HESS 2015-325

“Parameter Regionalization of a Monthly Water Balance Model for the Conterminous United States”

Major Manuscript Changes

Pg. 2, Line 1-2 (Abstract): removed “and model uncertainty information”

1. Introduction

Pg. 4, lines 81-89, 98: Re-formatted text to include some recent work recommended by referee 2

Pg. 5, lines 110-111: Removed the sentence “These methods ignore parameter interaction and often assume that model algorithms have linear responses to different parameters (Cuo et al., 2011)”

2.1 Monthly Water Balance Model

Pg. 6, lines 155-160: Removed definitions and descriptions of parameters and their ranges.

Pg. 7, lines 177-178: Substituted reference for url. Added reference (USEPA and USGS, 2010) to references list.

Pg. 7, lines 171: Added “Processes influenced by” to Figure 1 Caption

2.2 Fourier Amplitude Sensitivity Test

Pg. 8, lines 200, 217, 218; Pg. 9 lines 221, 230: Changed “first order partial variance (FOPV)” to a more meaningful term.

Pg. 8, line 204: deleted the statement “requiring much less information and parameter sets than other global methods

Pg. 8, lines 205-206: Added the sentence for seasonal adjustment factors.

Pg. 8, line 211: Deleted Fig.3 reference (Fig. 3 is replaced by a different figure).

Pg. 9, lines 222-224: Deleted caption for old Fig. 3

Pg. 9, lines 225-228: Simplified sentence based on Ref. 1 recommendation.

Pg. 9, lines 230-235: Clarified information on the number of FAST runs.

3 Parameter regionalization procedure

Pg. 10, lines 252-254: Added Fig. 3 (Schematic Flowchart)

3.1 Parameter sensitivities

Pg. 10, lines 265: Deleted “The patterns of” to start sentence

Pg. 11, lines 299-302: Added details for FAST results

Pg. 12, line 305: Changed FOPV to parameter sensitivities for caption of Figure 5.

3.2 Calibration regions

Pg. 12, lines 312-315: Modified this sentence to add clarification on the HRU grouping procedure

Pg. 12, lines 318-333: Substantially modified this paragraph to better explain the derivation and purpose of the two HRU classifications based on sensitivity analysis results

Pg. 13, lines 335-336: Changed reference for this sentence to Tang et al., 2007 from Pianosi et al., 2015 (removed Pianosi et al., 2015 from reference list)

Pg. 13, lines 342-333, 345-347: Modified text to add some clarification to additional classification steps.

Pg. 13, lines 349-351: Moved this sentence from earlier in the paragraph the end

Pg. 13, Lines 352-356: Modified figure caption

3.4.2 Grouped streamgage calibration

Pg. 16, lines 422-24: Added sentence defining USGS Reference streamgages

Pg. 16-17, lines 434-441: Added equation (Eq. 1) for the objective function used for grouped calibration.

Pg. 17, line 444: changed “variable” to “streamflow”

Pg. 17, lines 451-453: Added sentences clarifying how 25% error bound for SWe worked

Pg. 17, lines 456-457: added comment re-call this papers definition of a sensitive parameter

Pg. 17, line 460: deleted “on a monthly basis”

4.2.2 Nash-Sutcliffe efficiency

Pg. 21, lines 571-573: modified caption for figure 14.

5.1 Regionalized Parameters

Pg. 22, lines 582-586: Added some more details to help explain the results of Fig. 13

6 Conclusions

Pg. 24, line 638: removed "and model uncertainty information"

7 References

Added the following references:

Pg. 25, lines 688-690:

Bárdossy, A., Huang, Y., and Wagener, T.: Simultaneous calibration of hydrological models in geographical space, Hydrol. Earth Syst. Sci. Discuss., 12, 1123-11268, doi:10.5194/hessd-12-11223-2015, 2015.

Pg. 31, lines 806-808:

Qamar, M.U., Ganora, D., and Claps, P.: Monthly Runoff Regime Regionalization Through Dissimilarity-Based Methods, Water Resour. Manag., 29, 4735-4751, doi:10.1007/s11269-015-1087-7, 2015.

Pg. 32, lines 844-847:

USEPA (United States Environmental Protection Agency) and USGS (United States Geological Survey): NHDPlus User Guide, available at ftp://ftp.horizon-systems.com/NHDPlus/documentation/NHDPLUS_UserGuide.pdf (last access 12 Nov 2014), 2010.

Removed the following references:

Pg. 31, 804-805:

Pianosi, F., Sarrazain, F., and Wagener, T.: A Matlab toolbox for Global Sensitvity Analysis, Environ. Modell. Softw., 70, 80-85, doi:10.1016/j.envsoft.2015.04.009, 2015.

Figures

Fig. 3, Pg. 37 – removed previous fig. 3 (FAST parameter waves), replaced with schematic flowchart of Section 3

Fig. 5, Pg. 40 – modified y-axis to “Param Sens.” From “FOPV”

Hydrol. Earth Syst. Sci. Discuss., 12, C5918–C5922, 2016
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HESSD
12, C5918–C5922, 2016

Interactive Comment

Interactive comment on "Parameter regionalization of a monthly water balance model for the conterminous United States" *by* A. R. Bock et al.

A. R. Bock et al.

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Reviewer Minor Points: -p. 10024, lines 1-2 "to transfer ... model uncertainty information". What type of uncertainty information is transferred and how? This is mentioned here and in the conclusion but it is not clearly discussed throughout the paper.

AB: Mean Monthly errors for each calibration region (visualized in Figure 8 and 10a) can be estimated and added back to simulated streamflow estimates at ungaged locations as a source of model uncertainty. This is not explicitly discussed or applied in detail in this paper, so authors may need to add more detail at one location of text or remove.

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-p. 10026: lines 28: “these methods ignore parameter interaction, and often assume that model algorithms have linear responses to different parameters”. I think this sentence is misleading and I would suggest to delete it. Parameter interactions can be evaluated in local SA by computing second-order derivatives (see for example Norton, 2015). Also, when estimating local sensitivities the linearity assumption finds its rationale in the Taylor series expansion and hence it is quite reasonable.

AB: Authors agree to removing sentence.

-p. 10028, line 25 to the end of page: this list of parameter names and meaning does not add much to the information provided in the Table, I would probably avoid it.

AB: Authors agree, parameter definitions and functions are also well-explained in the cited McCable/Wolock papers listed in the reference section. Sentence at p. 10028, lines 23-24 “Table 1 lists. . .”, and climate adjustments sentence beginning with “The Ppt_adj and. . .” (p. 10029, lines 2-3) should be moved to the concluding sentence of the opening paragraph of Section 2.1. The remaining sentences can be removed.

-p. 10030, line 8: the term FOPV is not particularly self-explaining to readers not familiar with GSA. I would explain what it is (“contribution to output variance from ...”)

AB: Authors agree. The sentence “FAST is a variance-based global sensitivity algorithm that estimates the first-order partial variance (FOPV). . .” can be re-worded to “FAST is a variance-based global sensitivity algorithm that estimates the contribution to output variance. . .” . “Output Variance’ should replace FOPV in text, including the Y-axis labels for Figure 5 will be re-named to “Output Variance” with a single axis label.

-p. 10030, line 12: “much less information and parameter sets”. What do you mean by “information”? Unclear. As for "parameter sets, it is possibly less ambiguous if you call them parameter samples or even directly model evaluations

AB: This second half of the sentence is pretty ambiguous. The application of FAST discussed in the paper used a larger number of parameter sets than the minimally sufficient number suggested by R, so the sentence should probably be removed.

-p. 10032, lines 12-13: “The patterns of ...”. Sentence needs rewording

AB: Agreed. Change to: “Tsnow, Train, and Meltcoef all share similar patterns of areas with higher sensitivity across the CONUS.”

-p. 10032, lines 12-13: “The patterns of ...”. Sentence needs rewording

AB: Agreed. Change to: “Tsnow, Train, and Meltcoef all share similar patterns of areas with higher sensitivity across the CONUS.”

-p. 10033, line 25: “While this idea...”. What idea? The one described in the previous sentence? But then is it really in contrast with the one illustrated on lines 27-28? Please clarify.

AB: This is a good point on semantics. The emphasis should be on grouping proximate areas based on similar model behavior, rather than physiographic characteristics. The authors suggest this sentence be changed to: “This idea is rooted in the hypothesis that geographically proximate HRUs share similar forcings and conditions, and thus will behave similarly. This application uses similarity in SA results as a basis for organization, rather than similarity in physiographic characteristics.”

-p. 10034, lines 11-13: citation of Pianosi et al., 2015 does not seem to be appropriate here. That paper introduces a toolbox for Sensitivity Analysis but it does not discuss the issue of setting the threshold for sensitive and non-sensitive parameters. The threshold issue is (partially) discussed in Tang et al. (2007). Pianosi et al. have another paper under review which is more focused on the threshold issue, however it has not been published yet. The authors might cite that paper when it will be published (title is “Global Sensitivity Analysis of environmental models: Convergence and validation”, journal is Environmental Modelling and Software).

AB: We have referenced Tang et al (2007) already in the paper, so we will replace Painosi et al 2015 with Tang et al (2007). Thanks for the heads up on the upcoming paper.

-p. 10037, line 17: Please give a very brief definition of a reference streamgage.

AB: Reference quality stramgages are judged to be largely free of human alterations. From Kiang et al. (2013), these sites were “categorized as either reference quality or nonreference quality by calculating a hydrologic disturbance index (presence of dams, change in reservoir storage, number of canals, road density, proximity to major pollutant discharge site, estimates of water withdrawals, and fragmentation of undeveloped land), reviewing historical digital maps and imagery for evidence of hydrologic alteration and human activity, and reviewing comÂňments in USGS annual water data reports for information on regulation or diversions.”. We will paraphrase this to: “Reference streamgages are USGS streamgages deemed to be largely free of anthropogenic impacts and flow modificaitons, and can subsequently be used for estimation of natural flow statistics (Falcone, 2010; Kiang et al., 2013). ”

-p. 10038, line 9: “simulated streamflow” should be “simulated variable” (since one of the four is SWE and not runoff)

AB: Authors agree to the suggested change.

-p. 10038, line 20: Recall here that a parameter is deemed insensitive if sensitivity index is below 5%

AB: Authors agree to the suggested addition to text

-p. 10038, lines 21-23: “on a mean monthly based”. Unclear. Possibly it might just be dropped, since it was already said that monthly variables are used to compute the Zscores.

AB: Authors agree “mean monthly” should be removed from 21 and 23 since other terms were used in the objective function.

-caption of Fig. 1: “model parameters used in..." Maybe better: “processes influenced

HESSD

12, C5918–C5922, 2016

by the model parameters used in...”

AB: Authors agree to the suggested change

-Figure 3: maybe not needed. Anyway, if maintained, vertical axis should show units of measurements. Also, it would probably be better to show Drofac and Rfactor in a separate panel.

AB: Between the two suggestions (Remove or make two panesl), authors would prefer remove graphic (though Andy B. really likes this graphic).

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 12, 10023, 2015.

Hydrol. Earth Syst. Sci. Discuss., 12, C5964–C5970, 2016
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Interactive Comment

Interactive comment on "Parameter regionalization of a monthly water balance model for the conterminous United States" *by* A. R. Bock et al.

A. R. Bock et al.

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Author's Responses to referee #1:

Reviewer Main Points:

-[1] The parameter regionalisation procedure could be explained more effectively. In the first place, it would be good to have a schematic of the procedure to clearly see what is the role, inputs and outputs of each step (sensitivity analysis, classification of regions, individual calibration, grouped calibration, etc.).

AB: A schematic is a good idea. We will create an example for inclusion into the paper, as well as locations within the text where references to the schematic would be helpful.

-The structure of Sec 2-3-4 could be revised to better separate out the methodology from the illustration of results. For instance, I find a bit odd that sensitivity analysis results are presented in Sec. 3.1, before describing how they will be used in the proposed methodology. Another example is the first paragraph of Sec. 4.1, which explains why the individual streamgage calibration is needed, it would fit better in a "methods" section rather than the "results"section.

AB: We built the main methodology presented in the paper based on the results from the sensitivity analysis. Because we wanted to stress the independence of the sensitivity analysis from the calibration and regionalization procedure, we pushed the sensitivity analysis results to 3.1. The way sensitivity estimates are used for regionalization (described on page 10034,line 7 onward) needs to be explained more clearly, especially since this is the most novel aspect of the proposed methodology. Specifically:

-What is the connection between the first and second classification? They are independent from each other and then intersected to obtain the actual classification? Please clarify

-Description of the second classification (lines 10-11) is also unclear. What are the "unique combinations of parameter sensitivities"? How are they defined? What is their meaning?

AB: Correct, the two classifications are independent. The first classification (p. 10034, lines 6-9) derives regions based on hydrologic response units (HRUs) with unique combinations of magnitudes of the five parameter sensitivities (highest to lowest). The intent is to identify geographic regions of similar model response or behavior based on the numerical orders of the sensitivities.

AB: The second classification (p.10034, lines 10-11) identifies regions based on HRUs with unique combinations of parameters with FAST-based parameter sensitivities that

HESSD

12, C5964–C5970, 2016

exceed 5% (of the cumulative 100%). The intent with the second classification is to identify geographic regions with similar important parameters identified by the sensitivity analysis). The resulting polygons of these two classifications are merged to create the final region classification.

-Be more specific on how the two classification approaches work. Sentence on lines 7-8 of page 10034 is too generic, does it mean that the parameter ranking is the same in each region?

AB: Yes, all hydrologic response units (HRUs) identified within each region in classification 1 (p. 10034, lines 6-9) have the same ranking of the 5 model parameters from highest sensitivity to lowest sensitivity. Additionally, all HRUs within each region identified in classification 2 (p. 10034, lines 10-11) had the identical subset of parameters which exceeded 5% from FAST.

-From lines 17-20, I understand that the sensitivity-based classification is further refined using a more 'conventional' approach that looks at proximity and topographic divides. How does this refinement step works? Does it introduce significant changes in the classification? This is important to know in order to understand the value of the proposed sensitivity-based classification versus proximity or topography-based classification.

AB: This more conventional approach was necessary because of the lack of streamgages available for calibration in some of the calibration regions. The density of the stream gage network can be very sparse for some geographic regions of the U.S., especially in arid/semi-arid areas (see Kiang et al., 2013 in the discussion paper reference list). Following the "unsupervised" merging of the two classifications, the authors conducted a "supervised" classification of regions with less than 3 gages, where these regions where merged with geographically proximate regions with adequate streamgage representation that also shared the most similar parameter sensitivity results.

AB: The primary topographic divides utilized were topographically-derived boundaries

HESSD

12, C5964–C5970, 2016

from the NHDPlus or Hydrologic Unit Code boundaries (black lines in Figure 2). These are sub-boundaries of both the model discretization and many USGS water resource management efforts. We felt it was important to maintain these boundaries, especially for the western United States where orographic climate effects are very important to the hydrologic cycle.

