Consolidated Replies to Online Comments

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1 Introduction

In this document, we respond to each comment raised by the reviewers. The revised manuscript is attached.

2 Reply to RC1 - John Doherty

We appreciate Dr. Doherty's encouraging review. We have made substantial revisions to improve the grammar the revised submission. Regarding the choice of subjective likelihood function, it is possible that a more QOI-focused likelihood function could be found and applied to yield a greater decrease in QOI-5. The 3-component likelihood function was selected because it is used widely within the hydrologic modeling community and we were interested in assessing "common practice" in the simulation of brush management.

3 Reply to RC2 - Patrick Belmont

We appreciate Dr. Belmont's review and we agree that parameterization is an often overlooked but critical aspect of model usage.

1. *P3 Line 14: Im okay with the authors mostly referring readers to the 2011 paper for information about the study area. However, it would be helpful to include at least mean annual precipitation and temperature. A brief explanation of the seasonal pattern of rainfall would also be helpful. Readers should not have to look up another paper for this basic information.* We added a brief description of the average annual rainfall to the manuscript.

2. *P4 Line 12: The technique used to spatially average the precipitation data should be specified.* The precipitation data were combined via arithmetic

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averaging to yield a complete (filled), 5-minute precipitation record for the model. We added this information to the manuscript

3. *P4 Line 18: Did you evaluate how well the NCEP data correspond to your instrumental measurements for time periods during which your instruments were functioning properly? Documenting the error for days on which rainfall occurred would be useful.* We agree that the NCEP data may in fact be of lower quality and accuracy compared to the site-specific precipitation data. We did not specifically evaluate the error in the NCEP data, however, we did treat precipitation inputs as uncertain in the analysis, which should account for error in the NCEP precipitation estimates, among other errors. We have added this information to the manuscript.

4. *P6 Line 30: The authors could provide more explanation of the advantages and disadvantages of these two types of parameterization.* The only advantage of using the reduced parameterization is the improved computational demand required to implement an automated calibration. However the disadvantage of the reduced are numerous, including under-estimation of uncertainty in quantities of interest (as we show). The full parameterization requires more sophisticated and programmatic approaches to calibration, but includes that added benefit of an improved ability to express model input uncertainty. We have added similar language to the text.

5. *P 8 Line 30: Are these midpoint values the same as the default values for SWAT2012? If so, thats fine: : :its what most modelers would do, but the authors may want to clarify this point. If not, some justification is needed for using these values rather than the default values.* The midpoint of the basin-scale parameters excluded from the reduced parameterization does not necessarily correspond exactly to the values yielded by ArcSWAT. However, these midpoint values are still within the range of "acceptable" as defined by literature sources and site-specific expert knowledge. Additionally, for all HRU and precipitation multipliers (the vast majority of parameters in the full parameterization), the midpoint is 1.0, which essentially removes there affects from the analysis. We have added similar language to the text.

6. *P 9 Line 9: Each of these measures quantify slightly different components of model performance. The authors might want to include 1-2 sentences to explain the differences between the three and advantages of using all three.* We have added a brief description of the utility of NSE, percent bias and coefficient of determination as an objective function and how using these three measures together increases their effectiveness at identifying realizations the reproduce several aspects of the conditioning period observed streamflow.

7. *P 10 Line 6: This is still a very large number of realizations. It would be useful to know how many of them are effectively duplicates of one another. Also, it could be helpful to modify the conditioning measures to*

select for a narrower range of runs. Each of these realizations were drawn stochastically from the Prior distribution—Figure 3 in the manuscript shows how these realizations fit the three conditioning measures. The number of behavioral realizations is function of the conditioning measures and the size of the prior ensemble. That is, we could reduce the size of the behavioral ensemble by simply reducing the size of the prior ensemble. Furthermore, we feel the thresholds we selected for the three conditioning measures are appropriate and also commensurate with current hydrologic modeling practice. We note that requiring realizations to pass very strict conditioning measures risks overfitting with respect to the QOIs.

8. *P 11 Line 14: I agree with the authors that the possibility of a net increase is not entirely unexpected. Recognizing that the cutoff thresholds for the evaluation measures were somewhat arbitrary (if in line with most other literature) it would be interesting to know if the realizations that indicate an increase in ET are eliminated if stricter evaluation measures are applied.* We agree with Dr. Belmont that an increase in ET following brush management is not entirely unexpected and that stronger conditioning (through application of more strict conditioning measure thresholds) may affect the behavioral distribution of QOI-5. However, as shown on figure 8, conditioning of the full parameterization model has shifted the distribution slightly *towards* the positive ET region, although, in general, the behavioral distribution is only slightly affected by conditioning. Therefore, we would speculate that "tighter" conditioning measures would not eliminate the possibility of a simulated net increase in ET following brush management.

4 Reply to RC3 - Lieke Melsen

We appreciate the review by Dr. Melsen, especially the remarks regarding the value of the ET data.

1. *Daily discharge observations are used for a catchment of 1.4 km2, I guess the response time of the catchment is much shorter than this daily time step. In this way, probably some essential hydrological processes cannot be captured in the calibration- procedure. How do you think this affects your results?* We also recognize that our model is operating a lower temporal frequency than the actual watershed. Indeed, all models of natural systems are simplifications and must operate at lower spatial and temporal frequencies than the natural systems they simulate. However, we would speculate that this form of model simplification is not adversely affecting our results for the following reasons:

    (a) the focus of the modeling analysis is long-term water budget components

(b) both parameterizations reproduce observed streamflow acceptably well

(c) both parameterizations reproduce conditioning and forecast period verification QOIs

It is possible that higher-resolution conditioning data might condition additional parameters compared to the daily streamflow data. However, this conditioning is likely limited to parameters that influence high-frequency runoff generation processes, not necessarily parameters that influence long-term water budget components.

2. *Like I said before, I think it is an interesting study with interesting results that is probably representative for many modeling studies in which the uncertainty is underestimated. I do think, however, that maybe a more thoughtful calibration could potentially improve the results (I am not sure, of course; calibration is not a panace. Furthermore, the calibration-procedure applied in this study is probably representative for current modeling practice). I would be interested to see this in the discussion of the paper.* We agree with Dr. Melsen that a more "thoughtful" objective function could possibly yield a narrow behavioral distribution for QOI-5. However, we specifically select the three conditioning measures formulated from daily streamflow observations based on their wide-spread use on the hydrologic modeling community. We have added some discussion to this affect to the manuscript.

3. *Concerning the sensitivity analysis (p.5, l.28-29); I agree with the authors that selecting model parameters for calibration is often subjective. However, I think the common path in modeling is to conduct a sensitivity analysis (which is the subjective part, because; global or local method? which parameters to include? what parameter boundaries?), and based on that identify the parameters for calibration, whereas the authors chose a different approach; first select the parameters, and after that conduct a sensitivity analysis. Could you explain why you chose this procedure? Furthermore, for the readability, I would suggest to move section 2.7 to earlier in the methods, especially because you start with the sensitivity analysis in the results.* We appreciate this comment and have added to the manuscript to clarify this process and have reordered the sections of the manuscript. In short, we chose to use GSA to investigate which (uncertain) model inputs influence the conditioning measures (the calibration), the QOIs (the purpose of the model) or both. By including most (if not all) uncertain model inputs in the GSA and investigating both the conditioning and model purpose (e.g., QOIs) with GSA, practitioners can gain a clearer understanding of which model inputs are important for reproducing the past as well as which model inputs are important to simulate the QOIs.

4. *Last point; You have ET data at your disposal. This provides a great opportunity to use ET for your calibration. I would be really interested to see*

how the selection of behavioral parameter sets would be influenced if you add an ET-criterion, and how this would affect the QOIs related to ET. This does not require any additional calculations and potentially you could make a strong case to increase ET observations in order to improve the modeling of land-use change impacts (in other words; you could provide constructive suggestions to decrease the uncertainty. Or not, dependent on the results). Maybe this extra exercise it not really necessary in order to provide sufficient body for a paper, but it certainly could provide a strong message. We agree with Dr Melsen that the conditioning period ET may provide valuable conditioning of the parameters that influence QOI-5. We plan to address the value of the ET data for conditioning in another manuscript focused on dataworth analyses for this modeling analysis. However, we have added an additional paragraph to the discussion that also address the importance and potential value of the ET data.

5 Reply to RC5 - Tammo Steenhuis

We appreciate Dr Steenhuis' review. While Dr Steenhuis indicated the manuscript was "poorly written", we note that the other reviewers did not have issue with the construction or organization of the manuscript beyond some minor grammatical mistakes. We also note the model was conditioned with streamflow and validated with ET and streamflow under changed land-use conditions.

