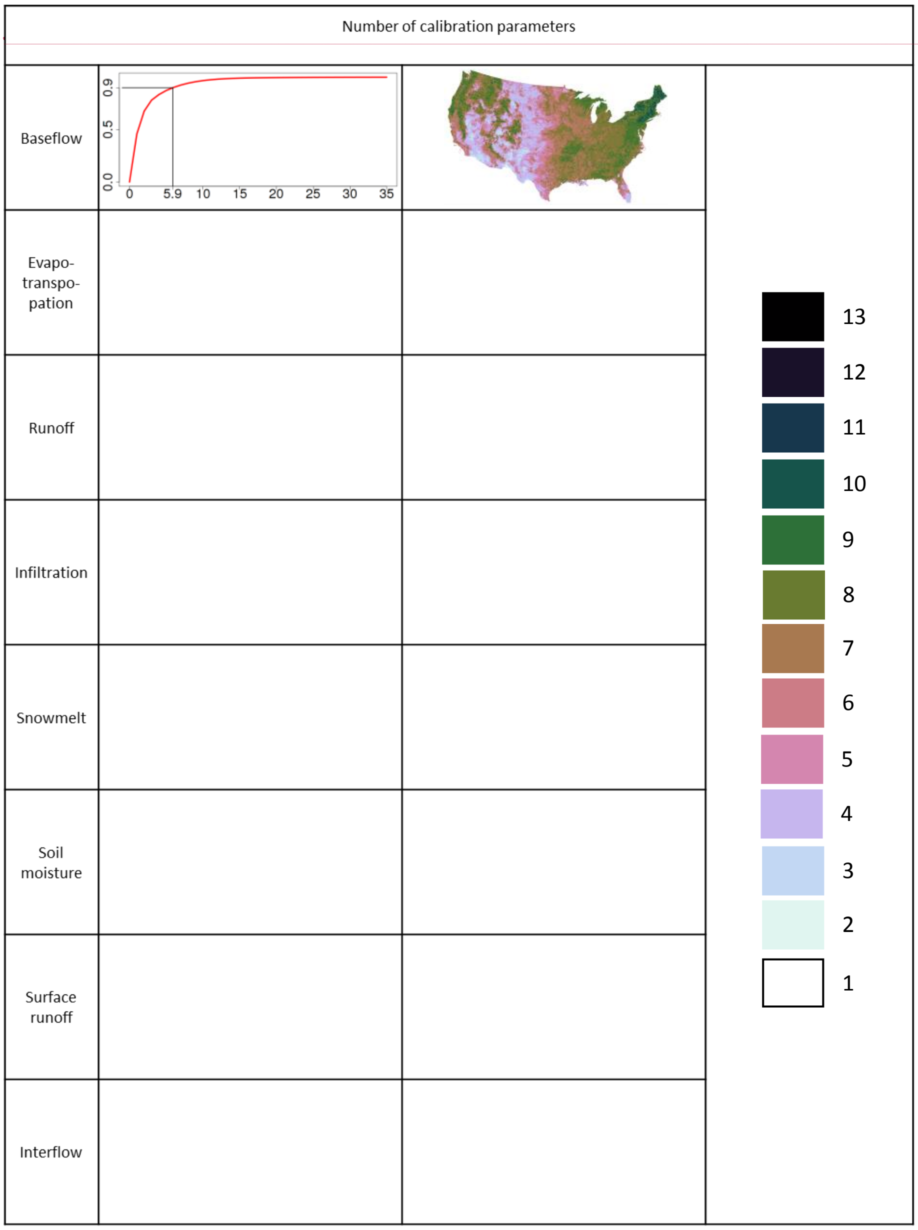


Figure ~~4~~3. Cumulative Precipitation-Runoff Modeling System parameter sensitivity across all HRUs in the continental Parameters Related to Processes. Parameter sensitivities have been averaged across all performance measures~~objective functions~~. The plots A-~~F~~ H summarize the counts for all 110,000 HRUs shown in the corresponding maps (I – P).