-[2] Some of the numerical results are a bit surprising and should be double-checked. In particular, in Fig. 5.a the fact that one parameter has sensitivity of exactly 100 and all others of exactly 0 seems odd.

AB: For regions with homogeneous, sub-tropical type climatic conditions, such as the Southeast, results such as Figures 5a and 5c were consistent across many of the objective functions we had used to measure parameter sensitivity with FAST (including parameter sensitivity measured for NSE at select reference streamgages). In areas such as the Lower Mississippi (Region 8, Figure 2), the amount of snowfall is negligible, so the three parameters that control snowfall and snowpack accumulation have negligible effect on total runoff. If there is minimal occurrence of snow in a region, then snow parameters won't be important, even in a complex model. For further discussion, a colleague has submitted a paper to HESS that strictly examines results of FAST applied to a 35-parameter daily streamflow model across the U.S.

-Also, the result of Figure 13 is very puzzling. As the authors note on page 10041 (line 27 onward), the groupNSE values are expected to be lower than the gageNSE values. Figure 13 instead shows many cases were groupNSE is much larger than gageNSE. I really struggle to believe that NSE can be increased so much and so often when using a model calibrated with a different objective function. The only explanation I can think of is that either the calibration algorithm in the gageNSE failed (for instance by getting stuck in a local minimum or being terminated too early) or that the comparison is not fair (for example that NSE refer to different time periods?). This needs clarification.

AB: What we wanted to emphasize with this plot is not a comparison of two calibration methods, but that the grouped calibration strategy that focuses on the sensitive parameters can provide just as much information as traditional NSE-based individual streamgage calibration. There is quite a bit of difference between the two calibration methods compared: the individual gage calibration used the entire period of record for each streamgage, while the grouped calibration uses an odd/even calibration/validation calibration strategy, different objective functions are used (NSE versus multi-term weighted objective function for the grouped calibration), and climate adjustments are derived for each streamgage in the individual calibration, and for the entire region in the grouped calibration.

Author's response to remaining minor remarks

-p. 10030, lines 14-15: please justify why you do not incorporate the adjustment factors in the FAST analysis

AB: We viewed the adjustment factors as more related to the forcing data itself and independent from the model structure.

-p. 10031, lines 6-7 "parameter ranges were based..." Are these the ranges in Table 1 and already commented on p.10028, line 24? If so, just refer to the Table here.

AB: The parameters listed in Table 1 were the bounding ranges. We will make the adjustment to the text.

-p. 10031, lines 7-9: What do you mean by "standard application"? Also, I suppose the R package uses the equation N = 2Nharm max(!) + 1 to determine the minimal number of runs. If so, better cite Cuckier et al (1973), which is where the formula comes from. Also, please mention what is this number in your case, it would help readers to get an idea of how computationally demanding is the proposed approach.

AB: "In standard application" is ambiguous and should be removed. We accept the referee's recommendations and the sentence on lines 8-10 should be re-worded to: "The fast R package can determine the minimal number of runs necessary to estimate the output variance all parameters (Cukier et al., 1973). For our application we generated an ensemble of 1000 sets (above the minimal number of 71 suggested by fast) to have the potential capability for further research into comparison of different sensitivity analysis methods."

-p. 10038, lines 1-4: The definition of the multi-term objective function is unclear. Are the four terms summed up? Why considering both mean monthly runoff and annual runoff (I would imagine that they convey the same information, the former being equal to the latter divided by 12)? I think inserting an equation with the mathematical definition of the objective function would help here.

AB: The objective function minimizes the sum of difference between the Z-scores of measured and simulated variables for four terms: Mean Monthly Streamflow (As shown in figures 8 and 10a), Monthly Streamflow (Raw monthly time series), Annual Streamflow (Time Series aggregated to annual time steps), and Mean Monthly SWE with a 25% error bound. The first three terms of the objective function were chosen because they conveyed information that can be used to easily inform other models (such as daily time-step models). Just to note, annual and mean monthly objective functions as we defined them are very different; the former is not equal to the latter/12.

We can include an equation with the appropriate text to help elucidate the different terms of the objective function.

-p. 10038, lines 14-16: Please clarify how the error bounds were taken into account. Did you modify the definition of the Z score for the SWE?

AB: Z-scores were calculated from basin mean monthly measured (SNODAS) and simulated SWE values. Upper and lower bounds of 25% were calculated for the mean monthly SWE Z-score (Zobs *1.25 for the upper bound; Zobs *.75 for the lower bound). If the simulated MWBM SWE value was contained within the upper and lower 25% bounds, the absolute difference was designated as 0. If the simulated MWBM SWE Z-score value was above the upper 25% error bound, the absolute Z-score difference was calculated between the simulated Z-score value and the value of the upper 25% Z-score bound. If the simulated Z-score was below than the lower 25% error bound, the absolute Z-score difference was calculated between the simulated Z-score value and the value of the lower 25% Z-score bound.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 12, 10023, 2015.

HESSD

12, C5964–C5970, 2016

Interactive Comment

Hydrol. Earth Syst. Sci. Discuss., 12, C5987–C5990, 2016
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12, C5987–C5990, 2016

Interactive comment on "Parameter regionalization of a monthly water balance model for the conterminous United States" *by* A. R. Bock et al.

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Author's Responses to referee #2:

Reviewer Main Points:

[1] Method Process diagram: A conceptual flow diagram is needed to explain the parameter regionalisation procedure more effectively. To visualize the most innovative aspect of the proposed methodology, connection between the first and second classification need more clarification. Figure 4 of the paper titled, "A different light in predicting ungauged basins: regionalization approach based on eastern USA catchments"

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[Shoaib et al., 2013] can be seen as an example.

AB: Authors agree and will add a schematic/flowchart, and modify the appropriate locations in the text to reference the figure. Thanks for the example

[2] My other concern on the paper is that the best MWBM results were not shown relatively as achieved in simulating low –and median flows across the CONUS. Representation of the relative variability of MWBM results in low –median and high flow will enhance the importance of the paper

AB: Analyzing the variability and distribution of the mean monthly model error (Figures 8 and 10) is something we are looking at analyzing and incorporating into further modeling efforts. We felt there are enough interesting results with the monthly model error alone to justify focusing on that aspect of the model for follow-up work and publication, and we decided not to try and push more of that content into this paper.

Reviewer Minor Points:

[3] -p. 10030, line 8: the term FOPV needs more explanation. It is not particularly self-explaining to readers who are not familiar with GSA.

AB: Authors agree to change "FOPV" to output variance. For the sentence on p. 10030 "FAST is a variance-based global sensitivity algorithm that estimates the first-order partial variance (FOPV)..." will be changed to "FAST is a variance-based global sensitivity algorithm that estimates the parameter contribution to output variance...". We will also change the Y-axis labels for Figure 5 to "Output variance".

-p. 10030, lines 14-15: Please clarify why you have avoid incorporating the seasonal adjustment factors in the FAST analysis

AB: We viewed the adjustment factors as more related to the forcing data itself and independent from the model structure.

-p. 10037, lines 24-25: The multi-term objective function is unclear. Inserting an equa-

HESSD

12, C5987–C5990, 2016

Interactive Comment

tion with the mathematical definition of the objective function would help here. Though NSE, logNSE are mentioned in the manuscript, it is not clear what the authors try to represent the term multi-term objective function. What about SQRT NSE?

AB: The objective function for the final grouped calibration minimizes the sum of difference between the Z-scores of measured and simulated variables for four terms: Mean Monthly Streamflow (As shown in figures 8 and 10a), Monthly Streamflow (Raw monthly time series), Annual Streamflow (Time Series aggregated to annual time steps), Mean Monthly SWE with a 25% error bound. The first three terms of the objective function were chosen because they conveyed information that can be used to easily inform other models (such as daily time-step models).

We will include an equation into the text.

-p. 10058 and 10066, Figure 6 and Figure 14 are not that clear. It is understandable after reading the text, but it could be much improved

AB: For figure 10058 We can add details to the figure caption to indicate these are the final calibration regions representing the merge/intersection of the two classifications discussed in Section 3.2. i.e.: "Final 110 Monthly Water Balance Model calibration regions derived across the CONUS differentiated by color. Streamgages in each calibration group were calibrated in a group-wise fashion to produce a single optimized parameter set for the entire region."

For Figure 14. We will more detail to the figure caption, i.e., "Median Nash Sutcliffe Efficiency (NSE) of all streamgages used for calibration within each calibration region".

-p.10056, Figure 4 could be improved by showing the relative scale of sensitivity. The figure can be more quantifiable, to make the methods more applicable.

AB: We considered this, but we really wanted the symbology in this figure to emphasize the gradation of the parameter sensitivities across the US, along with the "hot spots" for individual parameters. We felt the scaling the sensitivity relative to each parameter

HESSD

12, C5987–C5990, 2016

was the best way to illustrate this.

-A recently published papers on Monthly Runoff Regime Regionalization through Dissimilarity –based Methods[Qamar et al., 2015] and Simultaneous calibration of hydrological models in geographical space [Bárdossy et al., 2015] can be seen as added reference.

AB: Thanks for the additional information. We will read through the recommended works and consider where they might fit in the background and/or discussion.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 12, 10023, 2015.

HESSD

12, C5987–C5990, 2016

Interactive Comment

Parameter regionalization of a monthly water balance model for the conterminous United States

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Abstract

A parameter regionalization scheme to transfer parameter values ~~and model uncertainty information~~ from gaged to ungaged areas for a monthly water balance model (MWBM) was developed and tested for the conterminous United States (CONUS). The Fourier Amplitude Sensitivity Test, a global-sensitivity algorithm, was implemented on a MWBM to generate parameter sensitivities on a set of 109,951 hydrologic response units (HRUs) across the CONUS. The HRUs were grouped into 110 calibration regions based on similar parameter sensitivities. Subsequently, measured runoff from 1,575 streamgages within the calibration regions were used to calibrate the MWBM parameters to produce parameter sets for each calibration region. Measured and simulated runoff at the 1,575 streamgages showed good correspondence for the majority of the CONUS, with a median computed Nash-Sutcliffe Efficiency coefficient of 0.76 over all streamgages. These methods maximize the use of available runoff information, resulting in a calibrated CONUS-wide application of the MWBM suitable for providing estimates of water availability at the HRU resolution for both gaged and ungaged areas of the CONUS.

Comment [Bock1]: Response to Ref. 1 Minor Points: -p. 10024, lines 1-2 "to transfer ... model uncertainty information". What type of uncertainty information is transferred and how? This is mentioned here and in the conclusion but it is not clearly discussed throughout the paper.

1 Introduction

The WaterSMART program (http://water.usgs.gov/watercensus/WaterSMART.html) was started by the United States (U.S.) Department of the Interior in February 2010. Under WaterSMART, the National Water Census (NWC) was proposed as one of the U.S. Geological Survey's (USGS) key research directions with a focus on developing new hydrologic tools and assessments. One of the major components of the NWC is to provide estimates of water availability at a sub-watershed resolution nationally (http://water.usgs.gov/watercensus/streamflow.html) with the goal of determining: (1) if the Nation has enough freshwater to meet both human and ecological needs and (2) if this water will be available to meet future needs. Streamflow measurements do not provide direct observations of water availability at every location of interest; approximately 72 percent (%) of land within the conterminous U.S. is gaged, with approximately 13% of these gaged areas being unaffected by anthropogenic effects (Kiang et al., 2013). This creates the challenge of determining the best method to transfer information from gaged catchments to data-poor areas where results cannot be calibrated or evaluated with measured streamflow (Vogel, 2006). This transfer of model parameter information from gaged to ungaged catchments is known as hydrologic regionalization (Bloschl and Sivapalan, 1995).

Many hydrologic regionalization methods have focused on developing measures of similarity between gaged and ungaged catchments using spatial proximity and physical characteristics. These methods are highly dependent on the complexity of the terrain and scale at which the relations are derived. Spatial proximity is considered the primary explanatory variable for hydrologic similarity (Sawicz et al., 2011) because of the first-order effects of climatic and topographic controls on hydrologic response. Close proximity, however, does not always result in hydrologic similarity (Vandewiele and Elias, 1995; Smakhtin, 2001; Ali et al., 2012).

Physical characteristics have been used as exploratory variables to develop a better understanding of the relation between model parameters that represent model function, and physical properties of the catchment (Merz and Bloschl, 2004). The relation between model parameters and the relevant physical characteristics, expressed for example as a form of multivariate regression, can be transferred to ungaged catchments (Merz and Bloschl, 2004). Model parameter definitions are by nature ambiguous and often difficult to correlate to a small number of meaningful variables such as physical and climatic characteristics (Zhang et al., 2008); some studies have found no significant correlation between catchment attributes and model parameters (Seibert, 1999; Peel et al., 2000), whereas others found that high correlation does not guarantee parameters that result in reliable model simulations of measured data (Sefton and Howarth, 1998; Kokkonen et al., 2003; Oudin et al., 2010). Physical and hydrologic characteristics are also used to derive measures of similarity (or dissimilarity) from multi-dimensional attribute space, which can be used to identify donor catchments (Qamar et al., 2015), or classify catchments into discrete regions or clusters (Oudin et al, 2008, 2010; Samuel et al., 2011).~~Physical characteristics also are used to classify catchments into discrete regions or clusters based on similarity in multi-dimensional attribute space (Oudin et al, 2008, 2010; Samuel et al., 2011)~~. While these methods have indicated some success in simulating behavior of specific hydrologic components, such as base flow (Santhi et al., 2008) or monthly flow regimes (Qamar et al., 2015), other efforts utilizing discrete clusters performed poorly in explaining variability of measured streamflow (McManamay et al., 2011).

Comment [Bock2]: Added suggested recent reference from Ref. 2. "-A recently published papers on Monthly Runoff Regime Regionalization through Dissimilarity –based Methods[Qamar et al., 2015] and Simultaneous calibration of hydrological models in geographical space [Bárdossy et al., 2015] can be seen as added reference."

Two important components of the transfer of parameters to ungaged catchments are the identification of (1) influential (and non-influential) parameters, and (2) geographic extents and scales at which parameters exert control on model function. Reducing the number of parameters is important for calibration efficiency by reducing the structural bias of the model and the uncertainty of results where they cannot be verified or confirmed (Van Griensven et al., 2006). A high number of calibrated, poorly constrained parameters can often mask data or structural errors, which can go undetected and reduce the skill of the model in replicating results outside of calibration conditions (Kirchner, 2006; Bloschl et al., 2013; Bárdossy et al., 2015). This increases the potential for equifinality of parameter sets and higher model uncertainty that can be propagated to model results (Troch et al., 2003).

Comment [Bock3]: Added this recent reference at suggestion of Ref. 2: "-A recently published papers on Monthly Runoff Regime Regionalization through Dissimilarity –based Methods[Qamar et al., 2015] and Simultaneous calibration of hydrological models in geographical space [Bárdossy et al., 2015] can be seen as added reference."