1. *Streamflow is simulated using the Green and Ampt approach that is likely marginally sensitive to differences in amount of water evaporated by the plants either with trees or without trees. The variation in conductivity due to crust formation is likely a much more sensitive parameter The other words overland flow cannot be used for estimating evaporation. Baseflow could be used, but it is not clear from the article if any baseflow separation was done. Moreover, overland flow once generated during the most intense part of the storm might infiltrate down the hill (Stomph et al 2012) that is not simulated by SWAT while it may greatly affect the amount of surface runoff. Finally, the rainfall could be highly variable over the watershed affecting the runoff greatly with the Green and Ampt approach. The authors took the average precipitation of four stations. At a minimum it should have been investigated if using the four precipitation measurements could have better described the streamflow that the brush management.* While Dr. Steenhuis points to several potential structural problems with SWAT as well as other potential conceptualizations of the system. Agreed, no model is perfect and SWAT has limitations that have been well documented in the literature. Indeed, one of the focuses of our study was to quantify the uncertainty using common, industry-standard tools/approaches so that our results have a wider applicability., Nonetheless, several thousand realizations from both the reduced and full parameterization models that fit the conditioning-period streamflow exceptionally well, according

to commonly-accepted metrics. Furthermore, despite these shortcomings, the behavioral distributions from both parameterizations reproduce the two verification QOIs well.

2. *The authors write Note that many of the most influential parameters, specifically precipitation multipliers, plant growth parameters, and HRU scale parameters, are not in the reduced parameterization and are not included in typical hydrologic modeling analyses (Arnold et al., 2012b) Because other not experienced users do it wrong that is not a good reason not too include the parameters describing the system. Of course, under these circumstances the model fails with this reduced parameter set. Using this set of parameters does not advance science as is expected from a published manuscript.* Firstly, we do not feel that referring to all of the cited works in Arnold (2012) as "not experienced" is a fair or constructive comment. To our knowledge, all of the works cited in Arnold (2012) were subjected to peer review and are of high quality. As stated in the manuscript, we selected the reduced parameterization based on standard, current modeling practice. We then show that, indeed, the reduced parameterization is able to fit the observed conditioning-period streamflow well according to common metrics. We feel this is a validation of current modeling practice in as much as the reduced parameterization can reproduce the past. Our point is that just because the reduced parameterization reproduces the past streamflow doesn't indicate the reduced parameterization model is acceptable for robust simulation of the QOIs.

3. *The authors never question a priori the suitability of the SWAT model whether there is a chance that the model could simulate differences in evaporation based on the streamflow record before going through all the calculations and essentially proving that the SWAT model was not suitable for this problem. Would the authors have chosen an appropriate model that can simulate plant and root development together with evaporation, the results could be completely different and likely much more accurate. The article is all about parameters uncertainty while model uncertainty should have been investigated as well at a minimum.* As previously noted, both parameterization are able to fit the conditioning-period acceptably well according to commonly-accepted metrics. Furthermore, the SWAT model has emerged recently as a popular tool for simulating many hydrologic processes (beyond brush management and land-use change) For example, see `https://www.card.iastate.edu/swat_articles/citations-list/`

The importance of parameterization when simulating the hydrologic response of vegetative ~~land cover~~ land-cover change

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Abstract. Computer models of hydrologic systems are frequently used to investigate the hydrologic response of ~~land cover~~ land-cover change. If the modeling results are used to inform resource-management decisions, then providing robust estimates of uncertainty in the simulated response is an important consideration. Here we examine the importance of parameterization, a necessarily subjective process, on uncertainty estimates of the simulated hydrologic response of ~~land cover~~ land-cover change. Specifically, we applied the soil water assessment tool (SWAT) model to a 1.4 km^2 watershed in south Texas to investigate the simulated hydrologic response of brush management (the mechanical removal of woody plants), a discrete ~~land cover~~ land-cover change. The watershed was instrumented before and after brush-management activities were undertaken and estimates of precipitation, streamflow, and evapotranspiration (ET) are available; these data were used to condition and verify the model. The role of parameterization in brush-management simulation was evaluated by constructing two models, one with 12 adjustable parameters (reduced parameterization) and one with 1,305 adjustable parameters (full parameterization). Both models were subjected to global sensitivity analysis ~~,~~ as well as Monte Carlo and generalized likelihood uncertainty estimation (GLUE) conditioning to identify important model inputs and to estimate uncertainty in several quantities of interest related to brush management. Many realizations from both parameterizations were identified as "~~behavorial~~behavioral" in that they reproduce daily ~~average~~ mean streamflow acceptably well according to Nash-Sutcliffe model efficiency coefficient, percent bias, and coefficient of determination. However, the total volumetric ET difference resulting from simulated brush management remains highly uncertain after conditioning to daily ~~average~~ mean streamflow, indicating that streamflow data alone are not sufficient to inform the model inputs that most influence the simulated outcomes of brush management. Additionally, the reduced-parameterization model grossly underestimates uncertainty in the total volumetric ET difference compared to the full-parameterization model; total volumetric ET difference is a primary metric for evaluating the outcomes of brush management. The failure of the reduced-parameterization model to provide robust uncertainty estimates demonstrates the importance of parameterization when attempting to quantify uncertainty in ~~land cover~~ land-cover change simulations.

1 Introduction

Keywords

– brush management

- ~~land cover~~ land-cover change
- uncertainty analysis
- parameterization
- SWAT

Highlights

- simulated outcome of brush management, a ~~land cover~~ land-cover change, is largely uncertain
- a large number of model inputs influence the simulated outcomes of brush management
- level of parameterization does not affect fit to daily mean streamflow data
- level of parameterization does affect uncertainty estimates in quantities of interest

An important use ~~of~~ for computer models of hydrologic systems is simulation of the hydrologic response of ~~land cover~~ land-cover change (Fohrer et al., 2001; DeFries and Eshleman, 2004); many modeling analyses have been undertaken in attempt to better understand how changes in land cover may change the timing and quantity of runoff, recharge, and evapotranspiration (e.g., Schilling et al. (2014); Ahn and Merwade (2017); Chu et al. (2010)). Given the uncertainties that exist in nearly every hydrologic model input dataset, the potential exists for the simulated outcomes to be highly uncertain, even after conditioning to streamflow data. Given this potential uncertainty in model outcomes, quantifying uncertainty in the simulated results of ~~land cover~~ land-cover change is an important consideration, especially if simulation results are to be used in resource management decision making.

Previous research has shown that the subjective process of selecting which model inputs to treat as uncertain (e.g. parameterization) may affect uncertainty estimates in model outcomes (White et al., 2014). Herein, parameterization refers to the subjective and necessary process of selecting uncertain model inputs to treat as adjustable in the conditioning process. We investigate how parameterization may affect the uncertainty quantification process when simulating a discrete, vegetative ~~land cover~~ land-cover change, the mechanical removal of woody plants.

Woody plant encroachment into grasslands has been a worldwide phenomena in the past 150 years (Archer et al., 2011). This encroachment has several ramifications to the ecosystem, including changes to the hydrologic function and response of the surface-water basins (Archer et al., 2011). Woody species are commonly thought to ~~be a larger consumer~~ consume a larger quantity of water (by ~~plant transpiration) ,~~ transpiration) in comparison to native grasses (Tennesen, 2008). By removing the woody species and allowing native grasses to reestablish in the area (commonly referred to as "brush management"), changes in the hydrology in the watershed might occur (U.S. Department of Agriculture, 2009).

Many hydrologic modeling analyses have been completed to evaluate the feasibility of applying brush management in order to decrease the quantity of water transpired within a ~~basin~~given watershed. (Ben Wu et al., 2001; Lemberg et al., 2002; Brown and Raines, 2002; Afinowicz et al., 2005; Bumgarner and Thompson, 2012; Harwell et al., 2016). However, to date (2017), very few, if any, of the modeling-based, brush management feasibility studies have included uncertainty estimation in the simulated hydrologic response of brush management, even though substantial uncertainty in other applications of ~~SWAT-based hydrologic modeling~~ the soil water assessment tool (SWAT) model have been reported (Gassman et al., 2014).

To demonstrate the utility of including uncertainty estimation and to investigate how parameterization may affect the reliability of a model to resolve the hydrologic outcomes of simulated ~~land cover~~ land-cover changes, such as brush management, the soil water assessment tool (SWAT) (Arnold et al., 1998) was applied to a 1.4 km^2 watershed in South Texas. The ~~watershed has been the focus of previous investigations (Banta and Slattery, 2011); estimates of~~ same watershed assessed in this study was subject of a previous investigation in which multiple types of data (precipitation, streamflow, and ~~ET are available~~evapotranspiration [ET]) were collected (Banta and Slattery, 2011). The objectives of ~~this~~ our study are to (1) assess the reliability of a computer model to simulate pre- and post-treatment water budget components in the context of uncertainty, and (2) evaluate the role of model parameterization in the uncertainty estimation process by investigating the number of model inputs that influence the important model outputs.