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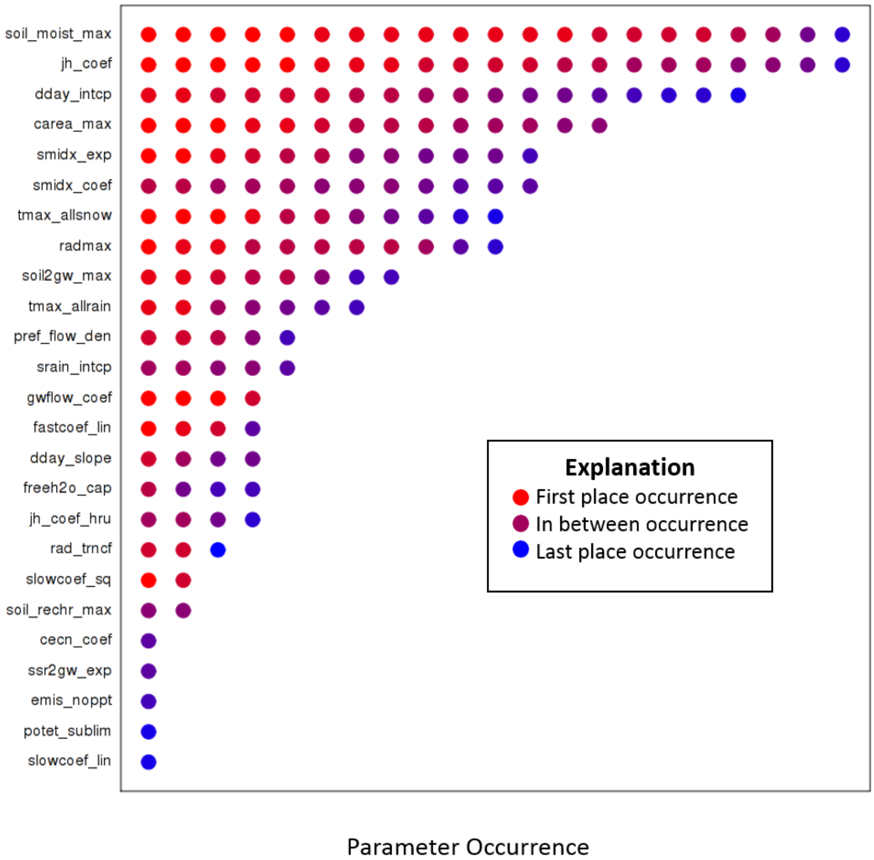

Figure ~~5~~4. Frequency of occurrence of the different parameter counts. The count of circles in the row adjacent to the parameter name indicates how many times the respective parameter occurs in the different categories in ~~table ~~Table ~~1~~2. The color of each circle indicates the ranking of that occurrence within the category, red corresponding to a higher ranking than blue.

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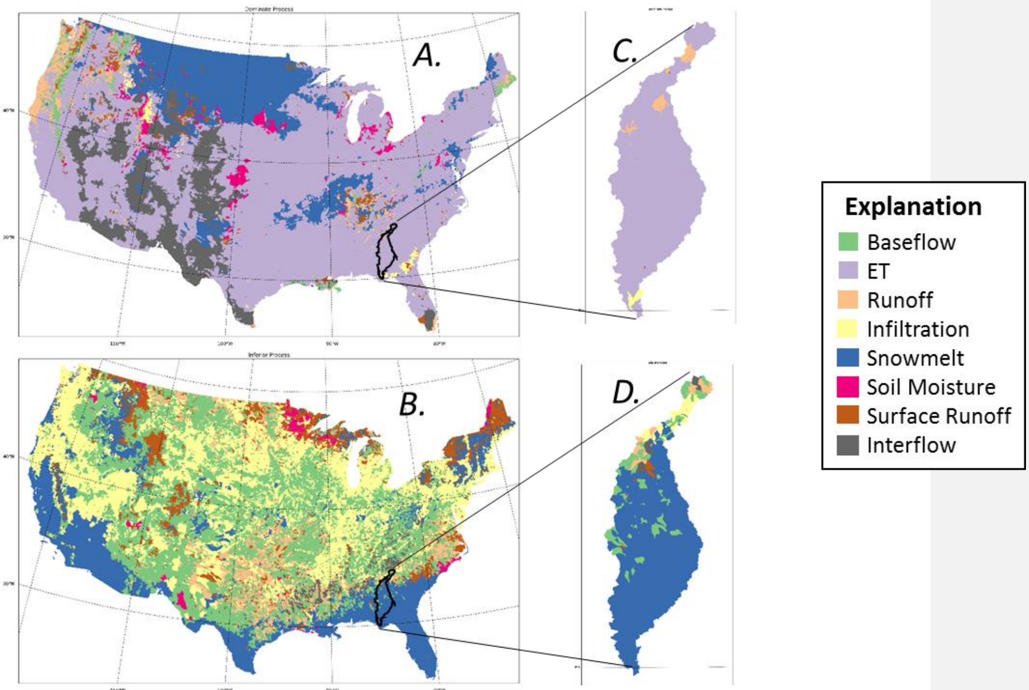
A.
B.
C.
D.
Explanation
Baseflow
ET
Runoff
Infiltration
Snowmelt
Soil Moisture
Surface Runoff
Interflow