Sensitivity analysis (SA) has advanced the understanding of parameter influence on model behavior and structural uncertainty. SA measures the response of model output to variability in model input and/or model parameter values. SA partitions the total variability in the model response to each individual model parameter (Reusser et al., 2011) and results in a more-defined set of parameters and parameter ranges. Identification of sensitive parameters and their ranges is important for hydrologic model applications as key model parameters can vary spatially across physiographic regions, and also temporally (Tang et al., 2007; Guse et al., 2013).

Until recently, the high computational demands of SA have limited most implementations of hydrologic model SA to local sensitivity algorithms that evaluate a single parameter at a time (Tang et al., 2007). ~~These methods ignore parameter interaction, and often assume that model algorithms have linear responses to different parameters (Cuo et al., 2011).~~ Global SA uses random or systematic sampling designs of the entire parameter space to quantify variation in model output (Van Griensven et al. 2006, Reusser et al. 2011). Some of these methods can account for parameter interaction and quantify sensitivity in non-linear systems. Global SA methods are computationally intensive (Cuo et al., 2011), but ever increasing computational efficiency has allowed for the development and application of a large number of global SA algorithms.

Comment [Bock4]: Response to Ref 1: “these methods ignore parameter interaction, and often assume that model algorithms have linear responses to different parameters”. I think this sentence is misleading and I would suggest to delete it.”

Previous work has suggested that isolating the key parameters that control model performance can be used to infer dominant physical processes in the catchment, as well as which components of the model dominate hydrologic response (Van Griensven et al. 2006, Tang et al., 2007, Reusser et al., 2011). To date, there has been little analysis of the use of SA for deriving measures of hydrologic similarity across catchments that can be applied towards hydrologic regionalization of model parameters. The spatially-distributed application of SA could be used to provide additional information for the delineation of homogeneous regions for parameter transfer based on similarity of model results from the SA. This strategy allows for the use of the existing model information and configuration to develop a calibration and regionalization framework without significantly changing the model structure or implementation

In this study, we present a hydrologic regionalization methodology for the CONUS that derived regions of hydrologic similarity based on the response of a Monthly Water Balance Model (MWBM) to parameter SA. Groups of streamgages within each region are calibrated together to define a single parameter set for each region. By extending model calibration to a large number of sites grouped by similarity through a quantified measure of model behavior, a more specific and constrained parameter space that fits each region can be identified.

2 Methods

2.1 Monthly Water Balance Model

The MWBM (Fig. 1) is a modular accounting system that provides monthly estimates of components of the hydrologic cycle by using concepts of water supply and demand (Wolock and McCabe 1999; McCabe and Markstrom, 2007). Monthly temperature (T) is used to compute potential evapotranspiration (PET) and to partition monthly precipitation (P) into rain and snow (Fig. 1). Precipitation that occurs as snow is accumulated in a snow pack (snow storage as snow water equivalent, or SWE); rainfall is used to compute direct runoff (R_{direct}) or overland flow, actual evapotranspiration (AET), soil-moisture storage recharge, and surplus water, which eventually becomes runoff (R) (Fig. 1). When rainfall for a month is less than PET, AET is equal to the sum of rainfall, snowmelt, and the amount of moisture that can be removed from the soil. The fraction of soil-moisture storage that can be removed as AET decreases linearly with decreasing soil-moisture storage; that is, water becomes more difficult to remove from the soil as the soil becomes drier and less moisture is available for AET. When rainfall (and snowmelt) exceeds PET in a given month, AET is equal to PET; water in excess of PET replenishes soil-moisture storage. When soil-moisture storage reaches capacity during a given month, the excess water becomes surplus and a fraction of the surplus ($R_{surplus}$) becomes R, while the remainder of the surplus is temporarily held in storage. The MWBM has been previously used to examine variability in runoff over the CONUS (Wolock and McCabe, 1999; Hay and McCabe 2002; McCabe and Wolock, 2011a) and the global extent (McCabe and Wolock, 2011b). Table 1 lists the MWBM parameters, with definitions and parameter ranges for calibration.

~~The parameter ranges were determined in previous work (Wolock and McCabe, 1999; Hay and McCabe, 2002). The *Drofac* parameter specifies the fraction of monthly P that becomes direct runoff. The *Rfactor* parameter specifies how much surplus in a month becomes runoff. The~~ ~~T_{rain} parameter specifies the temperature threshold above which all precipitation is rain. The~~ ~~T_{snow} parameter specifies the temperature threshold below which all precipitation is snow. The *Meltcoef* parameter specifies the proportion of snowpack that becomes runoff.~~ The *Ppt_adj* and *Tav_adj* parameters specify seasonal adjustments for precipitation and temperature, respectively. The seasonal adjustment

Comment [Bock5]: Response to Ref. 1: "-p. 10028, line 25 to the end of page: this list of parameter names and meaning does not add much to the information provided in the Table, I would probably avoid it."

~~The *Ppt_adj* and *Tav_adj*~~ parameters were included to account for errors in the precipitation and temperature data used in this analysis. Sources of systematic and non-systematic errors of climate forcing data are well documented from the precipitation gage-derived sources (Groisman and Legates, 1994; Adam and Lettenmaier, 2003). Interpolation of these systematic errors from point-scale to gridded domains may propagate these biases, especially in complex terrain (Clark and Slater, 2006; Oyler et al, 2015). The use of adjustment factors allows uncertainty associated with forcing data and model parameter values to be treated separately (Vrught et al., 2008).

Figure 1. Conceptual diagram of the Monthly Water Balance Model (McCabe and Markstrom 2007). Processes influenced by m~~M~~odel parameters used in Fourier Amplitude Sensitivity Test (FAST) are identified by green arrow and numbered (Table 1).

Table 1. Monthly Water Balance Model parameters and ranges.

The MWBM was applied to the CONUS with 109,951 hydrologic response units (HRUs) from the Geospatial Fabric (Viger and Bock, 2014), a national database of hydrologic features for national hydrologic modeling applications (Fig. 2). This HRU derivation is based on an aggregation of the NHDPlus dataset (USEPA and USGS, 2010~~http://www.horizon-systems.com/nhdplus/~~), an integrated suite of geospatial data that incorporates features from the National Hydrography Dataset (http://nhd.usgs.gov/), the National Elevation Dataset (http://ned.usgs.gov/), and the Watershed Boundary Dataset (http://nhd.usgs.gov/wbd.html). The sizes of the HRUs range from less than 1 square kilometer (km^2) up to 67,991 km^2, with an average size of 74 km^2.

Inputs to the MWBM by HRU are: (1) monthly P (millimeters), monthly mean T (degrees Celsius), (2) latitude of the site (decimal degrees), (3) soil moisture storage capacity (millimeters), and (4) monthly coefficients for the computation of PET (dimensionless). Monthly P and mean T were derived from the daily time step, 1/8^o gridded meteorological data for the period of record from January 1949 through December 2011 (Maurer et al., 2002). Monthly P and T data were aggregated for each HRU using the USGS Geo Data Portal (*http://cida.usgs.gov/climate/gdp/)* (Blodgett et al., 2011). Latitude was computed from the centroid of each HRU. Soil moisture storage capacity was calculated using a 1 km^2 grid derived

Comment [Bock6]: Changed based on Ref1 suggstion : "-caption of Fig. 1: "model parameters used in..." Maybe better: "processes influenced by the model parameters used in..."

Comment [Bock7]: Wanted to add full citation of NHDPlus base dataset instead of a url from the Soils Data for the Conterminous United States (STATSGO) (Wolock, 1997). The monthly PET coefficients were calculated by calibrating the Hamon PET values to Farnsworth et al. (1982) mean monthly free-water surface evapotranspiration. McCabe et al. (2015) describes these PET coefficient calculations in detail.

Figure 2. Hydrologic Response Units of the Geospatial Fabric, differentiated by color, overlain by NHDPlus region boundaries (R01-R18).

2.2 Fourier Amplitude Sensitivity Test

A parameter SA for the CONUS was conducted for the MWBM using the Fourier Amplitude Sensitivity Test (FAST) to identify areas of hydrologic similarity. FAST is a variance-based global sensitivity algorithm that estimates the ~~first-order partial variance (FOPV)~~contribution to ~~of~~ model output variance ~~(or objective functions)~~ explained by each parameter (Cukier et al. 1973, 1975; Saltelli et al. 2000). Advantages of using FAST over other SA methods are that FAST can calculate sensitivities in non-linear systems, and is extremely computationally efficient~~, requiring much less information and parameter sets than other global methods~~. The seasonal adjustment factors were not incorporated in~~to~~ the FAST analysis.~~;~~ We viewed the seasonal adjustment factors as related more to the forcing data, and for this application only parameters associated with model structure were included (first five parameters in Table 1).

FAST transforms a model's multi-dimensional parameter space into a single dimension of mutually independent sine waves with varying frequencies for each parameter, while using the parameter ranges to define each wave's amplitude (Cuker et al., 1973, 1975; Reusser et al., 2011) ~~(Fig. 3)~~. This methodology creates an ensemble of parameter sets numbering from 1 to N, each of which is unique and non-correlated with the other sets. Parameter sets are derived using the corresponding y-values along each parameter's sine wave given a value on the x-axis. The model is executed for all parameter sets using identical climatic and geographic inputs for each simulation. The resulting series of model outputs are Fourier-transformed to a power spectrum of frequencies for each parameter. Parameter sensitivity is calculated as the sum of the powers of~~for~~ the output variance for each parameter~~ (FOPV)~~, divided by the sum of the powers of all parameters (Total Variance). ~~FOPV~~ The parameter sensitivities ~~for all parameters~~ are scaled so that the ~~FOPV~~ sensitivities for all parameters sum to 1. Thus, p~~P~~arameters that explain a large

Comment [Bock8]: Renamed FOPV at suggestion of Ref 1.: "-p. 10030, line 8: the term FOPV is not particularly self-explaining to readers not familiar with GSA. I would explain what it is ("contribution to output variance from ...")" and Ref. 2: "[3] -p. 10030, line 8: the term FOPV needs more explanation. It is not particularly self-explaining to readers who are not familiar with GSA."

Comment [Bock9]: Deleted as per suggestion from Ref. 1: "-p. 10030, line 12: "much less information and parameter sets". What do you mean by "information"? Unclear. As for "parameter sets, it is possibly less ambiguous if you call them parameter samples or even directly model evaluations"

Comment [Bock10]: Clarified our justification for why we did not use seasonal adjustments in fast; Ref 1: "-p. 10030, lines 14-15: -p. 10030, lines 14-15: please justify why you do not incorporate the adjustment factors in the FAST analysis"

Comment [Bock11]: Ref 2: "-p. 10030, lines 14-15: Please clarify why you have avoid incorporating the seasonal adjustment factors in the FAST analysis"

Comment [Bock12]: Removed Figure 3 (FAST waves figure) per Ref. 1 suggestion: "-Figure 3: maybe not needed. Anyway, if maintained, vertical axis should show units of measurements. Also, it would probably be better to show Drofac and Rfactor in a separate panel."

amount of variability in the model output have higher values of~~large~~ (i.e. closer to 1) parameter sensitivity~~FOPV~~ values.

~~A portion (0 to 500 parameter sets) of the parameter sampling scheme for the Monthly Water Balance Model in the Fourier Amplitude Sensitivity Test (FAST). A total of 1000 parameter sets were generated for implementation in FAST.~~

FAST was implemented with the MWBM using the 'fast' library in the statistical software R (Reusser, 2012; R Core Team, 2013). ~~To help constrain the~~ P~~p~~arameter ranges used by FAST for generating wave amplitudes of parameter ensembles across the CONUS~~, parameter ranges~~ were based on table 1~~information from previous MWBM calibrations at selected streamgages (Hay and McCabe, 2002)~~. ~~In standard application,~~ T~~t~~he 'fast' R package pre-determines the minimal number of runs necessary to estimate the sensitivities ~~FOPV~~ for the given number of~~all~~ parameters (Cukier et al., 1973). For our application we generated an ensemble of 1000 parameter sets (as compared to the minimally suggested number of 71 estimated by 'fast') to have the capability to compare results of different sensitivity analysis methods. The computational efficiency of the MWBM allowed the parameter sets to be simulated quickly through parallel processing.

Many applications of SA in hydrologic modeling have evaluated parameter sensitivity for measured streamflow using performance-based measures such as bias, root mean squared error (RMSE), and the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970; Moriasi et al., 2007). In this study, parameter sensitivity is examined using two hydroclimatic indices that account for the magnitude and variability of both climatic input and model output: the (1) Runoff Ratio (RR), a ratio of simulated runoff to precipitation, and (2) Runoff Variability (RV) index, the standard deviation of simulated runoff to the standard deviation of precipitation (Sankarasubramanian and Vogel, 2003).

3 Parameter regionalization procedure

The MWBM parameter sensitivities from the FAST analysis using an ensemble of 1000 MWBM parameter sets were evaluated across the CONUS. The spatial patterns and magnitudes of parameter sensitivities then were used to organize the 109,951 HRUs across the CONUS into

Comment [Bock13]: More modificaitons related to comment Bock7

Comment [Bock14]: Modified based on suggestion by ref. 1: "-p. 10031, lines 6-7 "parameter ranges were based..." Are these the ranges in Table 1
and already commented on p.10028, line 24? If so, just refer to the Table here."

Comment [Bock15]: Changes at the suggestion of Ref .1: -p. 10031, lines 7-9: What do you mean by "standard application"? Also, I suppose the
R package uses the equation N = 2Nharm max(!) + 1 to determine the minimal number of runs. If so, better cite Cuckier et al (1973), which is where the formula comes from.
Also, please mention what is this number in your case, it would help readers to get an idea of how computationally demanding is the proposed approach.

hydrologically similar regions for parameter regionalization through MWBM calibration. Potential streamgages were identified for use in two automated calibration procedures. The calibration procedures were used to produce an ‘optimal’ set of MWBM parameters for each calibration region. The following sections describe the parameter regionalization procedure in detail (Fig. 3).~~.~~

Figure 3. Schematic flowchart of the parameter sensivitiy analysis and regionalization method described in this paper (Section 3).

Comment [Bock16]: Added flowchart schematic at request of both Refs. Ref1: -[1] The parameter regionalisation procedure could be explained more effectively. In the first place, it would be good to have a schematic of the procedure to clearly see what is the role, inputs and outputs of each step (sensitivity analysis, classification of regions, individual calibration, grouped calibration, etc.).”

Comment [Bock17]: Ref 2: [1] Method Process diagram: A conceptual flow diagram is needed to explain the parameter regionalisation procedure more effectively. To visualize the most innovative aspect of the proposed methodology, connection between the first and second classification need more clarification. Figure 4 of the paper titled, “A different light in predicting ungauged basins: regionalization approach based on eastern USA catchments” [Shoaib et al., 2013] can be seen as an example.”