1.1 Hydrologic Setting

The brush-management simulation described herein is applied to a 1.4 km^2 watershed in the Honeycreek State Natural Area in South Texas (Figure 1). For a complete description of the study area, see Banta and Slattery (2011)~~(note~~. Note the watershed analyzed in this study is referred to as the "treatment watershed" in Banta and Slattery (2011)~~)~~.

According to Banta and Slattery (2011), long-term average precipitation near the watershed is 34 inches per year and is equally distributed throughout the calendar year. The watershed generally has gentle slopes (less than 5 percent) with steeper slopes in the stream channel ravines. ~~The clay~~ Clay and clay loam soils overlie the Trinity aquifer outcrop ~~,~~ in the watershed; the Trinity aquifer is a regional karst aquifer system ~~. Prior to treatment, the study area~~ (Banta and Slattery, 2011). Before brush management was implemented, the watershed was largely dominated by ~~ashe juniper (Juniperus ashei). For the watershed studied in this analysis, approximately~~ Juniperus ashei (ashe juniper). Approximately 40% of the ~~land covered by predominately ashe juniper~~ ashe juniper land cover was mechanically cleared from the watershed during calendar year 2004 (Homer et al., 2007). ~~Following ashe juniper~~ The watershed configuration before removal of 40% of the ashe juniper is referred to as the "pre-treatment" configuration. Following ashe-juniper removal, the land returned to a native rangeland ~~land cover type~~ land-cover type (referred to hereinafter as the "post-treatment" configuration).

2 Model Construction

The SWAT model was used to simulate the hydrologic response of the watershed, including the effects of brush management. Specifically a SWAT2012 (Arnold et al., 2012b, a) model of the watershed was built using the ArcSWAT tool (Winchell et al., 2007). The resulting model files were incorporated into the model-independent framework of PEST++ V3 (Welter et al., 2015) to facilitate programmatic interaction with the model so that any model input quantity could be treated as a parameter and a variety of model outputs, including derived and processed quantities, can be included in the modeling analysis.

2.1 Datasets

Three datasets were needed to apply the ArcSWAT tool (Winchell et al., 2007), which discretized the watershed into hydrologic response units (HRUs):

- digital elevation model: The 10m National Elevation Dataset (NED) (Maune et al., 2007)
- soil data: The Soil Survey Geographic Database (SSURGO) (Staff, 2016)
- land-cover type: The National Land Cover Database (NLCD) (Homer et al., 2007)

These three datasets were used within the ArcSWAT tool to find unique land slope/soil/land cover combinations across the watershed. These unique combinations became HRUs in the SWAT model. ~~Note the~~ The NED digital elevation model for the watershed was smoothed with a 4-pixel width averaging kernel to remove apparent artifacts.

As part of ~~a previous study evaluating~~ the previous study that evaluated the effects of brush management at the Honey Creek State Natural Area (Banta and Slattery, 2011), daily total precipitation and ~~evapotranspiration (ET)~~ET, and daily ~~average~~ mean streamflow were measured during ~~2001 through 2010~~ 2001–10 (Figure 2)~~(for additional discussion of the methodology~~. The methods used to collect the input datasets ~~, see Banta and Slattery (2011))~~are described in Banta and Slattery (2011). The precipitation data were used as inputs to the SWAT model ~~while~~ whereas the ET and streamflow data were used for conditioning and model evaluation (described below). Because the SWAT model is sensitive to precipitation intensity, the original 5-minute measurements from four precipitation measurement stations in the study area were combined via arithmetic averaging to develop the precipitation input dataset—the averaging was needed to account for missing data ~~due to instrument issues and~~ caused by instrument issues in order to form a complete precipitation dataset. The National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) (Saha et al., 2014) Global Weather Database was used in the SWAT simulation as the input for weather data when on-site precipitation data were not available (Banta and Slattery, 2011). To account for errors induced by averaging precipitation data ~~,~~ and the use of lower-resolution NCEP precipitation data, we treat precipitation as uncertain; the treatment of model inputs as uncertain is discussed in detail ~~Parameterization section below~~in the Parameterization section.

2.2 ArcSWAT

The ArcSWAT tool (Winchell et al., 2007) was used with the previously-described datasets to constructed a SWAT2012 model of the watershed. Surface runoff is simulated with SWAT using the Green-Ampt excess rainfall method (Mein and Larson, 1973; Jeong et al., 2010).

The NLCD 2001 (Homer et al., 2007) land-cover data were modified so that areas of mixed brush-rangeland within the watershed were reclassified as rangeland, which is consistent with site-specific knowledge (Banta and Slattery, 2011).

The application of the ArcSWAT tool with the previously-described datasets resulted in a model with a single subbasin covering the 1.4 km^2 watershed study area with 47 distinct HRUs (Figure 1). A summary of the HRU characteristics is included in Table S1 of the supplementary material; the detailed HRU characteristics obtained by applying the ArcSWAT tool are included in the associated data release (White et al., 2017).

2.3 Model Configurations

The modeling analysis described herein includes two specific simulation periods that correspond to the pre-treatment and post-treatment ~~time periods~~configurations:

- **conditioning period:** 1 ~~Jan~~ January 2002 to 31 ~~Dec~~ December 2003 (pre-treatment ~~watershed conditions~~configuration)
- **forecast period:** 1 ~~Jan~~ January 2005 to 31 ~~Dec~~ December 2010 (post-treatment ~~watershed conditions~~configuration)

~~Note that~~ The conditioning period and forecast period models simulate years 2001 and 2004, respectively; the initial year of simulation for each model is used as a model warm-up period to remove any transient artifacts from initial conditions.

In a typical modeling feasibility study, the model is constructed and ~~calibrated~~ conditioned to pre-treatment (conditioning period) system states, then forecasts are made using the model related to how simulated brush management will affect the hydrology within the watershed.

Here, two distinct SWAT ~~model datasets were constructedto simulate the~~ models were constructed. The first SWAT model simulated the pre-treatment ~~(conditioning period) and~~ configuration and is hereinafter referred to as the “pre-treatment” model. The second SWAT model simulated the post-treatment ~~(forecast period) watershed conditions~~configuration and is hereinafter referred to as the “post-treatment” model. The only difference between the two SWAT models are specific inputs to HRUs 18, 20, 22, 32, which represented the area of watershed that was converted from evergreen forest (e.g., ashe juniper) to rangeland. Modifications to the input files for the listed HRUs were (herein, references to specific SWAT input variables are shown in all caps):

- maximum canopy interception - the CANMX variable in the .HRU input files
- plant growth cycle - the PLANT_ID and HEAT_UNITS variables in the .MGT input files

In this study, brush management is simulated by modifying the maximum canopy storage and inputs that control the simulated growth cycle for a representative area of the subbasin from evergreen forest to rangeland because this required few assumptions and allowed injection of the desired uncertainty into the simulation workflow. We modified the maximum canopy storage and the plant growth aspects of HRUs 18, 20, 22, and 32 ~~since~~ because these inputs directly affect the available precipitation for partitioning and simulated ET processes, respectively, ~~while plant growth parameters~~ whereas plant-growth variables affect the timing and intensity of simulated ET processes related to the annual ~~plant growth~~ plant-growth cycle. In the pre-treatment model, these model inputs were specified to represent ashe juniper land cover for HRUs 18, 20, 22, 32, ~~while~~ whereas in the post-treatment model, these inputs for HRUs 18, 20, 22, 32 were specified to represent rangeland land cover, effectively capturing the change in the simulated inputs that corresponds to the brush-management operations that occurred during 2004. See the SWAT theory (Neitsch et al., 2011) and input-output documentation (Arnold et al., 2012a) for more information on ~~these inputs .~~ the model inputs listed in the .HRU and .MGT files.

2.4 Parameterization

Parameterization is a critical part of any modeling analysis and has received considerable attention in the literature (Abbaspour et al., 2004; Romanowicz et al., 2005; Sexton et al., 2011; Zhenyao et al., 2013; Migliaccio and Chaubey, 2008; Cibin et al., 2010; Gitau and Chaubey, 2010; Du et al., 2013; Malone et al., 2015; Zhang et al., 2016). In this analysis, we investigated two parameterization designs:

- **reduced parameterization** uses the 12 model inputs listed on Table 1 of Arnold et al. (2012b) ~~as~~ to represent model input uncertainty. These 12 model inputs are the most cited SWAT model inputs ~~chosen for conditioning~~ treated as parameters when simulating surface-water runoff and ~~baseflow processes (Table 1). This~~ base-flow processes (Arnold et al., 2012b). The reduced parameterization was, therefore, representative of many SWAT modeling analyses in the literature. For the reduced parameterization model, inputs were adjusted at the ~~subbasin scale — that~~ watershed scale—that is, all 47 HRUs receive the same value for each of these 12 model inputs ~~. See Table 1for a listing of the reduced parameterization~~(Table 1).