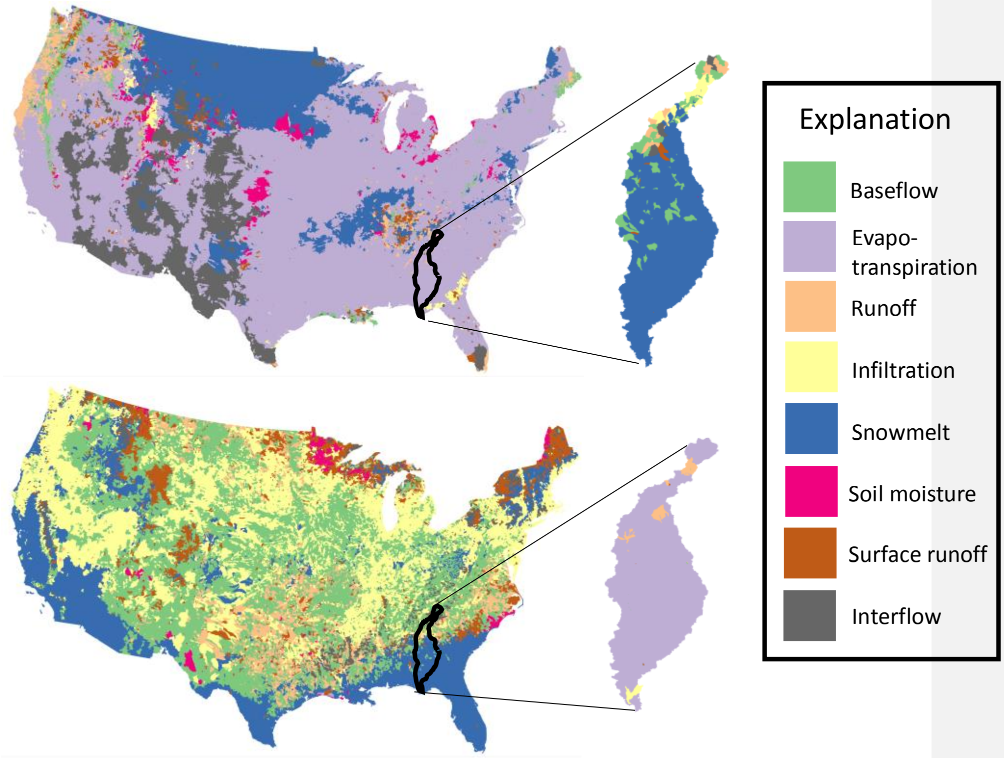

Figure ~~6~~5. Precipitation-Runoff Modeling System parameter sensitivity organized by process have been ranked for each hydrologic response unit for the entire conterminous United States (maps A and B) and for the Apalachicola – Chattahoochee – Flint River basin (maps C and D). The maps on the top (A and C) show the most dominate process, while the maps on the bottom (B and D) show the most inferior process.