3.1 Parameter sensitivities

The relative sensitivities derived from the FAST analysis using the RR and RV indices at each of the 109,951 HRUs across the CONUS were scaled so that the five MWBM parameter sensitivities derived for each HRU summed to 100 (Fig. 4). RR (Fig. 4a) is most sensitive to the parameter *Drofac* in regions where MWBM runoff is not dominated by snowmelt and orographic precipitation, such as arid and sub-tropical areas of the CONUS. MWBM parameters that control snowpack accumulation and melt (*Meltcoef*, *Tsnow*, and *Train*) are more important to the RR in the extensive mountain ranges in the Western CONUS, and northerly latitudes around the Great Lakes and in the Eastern CONUS. The RR indicates the highest sensitivity to the *Rfactor* parameter in mountainous areas of the CONUS and areas of the West Coast, and moderate to high sensitivity in areas where the sensitivity of RR to *Drofac* is low. ~~The patterns of~~ *Tsnow*, *Train*, and *Meltcoef* all share similar patterns across the CONUS. The spatial variability of the sensitivity of RR to *Meltcoef* indicates different physical mechanisms controlling *Metlcoef* parameter influence on RR in different areas of the CONUS. In the Western CONUS, the sensitivity of RR to *Meltcoef* is greatest in mountainous areas that accumulate and hold snowpack through the late spring, such as the Rocky Mountains, Cascade, and Sierra Nevada mountain ranges. In the Eastern and Midwestern CONUS, the sensitivity of RR to *Meltcoef* is greatest for HRUs with more northerly latitudes.

Comment [Bock18]: Changed based on redundancy notice by Ref1 : “-p. 10032, lines 12-13: “The patterns of ...”. Sentence needs rewording”

Figure 4. Relative sensitivity of the (a) Rainfall Ratio (RR) and (b) Runoff Variability (RV) indices to Monthly Water Balance Model parameters.

The spatial patterns of sensitivities of RV to the five MWBM parameters (Fig. 4b) show both similarities and deviations from the patterns shown in the RR maps. For the central part of the CONUS, the relative sensitivity for the parameter *Drofac* is high for both indices, and low for the parameter *Rfactor* for both indices. *Meltcoef*, *Tsnow*, and *Train* share the same relations between higher sensitivity and higher elevation (primarily in the western part of the CONUS), and higher sensitivity and more northerly latitude (primarily in the eastern half of the CONUS) for both indices. However, *Drofac* and *Rfactor* show distinctly different patterns of relative sensitivities for the eastern part of the CONUS for RV as compared to RR. The other three parameters follow the same general spatial patterns for RV as compared to RR, but with greater fine-scale spatial variation and patchiness. The differences between the spatial distributions of the sensitivities between the two indices highlight that applying SA to different model outputs can generate different levels of sensitivities for each parameter. In addition, the choice of objective function or model output for which to measure parameter sensitivity is important, as parameter sensitivities will differ depending on whether a user evaluating measures of magnitude, the variability of distribution, or timing (Krause et al., 2005; Kapangaziwiri et al, 2012).

Figure 5 illustrates the variability of parameter sensitivities between NHDPlus regions 08 (Lower Mississippi) and 14 (Upper Colorado) (see Fig. 2) for the RV and RR indices. The Lower Mississippi and Upper Colorado NHDPlus regions have a similar number of HRUs (4,449 and 3,879, respectively) and cover a similar area (26,285 and 29,357 km^2, respectively). The Lower Mississippi region has homogenous topography, with humid, subtropical climate, while the Upper Colorado region has highly variable topography, and thus highly variable climatic controls on hydrologic processes. For the Lower Mississippi region only one parameter dominates modeled RV variance (*Rfactor*, Fig. 5a) and modeled RR variance (*Drofac*, Fig. 5c). In contrast, for the Upper Colorado River region several parameters influence RV variability (*Drofac*, *Rfactor* and *Meltcoef*, Fig. 5b) and RR variability (*Drofac* and *Meltcoef*, Fig. 5d). In the Lower Mississippi Region, the amount of snowfall is negligible, so the three parameters that control snowfall and snowpack accumulation in the MWBM have negligible effect on simulated total runoff. The comparison of the parameter sensitivities for these two regions illustrates how variable parameter sensitivities are for different regions (i.e. different climatic and physiographic regions)

Comment [Bock19]: Added in response to Ref 1. Comment: "-[2] Some of the numerical results are a bit surprising and should be double-checked.
In particular, in Fig. 5.a the fact that one parameter has sensitivity of exactly 100 and all others of exactly 0 seems odd."

~~First-order partial variance (FOPV)~~Figure 5. Parameter sensitivities of Runoff Variability (RV; a-b) and Runoff Ratio (RR; c-d) indices for Monthly Water Balance Model parameters in the Lower Mississippi (R08) and Upper Colorado (R14).

3.2. Calibration regions

The spatial patterns and magnitudes of parameter sensitivities across the CONUS were used as a basis for organizing HRUs into hydrologically similar regions for parameter regionalization through MWBM calibration. ~~While ~~T~~t~~his idea is rooted in the hypothesis that geographically proximate HRUs share similar forcings and conditions, and thus will behave similarly.~~,~~ This application ~~the ~~uses similarity in~~of~~ SA results as a basis for organization, rather than similarity in physiographic characteristics~~ provides a quantification of similarity based on similar model responses to a wide ensemble of model conditions~~. The derived regions are subsequently used to simplify model calibration across the CONUS and provide a basis for the transfer and application of parameters to ungaged areas.

The parameter sensitivities derived ~~using ~~from the RR were used to organize the HRUs into two independently-derived calibration regions; the first derived by identifying HRUs with unique combinations of the order of parameter sensitivities to the RR (highest parameter sensitivities to lowest, i.e. 1-*Drofac* (78%), 2-*Rfactor* (16%), 3-*Meltcoef* (4%), 4-*Tsnow* (1%), 5-*Train* (1%)), and the second classification based upon identifying HRUs with unique sets of parameters whose sensitivities exceeded a specified threshold of parameter sensitivity (i.e. only *Drofac* and *Rfactor* using a 5% threshold in the first classification example). ~~Using the parameter sensitivities for each HRU, two different classifications of HRUs were derived. ~~The purpose of the first classification was to delineate regions of similar model response or behavior based on the order of importance of the MWBM parameters to the RR for each HRU. Thi~~s~~e~~ first~~ classification identified 16 distinct regions of HRUS across the CONUS based on the order of the ~~FOPV for the~~parameter sensitivities of the five parameters (derived using the RR index). Sizes of these regions ranged from 94 km^2 to almost 2 million km^2. The second classification delineated regions with an identical set of the most important parameters to the RR based on parameters whose sensitivities exceeded a 5% threshold. This step ~~e second classification ~~identified 12 regions of HRUs with unique combinations of parameter sensitivities~~ with FOPV ~~exceeding

Comment [Bock20]: Changed FOPV to parameter sensitivities based on comment/response Bock7

Comment [Bock21]: Modified this sentence in response to ref. 1: "-p. 10033, line 25: "While this idea...". What idea? The one described in the previous sentence? But then is it really in contrast with the one illustrated on lines 27-28? Please clarify."

Comment [Bock22]: This section is substantially modified based on the following suggestions/comments by the referees:

Comment [Bock23]: Ref1: -What is the connection between the first and second classification? They are independent from each other and then intersected to obtain the actual classification? Please clarify
-Description of the second classification (lines 10-11) is also unclear. What are the "unique combinations of parameter sensitivities"? How are they defined? What is their meaning?
- -Be more specific on how the two classification approaches work. Sentence on lines 7-8 of page 10034 is too generic, does it mean that the parameter ranking is the same in each region?

5%. There has been progress in providing quantitative thresholds for the identification of sensitive and non-sensitive parameters for hydrologic modelers (~~Pianosi et al., 2015~~Tang et al., 2007), but no definitive consensus yet exists. Therefore a 5% threshold was used based on visual delineation of major physiographic features such as mountain ranges across the CONUS. The sizes of this second group of regions ranged from 94 km^2 to more than 15 million km^2. Maps of the two groupings of HRUS were intersected to create a total of 49 regions across the CONUS. NHDPlus region ~~and sub-region~~ boundaries, proximity, and significant topographic divides were used to further divide the groups into 159 geographically unique calibration regions across the CONUS. The lack of streamgages available in some regions, especially areas with arid and semi-arid climates, necessitated merging regions together. Calibration regions that contained less than 3 streamgages from the 8,410 gages present in the Geospatial Fabric (see section 3.3) were combined with the proximate and most similar group ~~based on the~~which shared the most similar parameter sensitivities (both order and magnitude), ~~of parameter sensitivities~~ resulting in 110 calibration regions across the CONUS (Fig. 6). ~~Additionally,~~ W~~w~~ithin each region the FAST results for both the RR and RV indices were used to determine which parameters to calibrate~~e~~. Parameters with a median parameter sensitivity of 5% for the RR and RV among the region's HRUs were selected for group calibration. Parameters not shown as sensitive were kept at the default value for the group.

Figure 6. Final 110 Monthly Water Balance Model calibration regions differentiated by colors. A subset of streamgages within each calibration region were calibrated in a group-wise fashion to produce a single optimized parameter set for the entire region (Fig. 3). ~~Monthly Water Balance Model calibration regions differentiated by color.~~

3.3 Initial streamgage selection

The initial set of streamgages used for testing in the MWBM calibration procedures was selected from 8,410 streamgages identified in the Geospatial Fabric (Fig. 7). The Geospatial Fabric includes reference and non-reference streamgages from the Geospatial Attributes of Gages for Evaluating Streamflow dataset (GAGES-II, Falcone et al., 2010). Of the 8,410 streamgages in

Comment [Bock24]: Replaced this reference at the recommendation of ref. 1: -p. 10034, lines 11-13: citation of Pianosi et al., 2015 does not seem to be appropriate here. That paper introduces a toolbox for Sensitivity Analysis but it does not discuss the issue of setting the threshold for sensitive and non-sensitive parameters. The threshold issue is (partially) discussed in Tang et al. (2007). "

Comment [Bock25]: Some clairification added as per Ref 1. Comment: "-From lines 17-20, I understand that the sensitivity-based classification is further refined using a more 'conventional' approach that looks at proximity and topographic divides. How does this refinement step works? Does it introduce significant changes in the classification? This is important to know in order to understand the value of the proposed sensitivity-based classification versus proximity or topography-based classification."

Comment [Bock26]: Added clarification to caption based on ref. 2 comments: "-p. 10058 and 10066, Figure 6 and Figure 14 are not that clear. It is understandable after reading the text, but it could be much improved"

the Geospatial Fabric, 1,864 were identified as having reference-quality data with at least 20 years of record. These reference quality streamgages were judged to be largely free of human alterations to flow (Falcone et al., 2010). In the current study, reference quality was not considered in the initial streamgage selection because the 20 years of record was considered too restrictive. Therefore a subset of the 8,410 streamgages was selected for initial testing in the MWBM calibration procedures based on the following criteria:

(1) Remove streamgages with less than 10 years of total measured streamflow (120 months) within the time period 1950 – 2010.

(2) Remove streamgages with a drainage area defined by the Geospatial Fabric that are not within 5% of the USGS National Water Information System (NWIS) reported drainage area (U.S. Geological Survey, 2014). This eliminated many of the streamgages with smaller drainage areas due to the resolution of the Geospatial Fabric.

(3) Remove streamgages that did not have at least 75% of its drainage area contained within a single calibration region.

These criteria resulted in 5,457 potential streamgages for testing in the MWBM calibration procedures (Fig. 7). Streamflow at these streamgages was aggregated and converted from daily (cubic feet/second) to a monthly runoff depth (mm) (streamflow per unit area).

Figure 7. Streamgages tested in the study. GF notes geospatial fabric for national hydrologic modeling (Viger and Bock, 2014).

3.4 Monthly Water Balance Model calibration

Two automated calibration procedures were implemented to produce an ‘optimal’ set of MWBM parameters for each calibration region. The first procedure, Individual Streamgage Calibration, calibrated each of the 5,457 streamgages individually. Results from the individual calibrations were used to further filter the streamgages within the second procedure, Grouped Streamgage Calibration, which calibrated selected streamgages together by calibration region.

3.4.1 Individual streamgage calibration

The first calibration procedure was an automated process that individually calibrated each of the 5,457 streamgages from the initial streamgage selection with measured streamflow (U.S. Geological Survey, 2014). Results from these individual streamgage calibrations quantified the ‘best’ performance of the MWBM at each gage, providing a ‘baseline’ measure for evaluation.

The Shuffled Complex Evolution (SCE) global-search optimization algorithm (Duan et al., 1993) has been frequently used as an optimization algorithm in hydrologic studies (Hay et al., 2006; Blasone et al. 2007; Arnold et al., 2012), including previous studies with the MWBM (Hay and McCabe, 2010). Further details can be found in Duan et al. (1993). SCE was used to maximize a combined objective function based on: (1) Nash-Sutcliffe Efficiency (NSE) coefficient using measured and simulated monthly runoff and (2) NSE using natural log-transformed measured and simulated runoff (logNSE), using the entire period of record for each streamgage. The NSE measures the predictive power of the MWBM in matching the magnitude and variability of the measured and simulated runoff (Nash and Sutcliffe, 1970). The NSE coefficient ranges from $-\infty$ to 1, with 1 indicating a perfect fit, and values less than 0 indicating that measured mean runoff is a better predictor than model simulations. The NSE has been shown to give more weight to the larger values in a time series (peak flows) at the expense of lower values (low flows) (Legates and McCabe, 1999), so the logNSE was incorporated into the objective function to give weight to lowflow periods (Tekleab et al., 2011).

3.4.2 Grouped streamgage calibration

The second calibration procedure was an automated process that calibrated groups of streamgages together for each calibration region to derive a single set of MWBM parameters (Table 1) for each calibration region (Fig. 6). The NSE and logNSE values from the individual streamgage calibrations (described in the previous section) were used to identify streamgages that should not be used for grouped streamgage calibration. If the individual streamgage calibration was not ‘satisfactory’, then it was felt that it would not provide useful information for the grouped streamgage calibration procedure.

Satisfactory individual streamgage calibrations were identified with the following procedure:

(1) Eliminate all streamgages with NSE values < 0.3.

(2) If the number of remaining streamgages for a given calibration region is > 10, then eliminate all streamgages with NSE < 0.5.

(3) If the number of streamgages for a given calibration region is > 25, then eliminate all streamgages with NSElog < 0.

(4) If the number of remaining streamgages for a calibration region is < 5, check to see if any of the eliminated streamgages were reference streamgages (as defined in Falcone et al., 2010), then add the reference streamgages back in if the NSE value > 0.0. Reference streamgages are USGS streamgages deemed to be largely free of anthropogenic impacts and flow modifications (Falcone et al., 2010; Kiang et al., 2013).

Comment [Bock27]: Added details on reference gages at request of ref. 1: "-p. 10037, line 17: Please give a very brief definition of a reference streamgage."

These criteria, while somewhat arbitrary, were chosen so that no calibration region had less than 5 streamgages for the grouped streamgage calibration. Using the above criterion, of the 5,457 streamgages individually calibrated, 3,125 remained as candidates for the grouped streamgage calibration procedure.