- **full parameterization** used 1,305 model inputs. It builds on the 12 parameters of the reduced parameterization by adding unique multiplier parameters at the HRU scale for each of the 12 parameters in Table 1, and also includes many other model inputs that are not typically adjusted, albeit still uncertain, such as soil properties, and inputs that govern the simulation of plant growth, such as leaf area index (LAI) variables. The full parameterization also includes annual quartile precipitation multipliers to account for uncertainty and potential bias in precipitation estimates (Leta et al., 2015; Renard et al., 2011; Kavetski et al., 2006; Kuczera et al., 2006). See Table S1 of the Supplementary Material for a ~~listing~~ summary of the full parameterization and the associated data release (White et al., 2017) for a complete description of the full parameterization.

These two parameterizations represent ~~two~~ different approaches to hydrologic modeling. From a computational standpoint, the reduced parameterization is more desirable, ~~while~~ whereas the full parameterization offers the opportunity for a more complete expression of model input uncertainty.

The SWAT input CANMX is of particular importance in simulating brush management because it controls how much precipitation is available for partitioning, and it is directly affected by ~~land cover~~ land-cover changes. Therefore, CANMX potentially exhibits a strong control of the simulated outcomes of brush management. CANMX is not treated as uncertain in the reduced parameterization as it is not commonly treated as adjustable (Arnold et al., 2012b). However, CANMX is included in the full parameterization and ~~as~~ is parameterized as follows (herein, references to specific parameters are shown in italics):

- the parameter *canmx_v* represents the maximum canopy storage for evergreen forest land-cover type HRUs;

– the parameter *canmxfac_07* represents the portion of *canmx_v* that is applied to deciduous forest land-cover type HRUs; and

– the parameter *canmxfac_15* represents the portion of *canmx_v* that is applied to rangeland land-cover type HRUs.

In this way, we can incorporate uncertainty in the values of CANMX for all three land-cover types while also enforcing the relations we expect for the maximum canopy storage between the land cover types. This treatment for CANMX allows both the ~~pre-treatment~~ pre- and post-treatment models to receive the same parameter values ~~. Since~~ for the same land-cover types. Because HRUs 18, 20, 22 and 32 switch from evergreen land cover to rangeland land cover, the CANMX values assigned to these HRUs is in harmony with the CANMX values assigned to other HRUs. ~~Note that the~~ The HRUs-scale multipliers, named *canmx_XX*, where *XX* is the HRU number, still account for HRU-scale variability in CANMX for HRUs of the same land cover type. ~~The~~ In the reduced parameterization, the parameters *canmx_v*, *canmxfac_07* and *canmxfac_15* are specified values of 13.0 mm, 0.625 times 13.0 mm (8.13 mm) and 0.25 times 13.0 mm (3.25 mm), respectively, which corresponds to the midpoint of the respective parameter ranges.

The ~~specified parameter ranges from a~~ upper and lower bound of each parameter was defined using a combination of literature values (Abbaspour, 2015; Douglas-Mankin et al., 2010) and expert knowledge. Collectively, the upper and lower bounds of each parameter forms a multivariate uniform distribution (hereinafter ~~after~~ referred to as the ~~Prior parameter distribution), which~~ "Prior"). Conceptually, the "Prior" is the distribution of "acceptable" parameter values based on hydrologic system knowledge. ~~We note that defining a Prior is a necessarily subjective process; the Prior, summarized in the Supplementary Material, was defined using a combination of literature values (Abbaspour, 2015; Douglas-Mankin et al., 2010) and expert knowledge. The specified range~~ The upper and lower bound of each parameter is summarized in Table S1 of the Supplementary Material; The upper and lower bounds of the reduced parameterization are distilled on Table 1.

~~Using~~

2.5 Model interface

Both the pre- and post-treatment ~~models~~ SWAT models must be evaluated repeatedly to simulate hydrologic outcomes of brush management and evaluate the importance of parameterization in said outcomes. To accomplish this repeated evaluation, a model-independent interface to SWAT was constructed. This interface facilitated the translation of parameter values into SWAT model inputs files, the execution of both the pre- and ~~the two parameterizations, the~~ post-treatment SWAT models, and the post-processing of SWAT model output into quantities of interest.

To translate parameter values to SWAT model input files, parameters were assigned two characteristics:

1. Scale: a given parameter is either subbasin scale or HRU scale. Subbasin-scale parameters are applied to all 47 HRUs, whereas an HRU-scale parameter applies only to a specific HRU.

2. Type: a given parameter is either a multiplier-type parameter or a value-type parameter. Multiplier-type parameters are treated as scaling factors against the original SWAT model input variable(s), whereas value-type parameters replace the original SWAT model input variables(s).

The following steps represent a single model ~~forward run:~~ evaluation in the model interface:

1. Construct two“base” tables of HRU-scale inputs where the columns are the SWAT model inputs names and the rows are the 47 HRUs (one table for the pre-treatment model and one table for the post-treatment model). Populate these tables with the base input values from the ArcSWAT ~~process for both the pre- and post-treatment models~~tool.

2. ~~for each “value”-type basin-scale~~ For each value-type, subbasin-scale parameter, replace the values in the base tables for each corresponding column with the specified parameter value, assigning all HRUs the same value.

3. For each ~~“multiplier”-type basin-scale~~ multiplier-type, subbasin-scale parameter, multiply the corresponding column of the base tables by the specified parameter value, scaling all HRUs by the same value.

4. ~~apply~~ Apply *canmx_v*, *canmxfac_07* and *canmxfac_15* parameters to the CANMX column of both base tables according to the land cover type of each HRU using the previously-described relation between these parameters.

5. For each ~~“multiplier”-type~~ multiplier-type, HRU-scale parameter, multiply the corresponding row-column location in the base tables by the specified parameter value, scaling only a single entry in the table.

6. ~~translate~~ Translate the base tables into the appropriate SWAT input files for both the ~~pre-treatment~~ pre- and post-treatment models.

7. ~~apply~~ Apply precipitation multiplier parameters and write a new SWAT .PCP input file (Arnold et al., 2012a).

8. ~~apply plant growth~~ Apply plant-growth multiplier parameters and write a new SWAT ~~plant growth~~ plant-growth database file.

9. Run the pre-treatment model for ~~the time period~~ 2001 through 2010 (the pre-treatment model outputs are needed from ~~2005-2010~~ 2005–10 for calculation of brush-management quantities of interest).

10. Run the post-treatment model for ~~the time period~~ 2004 through 2010.

11. Post-process both model runs to formulate brush-management quantities of interest and conditioning measures (described ~~below~~in the Evaluation of Brush Management Simulations section).

The forward run process was completed many times as part of both the global sensitivity analysis and the uncertainty analysis (described in the Evaluation of Brush Management Simulations) . For the reduced parameterization, the HRU-scale parameters, precipitation parameters, and plant growth parameters were ~~specified~~ each assigned a value of 1.0, effectively removing ~~these parameters~~the influence of these parameters on the model outputs.

2.6 Evaluation of Brush Management Simulations

We used uncertainty quantification techniques to investigate how well the previously-described SWAT models simulate the effects of brush management on long-term water budget components. Specifically, ~~we use~~ after applying the global sensitivity analysis (GSA) method of Morris (Morris, 1991) (hereinafter referred to as the “method of Morris”), we used Monte Carlo analysis (MC) in conjunction with Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992) ~~conditioning~~ to construct prior and behavioral distributions for several model outputs that are important to simulating the outcomes of brush management, which we term quantities of interest (QOIs).

2.7 Quantities of Interest

Output from both the pre- and post-treatment model was processed into QOIs that encompass the simulated pre- and post-treatment long-term water budget components in the simulated watershed:

- **QOI-1:** volumetric conditioning-period (pre-treatment) ET-precipitation ratio
- **QOI-2:** volumetric conditioning-period (pre-treatment) streamflow-precipitation ratio
- **QOI-3:** volumetric forecast-period (post-treatment) ET-precipitation ratio
- **QOI-4:** volumetric forecast-period (post-treatment) streamflow-precipitation ratio
- **QOI-5:** volumetric forecast-period difference between the simulated treated and untreated watershed

The work of Banta and Slattery (2011) includes daily mean streamflow and daily total ET for the watershed during the forecast (post-treatment) period, which means measured values for QOI-1 through QOI-4 are available. Post-treatment streamflow measurements as well as pre- and post-treatment ET measurements are not available in most real-world applications of modeling to support brush management activities. Therefore, we treat QOI-1 through QOI-4 as verification measures to check how well the model reproduces long-term water-budget components, measures that are related to simulating the feasibility of brush management.

QOI-5 is the primary quantity we use to evaluate the effectiveness of brush management: how does the simulated long-term volumetric ET change as a result of brush management? QOI-5 is simulated by running the pre- and post-treatment models for 2004 to 2010 and summing the differences in simulated ET between the two simulations.

2.8 Monte Carlo and GLUE

Monte Carlo analysis (MC) (Tarantola, 2005) was used to investigate ~~how~~ the effects of SWAT model input uncertainty ~~influences~~ on brush-management QOIs. MC was chosen because it employees few assumptions and because the forward model run time is relatively short.

To perform the MC analysis, a one-million parameter set ensemble was drawn ~~using the prior, uniform distribution~~ from the “Prior” for each of 1,305 elements of the full parameterization using the python module pyEMU (White et al., 2016)~~(See~~

~~the Supplementary Material for the~~. Note the upper and lower bound of each parameter ~~)~~are provided in the data release (White et al., 2017) and are summarized in Table S1 in the Supplementary Material. Once the prior parameter ensemble was constructed, the SWEEP utility of the PEST++ software suite (Welter et al., 2015) was used to run the pre- and post-treatment SWAT models for each of the one million realized parameter sets in a distributed, parallel environment using the steps ~~outlined previously~~described in the Model Interface section. The result of this process yielded one million values for each of the conditioning measures and brush-management QOIs.

The reduced parameterization was evaluated in a similar fashion. The ~~full parameterization~~ full-parameterization prior ensemble was modified so that the value of ~~parameters~~ each parameter that was not included in reduced parameterization ~~were~~ was fixed at the value representing the midpoint of the ~~associated~~ parameter's range. In this way, parameters not included in the full parameterization were treated as if they were not in the analysis and are instead "fixed" or "known" model ~~inputs–just~~ inputs—just as they would be treated in a modeling analysis that only adjusted the 12 inputs of the reduced parameterization. ~~Note that while~~ Whereas the midpoint values of the fixed parameters may not be "best" in the sense that they reduce model-to-measurement misfit, they are nonetheless centered within the range of plausibility as described by the ~~prior parameter distribution~~"Prior".

The ~~reduced parameterization~~ reduced-parameterization prior ensemble was also evaluated using the SWEEP utility in a distributed parallel environment, yielding one million values for each of the conditioning measures and brush-management QOIs.

Once the prior ensembles of both the reduced and full parameterizations were evaluated, the GLUE method of Beven and Binley (1992) was used to condition the prior ensembles. The GLUE method was selected because it accommodates a subjective likelihood function, which allows the conditioning process to be flexible and can simultaneously accommodate several criteria (Beven and Binley, 1992). In this study, the ~~behavior~~ behavioral parameter ensembles are a subset of prior parameter ensembles which meet three criteria (~~also known~~ herein referred to as conditioning measures). Following Moriasi et al. (2007), we selected the following conditioning measures, which are based on daily ~~average~~ mean streamflow, to form the behavioral ensemble:

- **CM-1** conditioning-period (pre-treatment) Nash-Sutcliffe ~~efficiency~~ model efficiency coefficient (NSE) > 0.75
- **CM-2** conditioning-period (pre-treatment) percent bias $< 5\%$
- **CM-3** conditioning-period (pre-treatment) coefficient of determination (R^2) > 0.85

These conditioning measures are widely used to judge a hydrologic model's ability to reproduce observed daily ~~average~~ mean streamflow (Moriasi et al., 2007). Briefly, NSE is a statistic that determines the relative magnitude of simulated residual variance to the observed variance (Nash and Sutcliffe, 1970). Percent bias measures the tendency of the model to systematically over or under simulate the observed data, ~~while~~ whereas the coefficient of determination measures the colinearity between simulated and observed pairs. By using all three of these conditioning measures simultaneously, ~~we are seeking inputs to the model that~~ the parameter realizations that "best" reproduce different facets of the observed streamflow data are identified.

Realizations in ~~the each of~~ each of the prior ensembles that satisfied all three of conditioning measures are designated as "behavioral" and, taken together, comprise the reduced and full parameterization behavioral ensembles, respectively. ~~The~~ These behavioral ensembles represent parameter realizations that respect the ~~Prior~~ "Prior" but that also reproduce daily ~~average stream flow~~ mean streamflow acceptably well according to the three conditioning measures. That is, each parameter ~~set~~ realization in the full- and reduced-parameterization behavioral ensembles can be considered "calibrated" in that each of these parameter ~~sets~~ realizations results in simulated daily ~~average~~ mean streamflow that acceptably match the observed data according to the three conditioning measures.

2.9 Global Sensitivity Analysis

Given the ~~drastic~~ large difference in the number of parameters between the reduced (12) and full (1,305) parameterizations, the interested reader may be wondering how many of members of the reduced and full parameterizations influence either the conditioning measures or the QOIs or both. In an effort to address this question, we employed the ~~global sensitivity analysis (GSA)~~ method of Morris (Morris, 1991) ~~, which is known as~~ which is a "one-at-a-time" GSA method; each parameter is varied, in turn, across the specified range, effectively sampling the sensitivity of QOIs and conditioning measures across parameter space. We used the model independent implementation of the method of Morris ~~(Morris, 1991)~~ encoded in GSA utility of the PEST++ software suite ~~(Welter et al., 2015)~~ (Morris, 1991; Welter et al., 2015) with 20 discretization points across the range of each parameter.

2.10 ~~Quantities of Interest~~

~~There are several quantities, derived from simulation results, which we term quantities of interest (QOIs), that encompass the simulated pre- and post-treatment long-term water budget components in the simulated watershed:~~

~~volumetric conditioning-period (pre-treatment) ET-precipitation ratio volumetric conditioning-period (pre-treatment) streamflow-precipi ratio volumetric forecast-period (post-treatment) ET-precipitation ratio volumetric forecast-period (post-treatment) streamflow-precipitation ratio volumetric forecast-period difference between the simulated treated and untreated watershed~~

~~The work of Banta and Slattery (2011) includes daily average streamflow and daily total ET for the watershed during the forecast (post-treatment) period, which means "measured" values for QOI-1 through QOI-4 are available. Post-treatment streamflow measurements as well as pre- and post-treatment ET measurements are not available in most real-world applications of modeling to support brush management activities. Therefore, we treat QOI-1 through QOI-4 as verification measures to check how well the model reproduces long-term water-budget components, measures that are related to simulating the feasibility of brush management.~~

~~QOI-5 is the primary quantity we use to evaluate the effectiveness of brush management: how does the simulated long-term volumetric ET change as a result of brush management. QOI-5 is simulated by running the pre- and post-treatment SWAT models for the time period 2004 to 2010 and summing the differences in simulated ET between the two simulations. Note that only difference between the pre-treatment and post-treatment models is the simulated land cover and CANMX values for HRUs 18, 20, 22, and 32.~~

3 Results

The application of the ~~GSA~~ method of Morris ~~Morris (1991)~~ (Morris, 1991) reveals a considerable number of model inputs that influence the conditioning measures as well as the designated brush-management QOIs. Furthermore, the combined Monte Carlo and associated GLUE-based conditioning process (MC-GLUE) analysis reveals a relatively large difference in the estimated range of QOI-5 between the ~~full~~ reduced and full parameterization models.

3.1 Global Sensitivity Analysis

Of the 1,305 model inputs treated as parameters, the method of Morris analysis indicates only 194 parameters are non-influential to the three conditioning measures and five brush-management QOIs (See the Supplementary Material for a complete summary of the GSA results, including a table of the five most influential parameters for each QOI and conditioning measure [Tables S2 and ~~reduced parameterization models~~S3]). Note that many of the most influential parameters, specifically precipitation multipliers, plant growth parameters, and HRU-scale parameters, are not in the reduced parameterization and are not included in typical hydrologic modeling analyses (Arnold et al., 2012b).

3.2 Monte Carlo

~~The Monte Carlo and associated GLUE-based conditioning process (~~MC-GLUE ~~)~~ analysis yielded 7,155 and 6,846 realizations (out of the 1 million member prior ensembles) that ~~comprise~~ compose the behavioral ensembles for the reduced and full parameterizations, respectively. These behavioral ~~realizations~~ ensembles reproduce the pre-treatment daily ~~average~~ mean streamflow data acceptably well according to the three conditioning measures. The relation of prior and behavioral ~~relation among~~ ensembles to the three conditioning measures for ~~both~~ the reduced and full parameterizations can be seen graphically on Figure 3. ~~Figure 3 shows the conditioning measure results from running the full- and reduced-parameterization 1-million member ensembles each of the three conditioning measures.~~ The diagonal panes of Figure 3 show the histograms of each ~~of~~ the ~~3~~ three conditioning measures, ~~while~~ whereas the off-diagonal panes ~~showthe~~ show the relation between conditioning measures. Parameter realizations within the hatched boxes on Figure 3 collectively form the behavioral ensembles for both the ~~full-~~ reduced and ~~reduced-parameterization.~~

full parameterization.