The grouped streamgage calibration procedure used the SCE global-search optimization algorithm with a multi-term objective function (Eq. 1). Measured and simulated values for selected streamgages contained within a calibration region were scaled to~~by~~ Z-scores to remove differences in magnitudes between streamgages (Eq. 2). The multi-term objective function minimized the sum of the absolute differences between Z-scores from four measured and simulated time series: ~~(~~mean monthly runoff (MMO,MMS), monthly runoff (MO,MS), ~~mean monthly runoff,~~ annual runoff (AO,AS) (U.S. Geological Survey, 2014), and monthly snow water equivalent (SO,SS~~SWE)~~) for all selected streamgages within a given calibration region:

~~. The observed and simulated Z-scores (Z) were calculated at each streamgage as:~~

$$min \sum_{i=1}^{n} [3|\mathrm{MMO_i} - \mathrm{MMS_i}| + |\mathrm{MO_i} - \mathrm{MS_i}| + |\mathrm{AO_i} - \mathrm{AS_i}| + 0.5|\mathrm{SO_i} - \mathrm{SS_i}|] \qquad \text{(Eq.1)}$$

$$\text{where} \begin{cases} 0 \text{ if } 0.75 < \mathrm{SO_i} - \mathrm{SS_i} < 1.25 \\ |\mathrm{SO_i} - \mathrm{SS_i}| \; if \; \mathrm{SS_i} < \mathrm{SO_i}^{0.75} \\ |\mathrm{SO_i} - \mathrm{SS}_i| \; \mathrm{SS_i} > \mathrm{SO_i}^{1.25} \end{cases}$$

The measured and simulated Z-scores were calculated as:

Z = (x-u)/σ (Eq. 2~~1~~)

where x is the time-series value, u is the mean, and σ the standard deviation of the measured and simulated variable~~streamflow~~.

'Measured' SWE was determined for each HRU from the Snow Data Assimilation System (SNODAS; National Operational Hydrologic Remote Sensing Center, 2004) and included a +/- 25% error bound. The unconstrained automated calibration (without a restriction on SWE) led to unrealistic sources of snowmelt in the summer that enhanced the low-flow simulations. The 25% error bound is arbitrary; calibrating to the actual SNODAS SWE values was found to be too restrictive, but adding this error bound to the SWE values resulted in better overall runoff simulations. The absolute difference of the simulated SWE Z-scores within +/- 25% of the measured SWE Z-score were designated as 0. Otherwise, the absolute difference was computed between the simulated SWE Z-score and either the upper or lower bounds (Eq. 1).

The grouped calibration procedure was run for all 110 calibration regions. For each calibration region the seasonal adjustment parameters and the sensitive parameters (identified by the FAST analysis -- section 3.1) were calibrated; parameters deemed not sensitive (parameter sensitivit~~i~~y < 5% of total variance) were set to their default values (see Table 1). The entire period of the streamflow record for each streamgage was split by alternating years. After calibration, mean monthly measured and simulated Z-scores for runoff at all selected streamgages within a calibration region were compared ~~on a mean monthly basis~~.

Figure 8 shows an example of the graphic used to evaluate the measured and simulated mean monthly Z-scores for 21 streamgages selected for the region located in the Tennessee River calibration region (part of NHDPlus Region R06 in Fig. 2); the orange, red, and black dots indicate calibration, evaluation, and the entire period of record, respectively. A tight grouping around the one-to-one line indicates good correspondence between measured and simulated Z-

Comment [Bock28]: Added equation fo the objective function at the request of ref. 1 and ref. 2.
Ref 1: "-p. 10038, lines 1-4: The definition of the multi-term objective function is unclear. Are the four terms summed up? Why considering both mean monthly runoff and annual runoff (I would imagine that they convey the same information, the former being equal to the latter divided by 12)? I think inserting an equation with the mathematical definition of the objective function would help here."

Comment [Bock29]: Ref 2: -p. 10037, lines 24-25: The multi-term objective function is unclear. Inserting an equa tion with the mathematical definition of the objective function would help here. Though NSE, logNSE are mentioned in the manuscript, it is not clear what the authors try to represent the term multi-term objective function. What about SQRT NSE?

Comment [Bock30]: Both reviewers wanted an equation of the objective function included

Comment [Bock31]: Changed at the suggestion of ref. 1: "-p. 10038, line 9: "simulated streamflow" should be "simulated variable" (since one of the four is SWE and not runoff)"

Comment [Bock32]: Clarified SWE Z-scores at request of ref.1: "-p. 10038, lines 14-16: Please clarify how the error bounds were taken into account. Did you modify the definition of the Z score for the SWE?"

Comment [Bock33]: Added clarifying statement at the recommendation of ref. 1: "Recall here that a parameter is deemed insensitive if sensitivity index is below 5%"

Comment [Bock34]: redundant, deleted at recommendation of ref. 1: "p. 10038, lines 21-23: "on a mean monthly based". Unclear. Possibly it might just be dropped, since it was already said that monthly variables are used to compute the Zscores."

scores. Points closer to the upper right corner of each plot represent high-flow periods. Points closer to the lower left corner of the plot represent low-flow periods. Streamgages within a calibration region were assigned the same parameter values; therefore streamgages that plotted outside (two standard deviations) of the one-to-one line were considered to not be representative of the calibration region, and the calibration procedure for that calibration region was repeated without those streamgages.

Figure 8. Measured versus simulated mean monthly Z-scores for the Tennessee River calibration region (see Fig. 10b for location). Orange is calibration, red is evaluation, and black is all years.

The goal of the second calibration procedure was to find a single parameter set for each calibration region. Past applications of the MWBM (Wolock and McCabe, 1999, McCabe and Wolock, 2011a) used a single set of fixed MWBM parameters for the entire CONUS. Many of the streamgages included in the second calibration procedure could be affected by significant anthropogenic effects; the seasonal adjustment factors, calibrated at each individual streamgage, could account for these effects and result in satisfactory NSE values. Streamgages that were removed due to poor performance in the second calibration were assumed to have anthropogenic effects not consistent with the streamgages that plotted along the one-to-one line. Poor performance may result because the MWBM fails to reliably simulate runoff for a watershed because of model limitations (i.e. not including all important hydrologic processes), but the calibration regions are assumed to be homogeneous based on the FAST analysis. Therefore it is assumed that if some of the streamgages within a region have satisfactory results, then the MWBM is able to simulate runoff in that region.

4 MWBM calibration region results

4.1 Individual streamgage calibration results

The individual streamgage calibrations provided information regarding: (1) the potential suitability of a given streamgage for inclusion in a grouped calibration, and (2) a ‘baseline’ measure for evaluation of the grouped calibration results. Reference and non-reference streamgages were considered in this application; if the runoff at a streamgage could not be calibrated individually to a 'satisfactory' level (based on criterion outlined in section 3.4.2), then it was felt that it would not provide useful information for the grouped streamgage calibration procedure. Figure 9 shows the NSE (Fig. 9a) and logNSE (Fig. 9b) coefficients from the individual streamgage calibrations for the CONUS. Scattered throughout the CONUS are NSE and logNSE values less than 0.0 (triangles in Fig. 9). These poor results are likely streamgages with poor streamflow records, either due to measurement error or anthropogenic effects (dams, water use, etc.).

Figure 9. Individual streamgage calibration results: (a) Nash-Sutcliffe Efficiency (NSE) coefficient and (b) log of the NSE (logNSE).

4.2 Grouped streamgage calibration results

4.2.1 Mean monthly z-scores

Figure 10a shows a scatterplot of measured versus simulated mean monthly Z-scores for runoff, similar to Figure 8, but based on all available years (the black dots in Fig. 8) for all the final calibration streamgages (1,575 streamgages). Four regions are highlighted to illustrate the monthly variability in MWBM results across the CONUS (see Fig. 10b for locations). The four regions are: New England (67 streamgages, red); Tennessee River basin (21 streamgages, orange); Platte Headwaters (15 streamgages, blue); and Pacific Northwest (33 streamgages, green) (Fig. 10b).

Figure 10. (a) Measured versus simulated mean monthly Z-scores for runoff at all streamgages and (b) location of highlighted streamgages for four calibration regions: New England (67 streamgages, red); Tennessee River (21 streamgages, orange); Platte Headwaters (15 streamgages, blue); and Pacific Northwest (33 streamgages, green).

In Fig. 10a, three of the regions (New England, Tennessee River, and Pacific Northwest), show simulated Z-scores that correspond favorably to measured Z-scores for each of the twelve months, including periods of low and high runoff. These regions represent marine or humid climates with homogenous physio-climatic conditions and an even spatial distribution of streamgages, where models should be expected to perform well (see Fig. 9) There is a higher variability in model results for the high-flow months (May - June) for streamgages within the Platte Headwaters (Fig. 10a; blue dots) than for low-flow months. This variability may be related to factors controlling the magnitude and timing of snow melt runoff (Fig. 9).

For each calibration streamgage, a set of four months were identified that represent different parts of the measured mean monthly hydrograph (highest- and lowest- flow month and the two median-flow months). The measured and simulated mean monthly streamflow Z scores corresponding to the four months are plotted as cumulative frequencies (Fig. 11) to compare how well the simulated Z scores matched measured Z scores for different parts of the hydrograph over the entire set of calibration gages. For the highest-flow, there is an under-estimation of runoff, with the greatest divergence between the two distributions in the middle to lower half of the distribution (Fig. 11a). For the median-flow, the measured and simulated Z scores are well matched. For the 10 lowest-flow, simulated Z scores are greater than measured Z scores, with the greatest divergence between the two distributions in the middle to upper half of the distribution (Fig. 11c).

Figure 11. Z-score cumulative frequency for (a) highest-, (b) median-, and (c) lowest-flow months.

The median Z-score errors (simulated - measured) by region for the (a) highest-, (b) median-, and (c) lowest-flows are shown in Figure 12. The largest errors are for the highest-flows (Fig. 12a). The MWBM simulations under-estimate the highest flows for much of the CONUS. The errors for median-flows are fairly uniform and consistent across the CONUS (Fig. 12b), with a median error close to 0. For the lowest-flow months the MWBM over-estimates low flows for a large portion of the Midwest (Fig. 12c).

Figure 12. Z-score error (simulated - measured) for (a) highest-, (b) median-, and (c) lowest-flow months.

4.2.2 Nash-Sutcliffe efficiency

Figure 13 compares the NSE from the individual streamgage calibrations (gageNSE) with the grouped calibrations (groupNSE) for all final streamgages used in the second calibration procedure. NSE values > 0.75 (dashed line) and > 0.5 (solid line) indicate very good and satisfactory results (Moriasi et al., 2007). Overall, most NSE values fall above the 0.5 NSE threshold of satisfactory performance (median of gageNSE and groupNSE = 0.76). The gageNSE values are used here as a 'baseline' for evaluation of the groupNSE results. The groupNSE values were not expected to be greater than the gageNSE values since (1) NSE was not used as an objective function in the grouped calibration, and (2) grouped calibrations found the 'best' parameter set for a set of streamgages versus an individual streamgage. Figure 13 shows an equal distribution of NSE values around the one-to-one line, indicating that the grouped calibration provided additional information over the individual streamgage calibrations (cases where groupNSE are greater than gageNSE in Fig. 13). The difference between the gageNSE and groupNSE becomes larger as the NSE values decrease, reflecting the increasing uncertainty in the grouped calibrations in areas with lower gageNSE values.

Figure 13. Nash Sutcliffe Efficiency from individual (gageNSE) and grouped (groupNSE) calibration. Calibration regions in New England (67 streamgages, red); Tennessee River (21 streamgages, orange); Platte Headwaters (15 streamgages, blue); and Pacific Northwest (33 streamgages, green) are highlighted (see Fig. 10b for location).

Four regions are highlighted in Fig. 13 to illustrate the variability of NSE across the CONUS (see Fig. 10b for locations). The highlighted regions in New England (red), Tennessee River (orange), and Pacific Northwest (green), show good groupNSE and gageNSE results. Four of the 15 streamgages in the Platte Headwaters (blue) have groupNSE values $\leq$ 0.5. This is probably related to simulation error during the snowmelt period (May - June, Fig. 10a).

Figure 14 shows the median groupNSE by calibration region for the CONUS. The pattern is very similar to that shown for the individual streamgage calibration results in Fig. 9a and highlights the problem areas shown in Fig. 12.

Figure 14. ~~Median Nash Sutcliffe Efficiency (NSE) by calibration region.~~Median Nash Sutcliffe Efficiency (NSE) by calibration region of streamgages used for calibration.

Comment [Bock35]: Added clarification to caption based on ref. 2 comments: "-p. 10058 and 10066, Figure 6 and Figure 14 are not that clear. It is understandable after reading the text, but it could be much improved"

5 Discussion

This study presented a parameter regionalization procedure for calibration of the MWBM, resulting in an application that can be used for simulation of hydrologic variables for both gaged and ungaged areas in the CONUS. The regionalization procedure grouped HRUs on the basis of similar sensitivity to five model parameters. Parameter values and model uncertainty information within a group was then passed from gaged to ungaged areas within that group.

5.1 Regionalized parameters

Results from this study indicate that regionalized parameters can be used to produce satisfactory MWBM simulations in most parts of the CONUS (Fig. 13). Despite the differences between the individual streamgage calibration and grouped calibration, Figure 13 illustrates that the grouped calibration strategy, which focused only on ~~only~~ sensitive parameters, can provide just as much information as the individual streamgage calibration with no constraints on the parameter~~s~~ optimization other than the default ranges. The MWBM is a simple hydrologic model as it has minimal parameters, which are conceptual in nature (not physically based). It may be that this type of model is best for regionalization when parameter sensitivity can be identified and HRU behavior can be classified by a small number of clearly defined spatial groups. More complicated models with many more interactive parameters may not respond as well to this simple type of regionalization; more parameters may lead to more parameter interaction and situations of equifinality which might confuse the analysis.

Comment [Bock36]: Clairifcation to ref. 1 comment: "-Also, the result of Figure 13 is very puzzling. As the authors note on page 10041 (line 27 onward), the groupNSE values are expected to be lower than the gageNSE values. Figure 13 instead shows many cases were groupNSE is much larger than gageNSE. I really struggle to believe that NSE can be increased so much and so often when using a model calibrated with a different objective function."

The adjustments of precipitation and temperature parameters for the individual streamgage calibrations accounted for local errors such as rain gage under catch of precipitation. In addition these climate adjustments also account for local anthropogenic effects on streamflow (e.g. dams, diversions) since streamgages were not screened for these effects prior to individual streamgage calibration. In the grouped streamgage calibrations, the same precipitation and temperature adjustments are applied at every streamgage within the calibration region, making these climate adjustments more of a regional adjustment and producing more of a 'reference' condition for each calibration region.

5.2 Parameter sensitivities and dominant process

The MWBM parameter sensitivities varied by hydroclimatic index (RR and RV) and across the CONUS (Fig. 4). The parameter sensitivity patterns give an indication of dominant hydrologic processes based on MWBM. The dominant process can be seasonal and MWBM performance may be enhanced by extending the use of SA along the temporal domain to identify and temporally vary the parameters that are seasonally important to the MWBM. For example, error in peak flow months is the primary cause for poor model performance in the Platte Headwaters (Fig. 10). For the Platte Headwaters, the final parameter set performed well for simulated Z-scores for the regionalized low- and median-flow conditions (Fig. 10a, July through April), but was not able to replicate measured mean monthly flows for May and June. In this case, the dominant processes controlling hydrologic behavior change with season and the parameters controlling the dominant response may have to change accordingly (Gupta et al., 2008; Reusser et al., 2011).

5.3 Model accuracy

The pattern of MWBM accuracies shown in Fig. 9 and 14 are similar to those shown by Newman et al. (2015; Fig. 5a) in which a daily time-step hydrologic model was calibrated for 671 basins across the CONUS. Our study and the Newman et al. (2015) study both indicate the same ‘problem areas’ with the poorest performing basins generally being located in the high plains and desert southwest. Newman et al. (2015) attributed variation in model performance by region to spatial variations in aridity and precipitation intermittency, contribution of snowmelt, and runoff seasonality.

The inferior MWBM results in the ‘problem areas’ can be attributed to multiple factors which likely include inadequate hydrologic process representation and errors in forcing data (e.g. climate data), and/or measured streamflow. Archfield et al. (2015) state that the performance of continental-domain hydrologic models is considerably constrained by inadequate model representation of dominant hydrologic processes. For example, the simplicity of the MWBM presents limitations on the representation of deeper groundwater reservoirs, gaining and losing stream reaches, simplistic AET, and the effects of surface processes (infiltration and overland flow) that need to be represented at finer time steps than monthly.

The dominant hydrologic processes in the 'problem areas' appear to be poorly represented at the daily (Newman et al., 2015) and monthly time steps. This may be due to inadequate forcing data~~s~~, the quality of which 'is paramount in hydrologic modeling efforts' (Archfield et al., 2015) and/or the lack of 'good' reference streamflow data for calibration and evaluation. Both surely play a role and emphasize the need for incorporation of additional datasets so that calibration and evaluation of intermediate states in the hydrologic cycle are examined.

6 Conclusions

A parameter regionalization procedure was developed for the CONUS that transferred parameter values ~~and model uncertainty information~~ from gaged to ungaged areas for a MWBM. The FAST global-sensitivity algorithm was implemented on a MWBM to generate parameter sensitivities on a set of 109,951 HRUs across the CONUS. The parameter sensitivities were used to group the HRUs into 110 calibration regions. Streamgages within each calibration region were used to calibrate the MWBM parameters to produce a regionalized set of parameters for each calibration region. The regionalized MWBM parameter sets were used to simulate monthly runoff for the entire CONUS. Results from this study indicate that regionalized parameters can be used to produce satisfactory MWBM simulations in most parts of the CONUS.

Comment [Bock37]: Response to Ref. 1 Minor Points: -p. 10024, lines 1-2 "to transfer ... model uncertainty information". What type of uncertainty information is transferred and how? This is mentioned here and in the conclusion but it is not clearly discussed throughout the paper.

The best MWBM results were achieved simulating low- and median-flows across the CONUS. The high-flow months generally showed lower skill levels than the low- and median-flow months, especially for regions with dominant seasonal cycles. The lowest MWBM skill levels were found in the high plains and desert southwest and can be attributed to multiple factors which likely include inadequate hydrologic process representation and errors in forcing data and/or measured streamflow. Calibration and evaluation of intermediary fluxes and states in the MWBM through additional measured datasets may help to improve MWBM representations of these model states by helping to constrain parameterization to measured values.

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Comment [Bock38]: Added this relevant reference at recommendation of Ref. 2

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Comment [Bock39]: Removed reference based on modifications to text (comment Bock 23)

Comment [Bock40]: Added reference at recommendation of ref. 2.

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Comment [Bock41]: Wanted to add full citation of the NHDPlus base data set

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Parameter	Definition	Range	Default
1. Drofac	Controls fraction of precipitation that becomes runoff	0, 0.10	0.05
2. Rfactor	Controls fraction of surplus that becomes runoff	0.10, 1.0	0.5
3. Tsnow	Threshold above which all precipitation is rain (^{o}C)	-10.0, -2.0	-4.0
4. Train	Threshold below which all precipitation is snow (^{o}C)	0.0, 10.0	7.0
5. Meltcoef	Proportion of snowpack that becomes runoff	0.0, 1.0	0.47
6. Ppt_adj	Seasonal adjustment factor for precipitation (%)	0.5, 2.0	1
7. Tav_adj	Seasonal adjustment for temperature (^{o}C)	-3.0, 3.0	0

Table 1. Monthly Water Balance Model parameters and ranges.

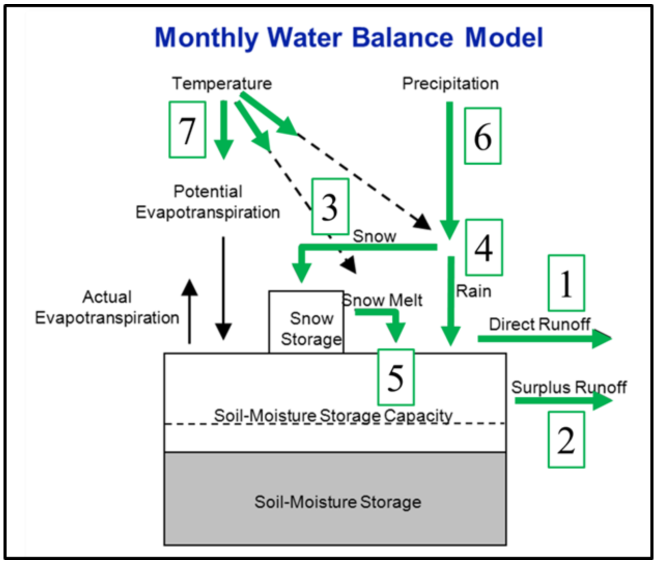


Figure 1. Conceptual diagram of the Monthly Water Balance Model (McCabe and Markstrom 2007). Processes influenced by m~~M~~odel parameters used in Fourier Amplitude Sensitivity Test (FAST) are identified by green arrow and numbered (Table 1).

Comment [Bock42]: Changed based on Ref1 suggstion : "-caption of Fig. 1: "model parameters used in..." Maybe better: "processes influenced by the model parameters used in..."

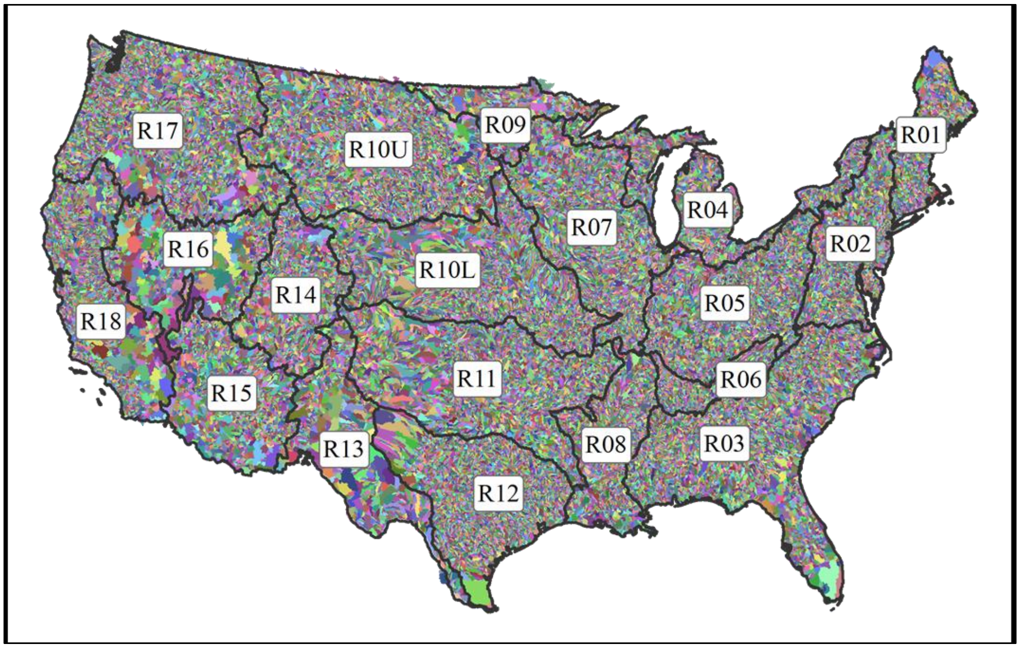
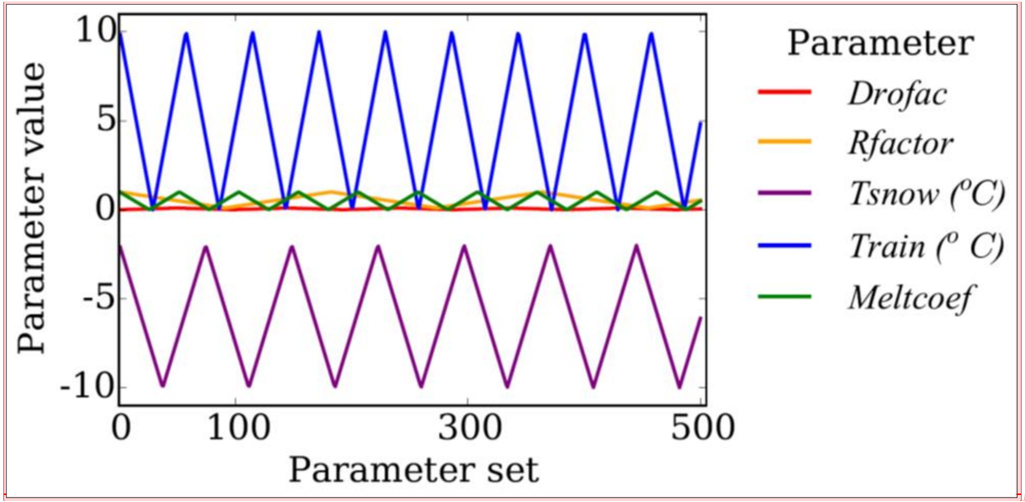


Figure 2. Hydrologic Response Units of the Geospatial Fabric, differentiated by color, overlain by NHDPlus region boundaries (R01-R18).



~~Figure 3. A portion (0 to 500 parameter sets) of the parameter sampling scheme for the Monthly Water Balance Model in the Fourier Amplitude Sensitivity Test (FAST). A total of 1000 parameter sets were generated for implementation in FAST.~~

Comment [Bock43]: Remove Fig. 3 at suggestion of Ref. 1: "-Figure 3: maybe not needed. Anyway, if maintained, vertical axis should show units
of measurements. Also, it would probably be better to show Drofac and Rfactor in a separate panel."

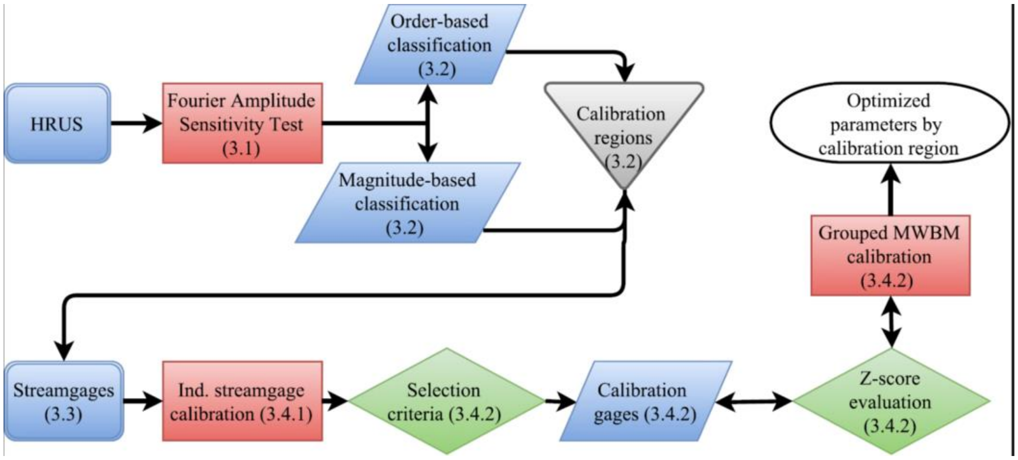


Figure 3. Schematic flowchart of the parameter sensivitiy analysis and regionalization method described in this paper (Section 3).