3.3 ~~Global Sensitivity Analysis~~

~~Of the 1,305 model inputs treated as parameters, the method of Morris analysis indicates only 194 parameters are non-influential to the 3 conditioning measures and 5 brush-management QOIs (See the Supplementary Material for a complete summary of the GSA results, including a table of the 5 most influential parameters for each QOI and conditioning measure). Note that many of the most influential parameters, specifically precipitation multipliers, plant growth parameters, and HRU-scale parameters, are not in the reduced parameterization and are not included in typical hydrologic modeling analyses (Arnold et al., 2012b).~~

3.2.1 Verification QOIs

In general, for both the reduced and full parameterizations, the behavioral distributions for ET-based QOIs (QOI-1 and QOI-3) are similar to ~~the respective~~ prior distributions; conditioning has slightly shifted the distributions towards larger ~~values of~~ precipitation-ET ratios but has not substantially decreased the width of the distributions. The similarity between prior and behavioral ~~ensembles~~ distributions indicates the conditioning process has not changed the uncertainty that exists in model simulated ET. The prior and behavioral ~~ensembles~~ distributions of reduced and full parameterizations bracket ~~, at the 95% confidence level, the~~ the measured value for ~~verification~~ QOI-1, QOI-2 and QOI-3 at the 95% confidence level (Figures 4, 5, and 6).

QOIs related to streamflow (QOI-2 and QOI-4) have markedly different behavioral distributions compared to ~~priors~~prior distributions, indicating considerable conditioning of streamflow-sensitive parameters. The measured value for QOI-4 ~~,~~ (volumetric forecast-period ~~(~~[post-treatment~~)~~] streamflow-precipitation ratio~~, was not captured~~) was not bracketed at the 95% confidence level by either behavioral distribution or the prior distribution of the reduced parameterization (Figure 7).

3.2.2 ~~forecast~~ Forecast QOI

The prior uncertainty in the QOI-5 ~~, the simulated~~ (the simulated difference between the total forecast-period ET ~~difference between the treated and untreated watershed,~~ in the pre- and post-treatment models) was substantially larger for the full parameterization compared to the reduced parameterization (Figure 8): the reduced parameterization prior uncertainty ranged from approximately -4.1 ~~%~~ to -2.1%~~while~~, whereas the full parameterization model yielded a prior uncertainty that ranged from approximately -7.5 ~~%~~ to +0.5%. Note a negative ET difference indicates a decrease in ET as a result of simulated brush management. The larger range yielded by the full parameterization is a direct outcome of specifying more uncertain parameters that influence QOI-5.

QOI-5 behavioral uncertainty from the reduced parameterization is substantially different than the prior ~~and included values only in the range~~ uncertainty; the 95% confidence interval of the reduced parameterization behavioral distribution ranges from -2.5 to -2.0%. The behavioral ~~uncertainty in~~ distribution of QOI-5 yielded by the full parameterization is similar to the prior distribution, but shifted slightly towards positive values~~, ranging~~; the 95% confidence interval of the full parameterization behavioral distribution ranges from -6.2 to +0.5% (Figure 8~~A~~a). Only slight differences between the prior and behavioral distributions for the full parameterization, again, indicate the selected conditioning process did not substantially change the reliability in simulated long-term changes in ET as a result of brush management. We attribute the differences in QOI-5 distributions between the ~~full and reduced~~ reduced and full parameterizations to the model error generated by using a reduced set of parameters to represent SWAT model input uncertainty. Note the prior distribution for the reduced parameterization was also non-parametric compared to the full parameterization counterpart, a numerical artifact we also attribute to the model error induced by the reduced parameterization.

4 Discussion

The full-parameterization behavioral distribution of QOI-5 included a range of possible outcomes from a net decrease to a slight net increase in the ET component of the long-term water budget (Figure 8). This ~~is a direct outcome of~~ range of possible outcomes stems from the number of model inputs that were identified as uncertain and treated as parameters in the MC-GLUE analysis. The possibility of a net increase in ET following brush management is not ~~an unexpected or unprecedentedresult~~ unprecedented. Harwell et al. (2016) showed a net decrease in surface-water yield following simulated brush-management activities for one of their simulated subbasins. Furthermore, we have demonstrated that conditioning ~~/calibration~~ of a hydrologic model to daily ~~average~~ mean streamflow does not necessarily increase the reliability of forecasts made with the model.

~~We must stress that the results of our analysis can not be directly extrapolated to hydrologic settings that are dissimilar to the one described herein. However, this study has clearly demonstrated~~ This study demonstrates the importance of robust uncertainty quantification to support simulations of brush management, and, more generally, simulating the hydrologic outcomes of ~~land cover~~ land-cover change. Without uncertainty quantification, the ~~results~~ simulated outcomes of simulating brush management are simply ~~a single point~~ single points on the behavioral QOI distributions, which conveys no information related to the reliability of the model results. The failure of the reduced-parameterization model to provide robust uncertainty estimates demonstrates the importance of parameterization when attempting to quantify uncertainty in ~~land cover~~ land-cover change simulations. The results of our analysis should not be directly extrapolated to other hydrologic settings that are different from the one described herein.

The MC-GLUE analysis showed that using a reduced parameterization to represent model input uncertainty leads to a misrepresentation and critical underestimation of the uncertainty in QOI-5, leading to artificially high confidence that brush-management activities will decrease the ET component of the water budget by approximately 2.0 to 2.5%. By including a more representative and complete set of parameters to ~~capture~~ represent model input uncertainty, the resulting QOI-5 uncertainty estimate more appropriately conveys the reliability in the modeled outcome of brush management.

A clear link between level of parameterization and uncertainty estimates for the simulated results of brush management has been demonstrated, and issues ~~, such~~ such as underestimation of uncertainty and numerical artifacts ~~,~~ are shown to be associated with a reduced parameterization. Furthermore, the results of applying the ~~GSA~~ method of Morris ~~(Morris, 1991)~~ revealed more than 1,100 model inputs that were identified as uncertain and that also influence conditioning measures, QOIs or both. Following Sexton et al. (2011), parameters that influence the QOIs must be included in the uncertainty analysis, even if said parameters do not influence the likelihood function (e.g., they are not "identified" by the conditioning data). The demonstrated issues with the level of parameterization raise questions related to the concept of "overparameterization" (Jakeman and Hornberger, 1993) in the context of simulating the hydrologic outcomes of ~~land cover~~ land-cover change. Each of the inputs that were selected for adjustment in the full-parameterization model were deemed uncertain at the start of the modeling analysis; ~~while~~ whereas other practitioners may choose different prior distributions and/or ranges for these parameters, we doubt any practitioners would state these model inputs are known with ~~absolute~~ certainty.

There are two avenues to reduce QOI-5 uncertainty: ~~either~~ (1) collect information directly about the model ~~inputs~~ input variables that most influence ~~QOI-5–reduce~~ QOI-5—that is, reduce the prior uncertainty of the parameters that represent these ~~inputs—or~~ inputs or (2) collect additional hydrologic observations that, through conditioning, reduce the uncertainty of parameters that influence QOI-5. We recognize that the ET observation data used to formulate QOI-1 could in fact be used as a condition measure. Given the similarity between QOI-1 and QOI-5, it is possible that the conditioning period ET data ~~would~~ could be used to further condition several parameters that influence QOI-5, thereby reducing the behavioral uncertainty of QOI-5. However, ~~these~~ the conditioning-period ET data provide a valuable validation of the model's performance, and using these data as a conditioning measure would provide unique and atypical conditioning.

~~We recognize that specifying how brush management is simulated requires some subjectivity, which is part of the necessary subjectivity inherent in environmental modeling, and we recognize that others have used different strategies to simulated brush management with SWAT. In this study, brush management is simulated by modifying the maximum canopy storage and inputs that control the simulated growth cycle for a representative area of the subbasin from evergreen forest to rangeland because this required few assumptions and allowed injection of the desired uncertainty into the simulation workflow.~~

5 Conclusions

This study provided an analysis of the ability of ~~the~~ a SWAT model to forecast how brush management affects the long-term water balance within a watershed~~has been undertaken~~. The analysis relies on measured streamflow and independently-derived evapotranspiration estimates to condition the parameterized model inputs as well provide a verification of the model's performance during the forecast period. The ~~global sensitivity analysis~~ method of Morris ~~(Morris, 1991) global sensitivity analysis (GSA) technique~~ was used to investigate model input influence on conditioning measures and brush-management quantities of interest (QOIs). Following the ~~GSA~~method of Morris, Monte Carlo and GLUE analyses were used to estimate the uncertainty of brush-management QOIs for the reduced and full parameterization schemes~~, respectively~~.