Comment [Bock44]: Both reviewers wanted a flow chart added

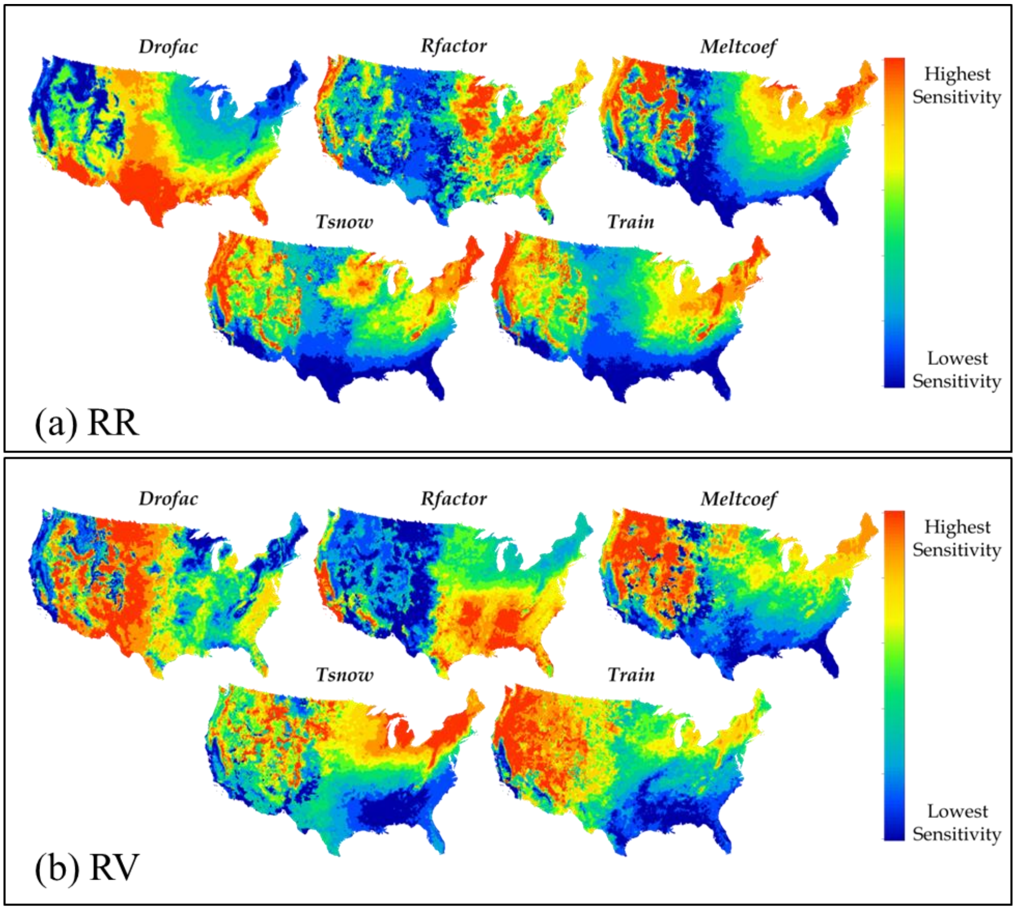
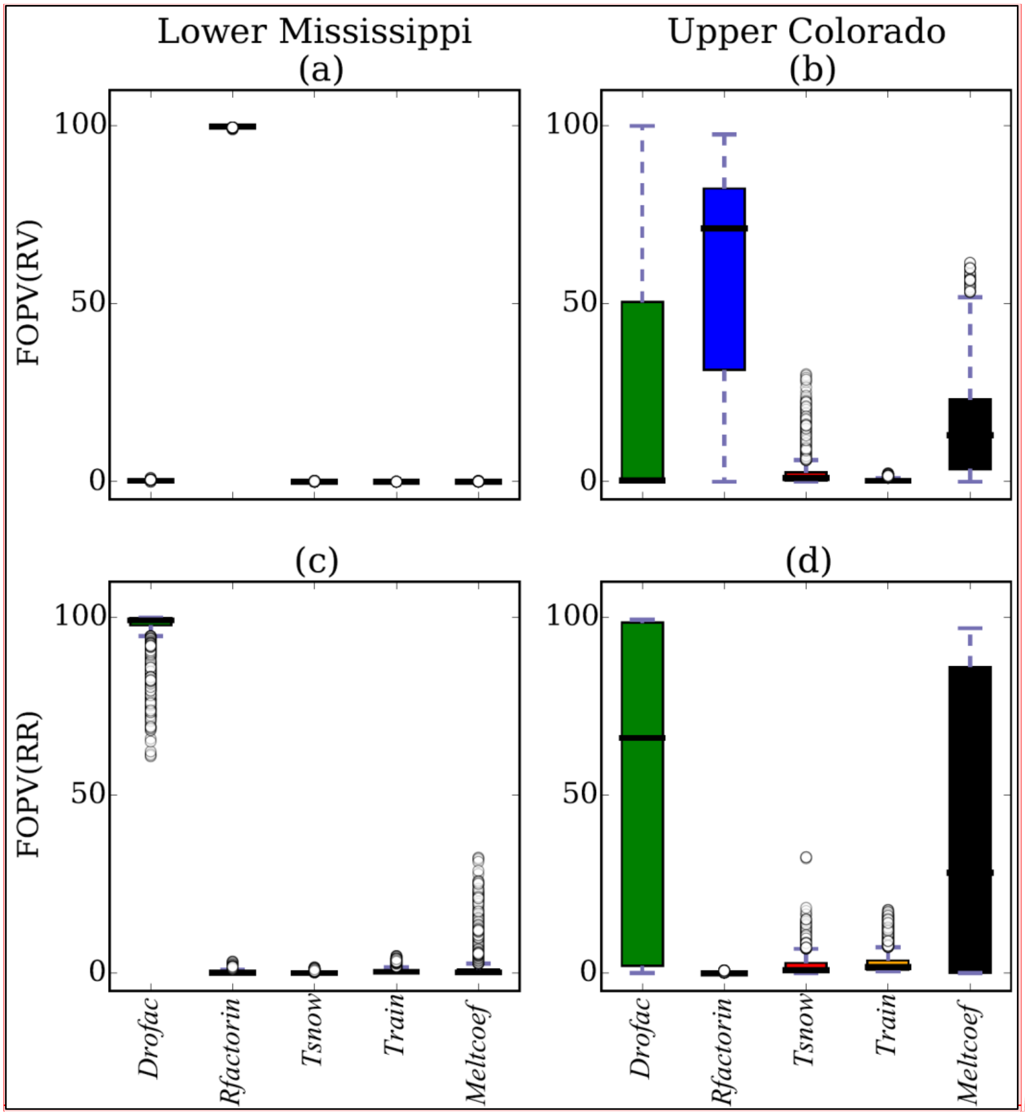


Figure 4. Relative sensitivity of the (a) Rainfall Ratio (RR) and (b) Runoff Variability (RV) indices to Monthly Water Balance Model parameters.

933



Comment [Bock45]: Old picture with FOPV as y-axis labels

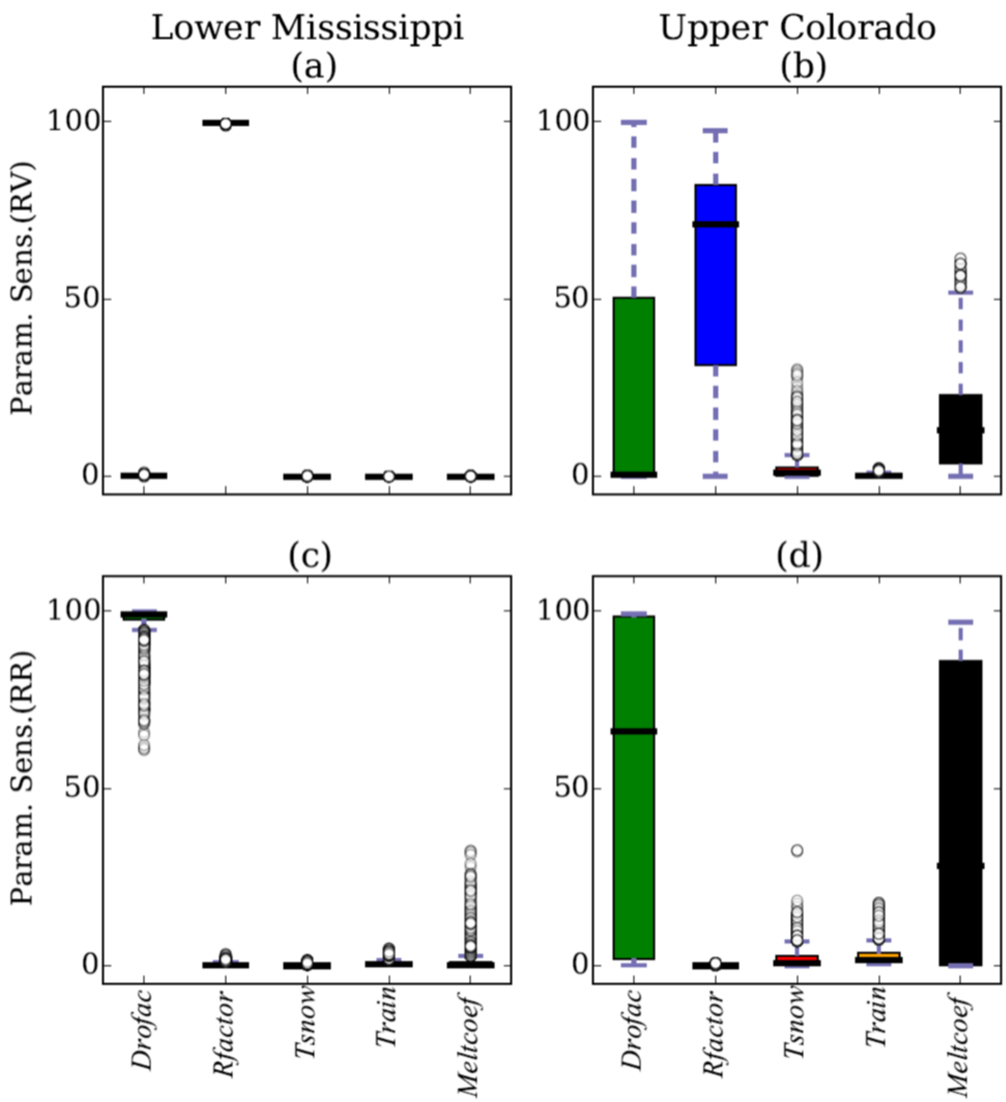


Figure 5. ~~First-order partial variance (FOPV)~~Parameter sensitivities of Runoff Variability (RV; a and b) and Runoff Ratio (RR; c and d) indices for Monthly Water Balance Model parameters in the Lower Mississippi (R08) and Upper Colorado (R14).

Comment [Bock46]: New figure with Param. Sens. As y-axis labels

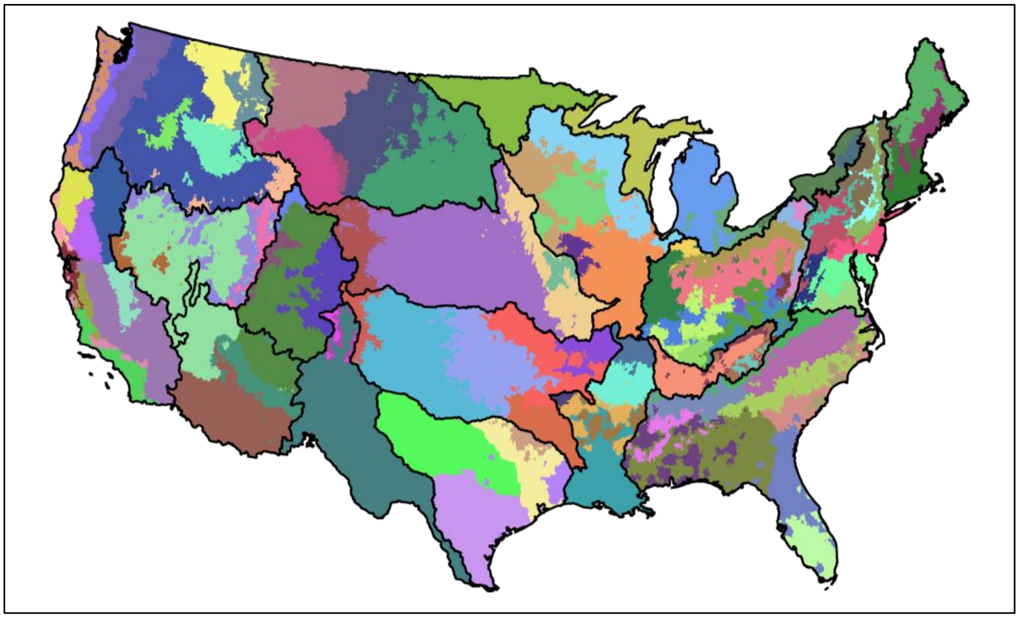


Figure 6. Final 110 Monthly Water Balance Model calibration regions differentiated by colors. A subset of streamgages within each calibration region were calibrated in a group-wise fashion to produce a single optimized parameter set for the entire region (Fig. 3).

Comment [Bock47]: Added clarification to caption based on ref. 2 comments: "-p. 10058 and 10066, Figure 6 and Figure 14 are not that clear. It is understandable after reading the text, but it could be much improved"

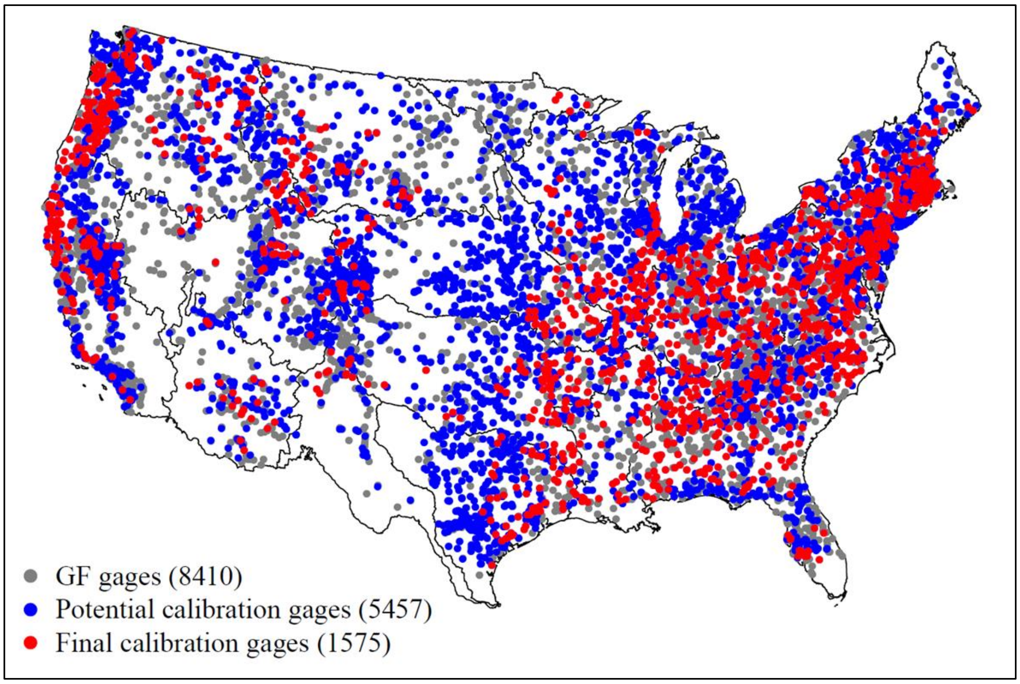


Figure 7. Streamgages tested in the study. GF notes geospatial fabric for national hydrologic modeling (Viger and Bock, 2014).

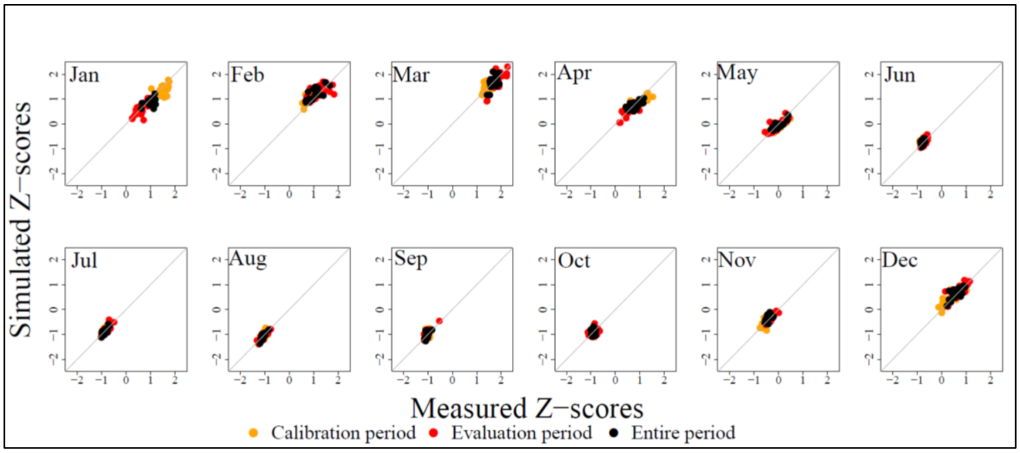


Figure 8. Measured versus simulated mean monthly Z-scores for the Tennessee River calibration region (see Fig. 10b for location). Orange is calibration, red is evaluation, and black is all years.

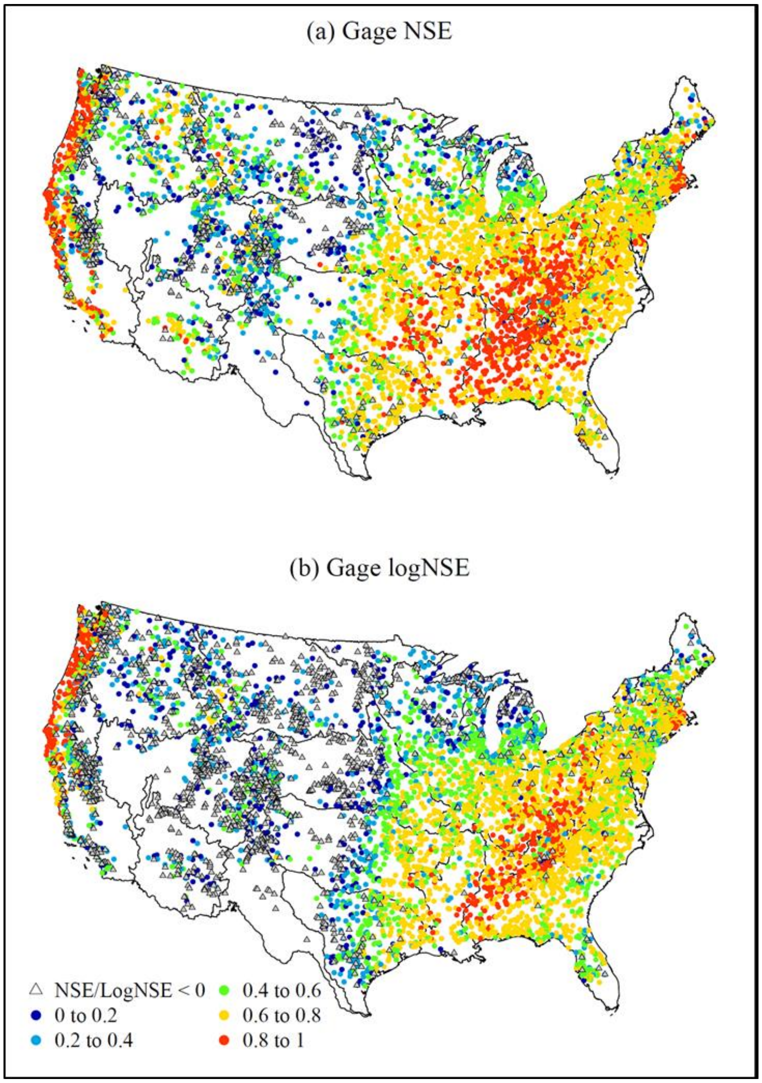


Figure 9. Individual streamgage calibration results: (a) Nash-Sutcliffe Efficiency (NSE) coefficient and (b) log of the NSE (logNSE).

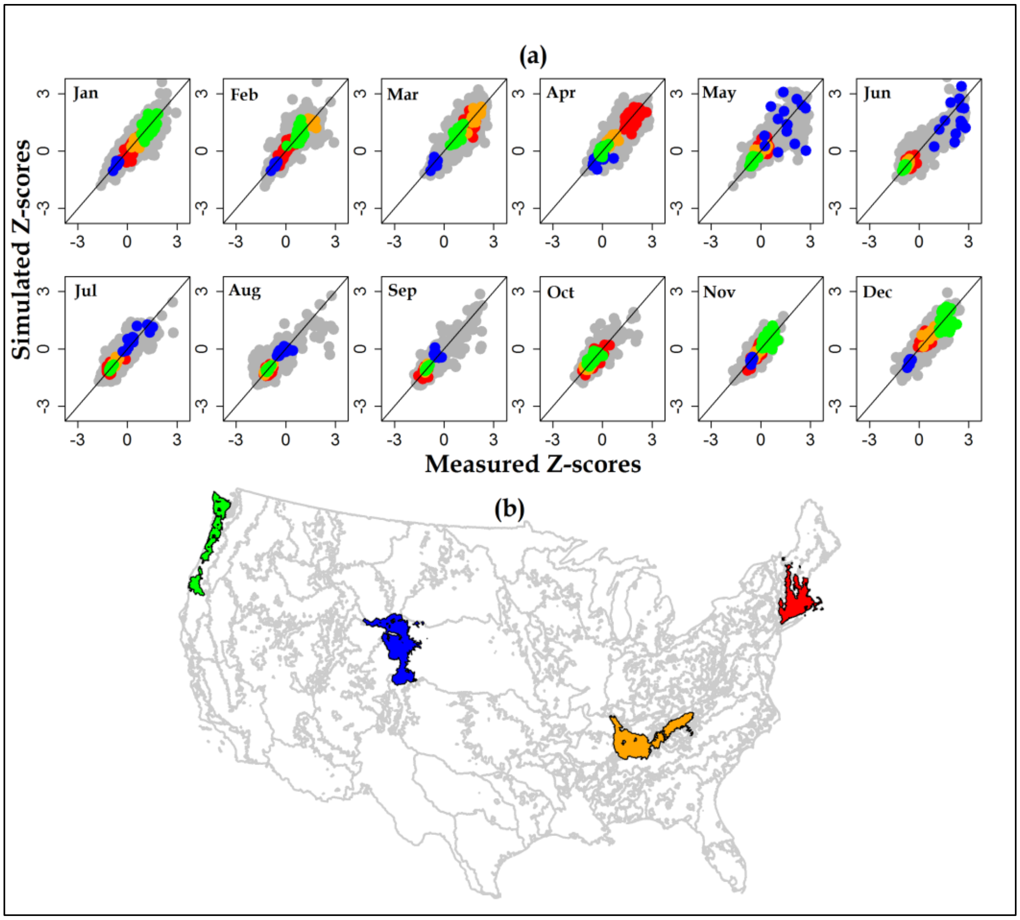


Figure 10. (a) Measured versus simulated mean monthly Z-scores for runoff at all streamgages and (b) location of highlighted streamgages for four calibration regions: New England (67 streamgages, red); Tennessee River (21 streamgages, orange); Platte Headwaters (15 streamgages, blue); and Pacific Northwest (33 streamgages, green).

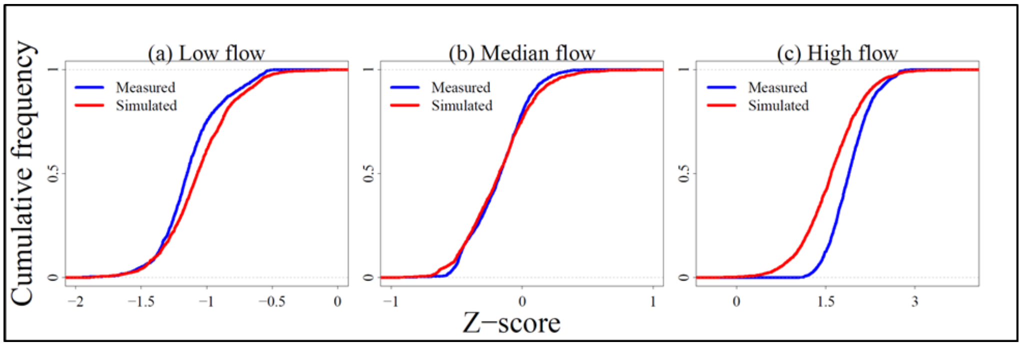


Figure 11. Z-score cumulative frequency for (a) highest-, (b) median-, and (c) lowest-flow months.

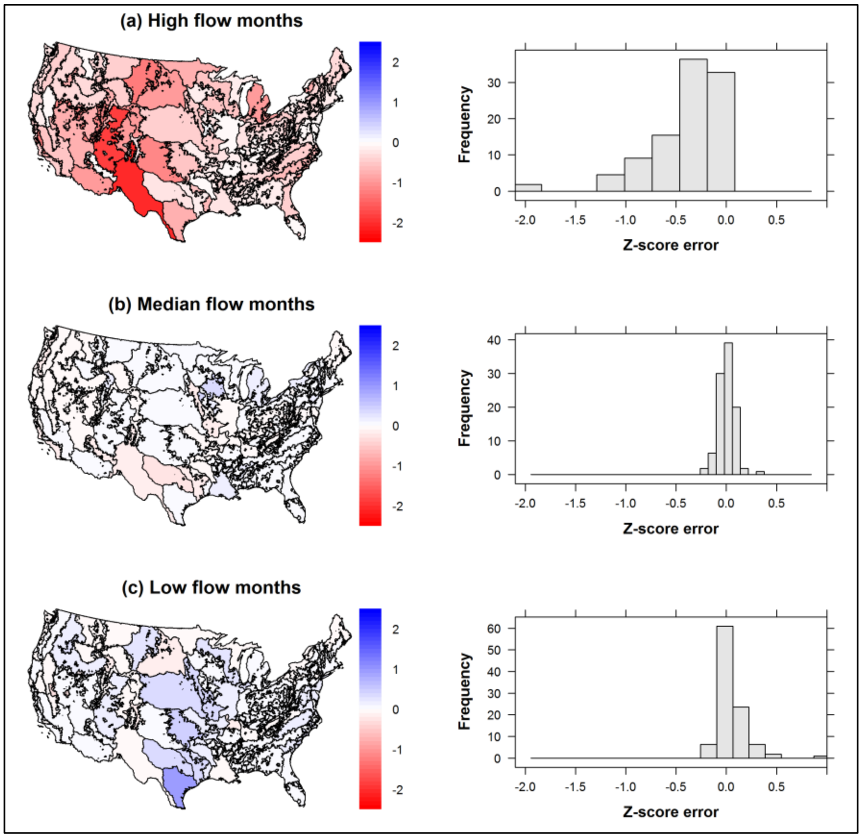


Figure 12. Z-score error (simulated - measured) for (a) highest-, (b) median-, and (c) lowest-flow months.

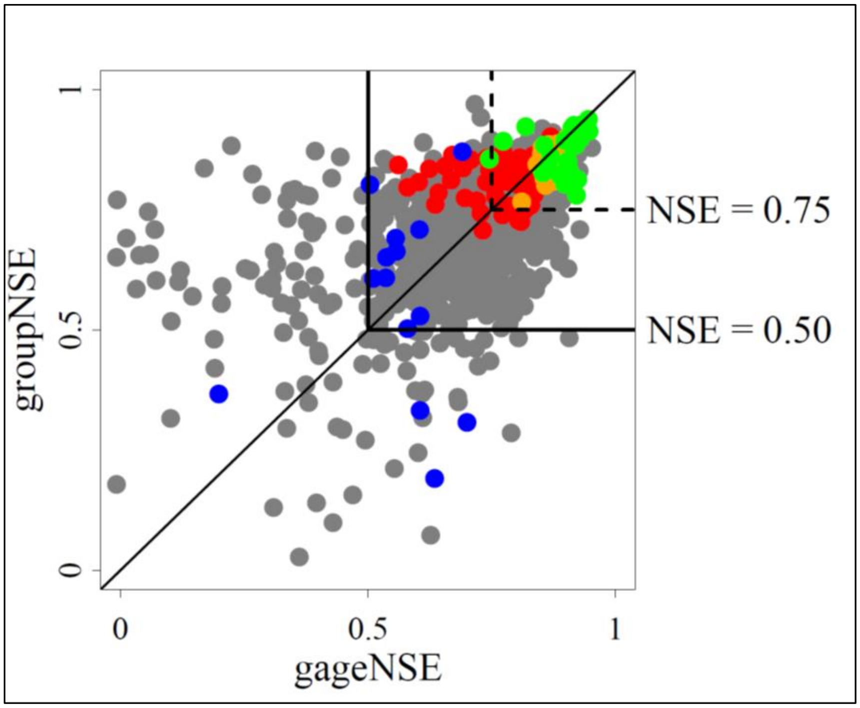


Figure 13. Nash Sutcliffe Efficiency from individual (gageNSE) and grouped (groupNSE) calibration. Calibration regions in New England (67 streamgages, red); Tennessee River (21 streamgages, orange); Platte Headwaters (15 streamgages, blue); and Pacific Northwest (33 streamgages, green) are highlighted (see Fig. 10b for location).

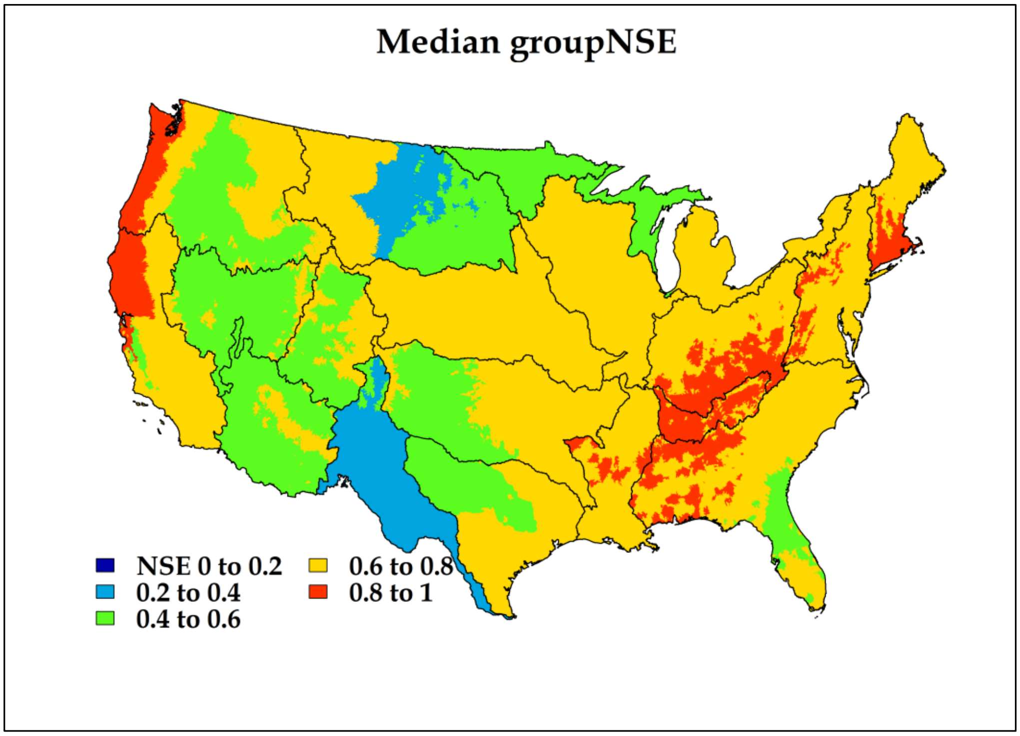


Figure 14. Median Nash Sutcliffe Efficiency (NSE) by calibration region of streamgages used for~~by~~ calibration ~~region~~.

Comment [Bock48]: Added clarification to caption based on ref. 2 comments: "-p. 10058 and 10066, Figure 6 and Figure 14 are not that clear. It is understandable after reading the text, but it could be much improved"