~~The~~ Our analysis reveals the importance of robust uncertainty quantification when simulating the outcomes of brush management, especially as it relates to how the model is parameterized. Failure to specify a complete and encompassing parameterization is shown to lead to an underestimation of uncertainty in simulated brush-management outcomes, which may lead to suboptimal water resource decision making.

Given the number of identified uncertain model inputs and the associated specified uncertainty in said inputs, the model-simulated change in the long-term ET in the watershed is largely uncertain and includes a range of possible outcomes from a net negative to a slightly net positive change in long-term ET component of the water budget. The resulting uncertainty in one of the primary metrics of brush-management effectiveness underscores the importance of robust and conservative uncertainty quantification. Watersheds with different hydrologic response characteristics will obliviously behave differently, but, if modeling is used to evaluate brush-management outcomes, robust uncertainty quantification is needed to place the model results in a representative context.

~~6 Code availability~~

~~The python scripts used to generate the prior ensembles and to post-process the ensembles are included in the model archive.~~

6 Data availability

~~The ET, precipitation and streamflow data used for conditioning and verification are available for download as the appendices to Banta and Slattery (2011) at the U. S. Geological Survey Publication Warehouse ()~~

~~The model archive for this analysis includes all~~

A data release that supports the analyses presented herein is available at https://doi.org/10.5066/F7WH2NGR (White et al., 2017). The data release includes files and data ~~used as part of this study and is available for download at !!!to be released concurrent with publication!!!. The model archive includes:~~ needed to reproduce our analyses, including:

1. ESRI ArcMAP 10.2.2 project that includes the ArcSWAT version 2012.10.2.18 project used to create the base model

2. base SWAT2012 input files generated by the ArcSWAT tool

3. PEST++ interface files including python pre- and post-processing scripts

The comma-separated value files ~~of parameters and QOIs for prior ensembles of both the full and reduced parameterizations~~ used in the reduced and full parameterization Monte Carlo can be generated from the files provided in the data release (White et al., 2017). The ET, precipitation, and streamflow data used for conditioning and verification are available for download as the appendixes to Banta and Slattery (2011) at the U.S. Geological Survey Publication Warehouse (http://pubs.usgs.gov/sir/2011/5226/)

~~Supplementary Material include: HRU summary table parameter description table GSA method of Morris top 5 list GSA method of Morris summary table~~

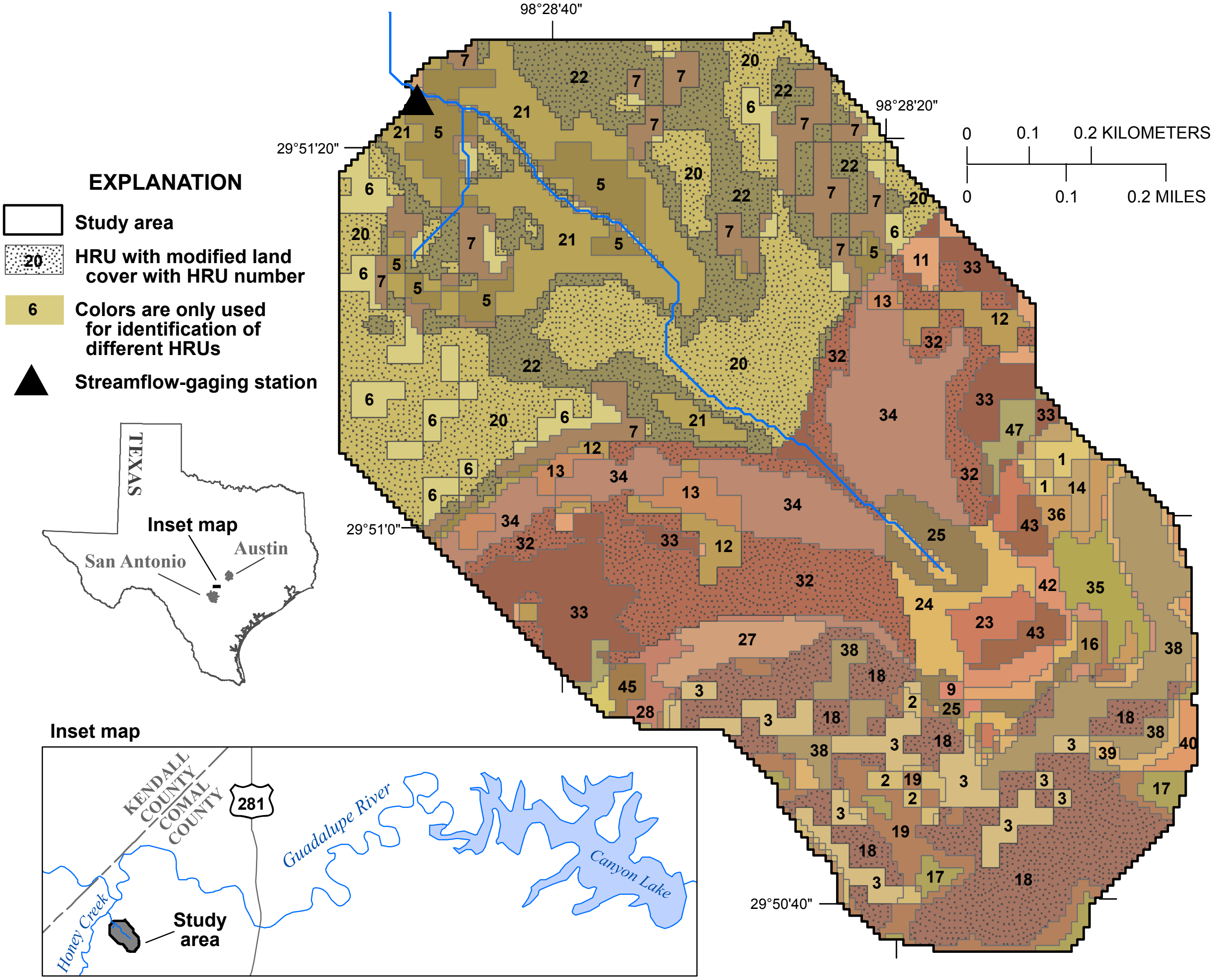

Figure 1. Study area and watershed location. The 47 HRUs yielded by the ArcSWAT tool (Winchell et al., 2007). The model inputs of HRUs 18, 20, 22, and 32 (stippled pattern) were modified to simulate the brush-management activities. Streamflow-gaging station (U.S. Geological Survey streamflow-gaging station 08167353) is on an unnamed stream. Base map from U.S. Geological Survey digital data, 1:24,000 Universal Transverse Mercator projection, Zone 15 North American Datum of 1983.

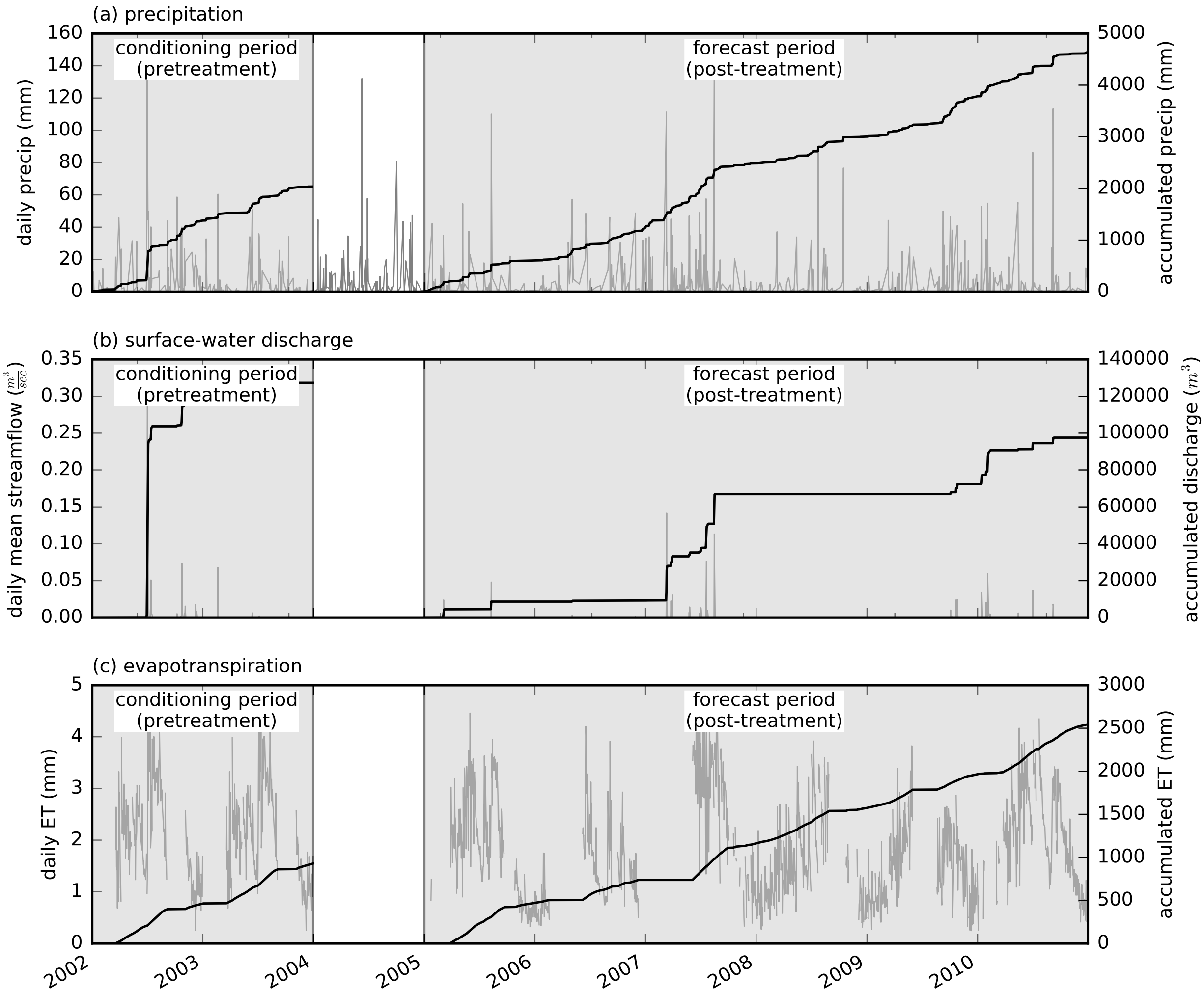

Figure 2. Summary of (a) precipitation, (b) streamflow, and (c) evapotranspiration used in the modeling analysis. Accumulated values for the conditioning and forecast period are shown in heavy black lines. Precipitation, streamflow and evapotranspiration estimates are from Banta and Slattery (2011).

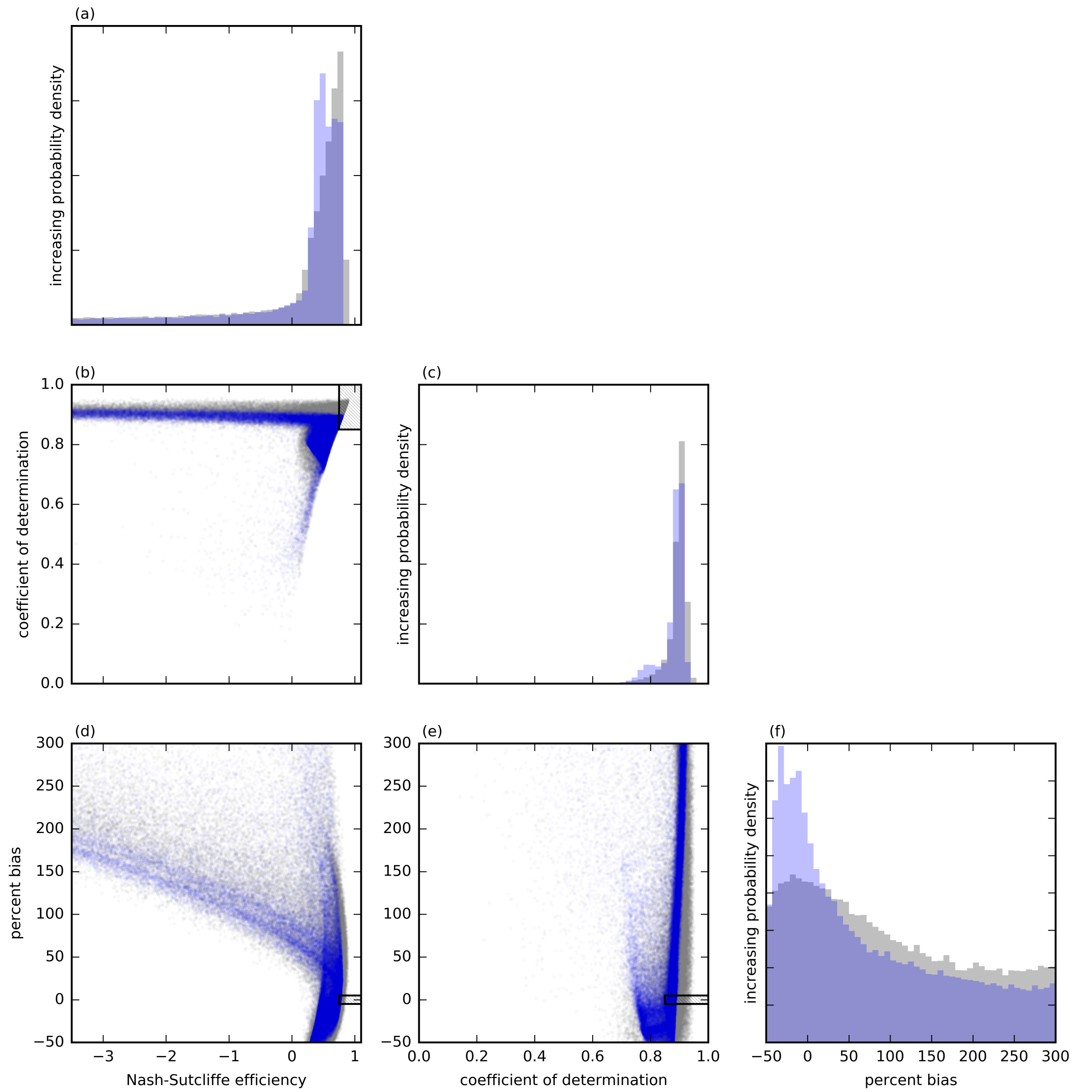

Figure 3. Values of conditioning measures for the full (gray) and reduced (blue) parameterizations. The diagonal panes (~~(~~[a~~)~~], ~~(b)~~[c], and ~~(c~~[f]) ~~)~~show distribution of each conditioning measure; the off-diagonal panes (~~(~~[b~~)~~], ~~(~~[d~~)~~] and ~~(~~[e]) ~~)~~show the relation between respective conditioning measures. The hatched boxes mark the 3-dimensional behavioral region; realizations within the hatched boxes comprise the behavioral ensembles of each parameterization.

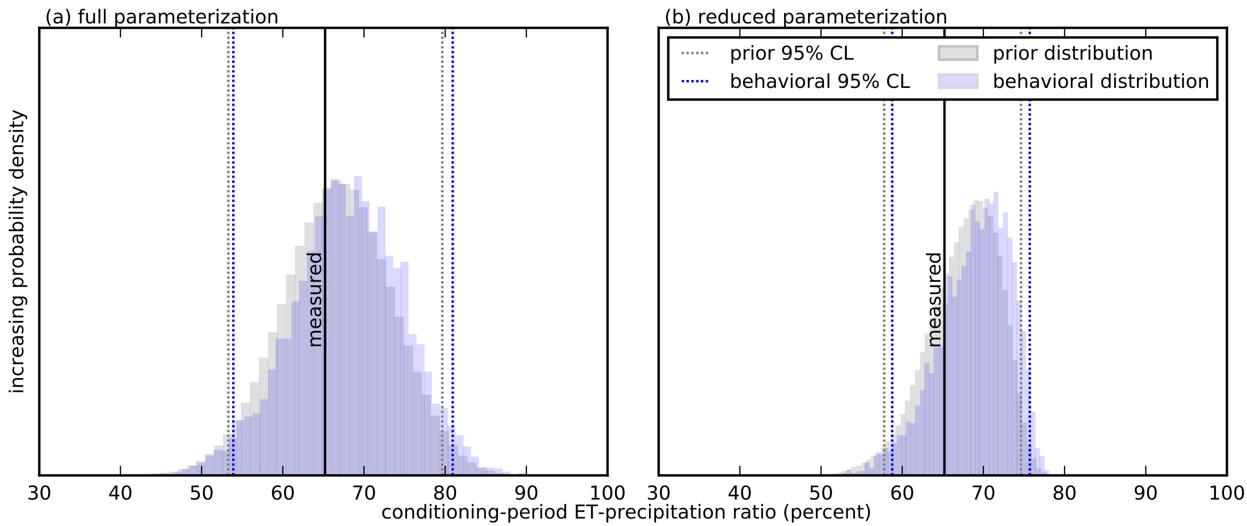

Figure 4. Quantity of interest QOI-1: Simulated conditioning period (pre-treatment) ET as a percentage of precipitation. The prior and behavioral ~~distributions of~~ 95% confidence intervals—defined by the confidence limits (CL)—of both model parameterizations ~~capture~~ bracket the measured value. However, the conditioning process has little affect on uncertainty as the behavioral distribution is similar to the prior distribution.

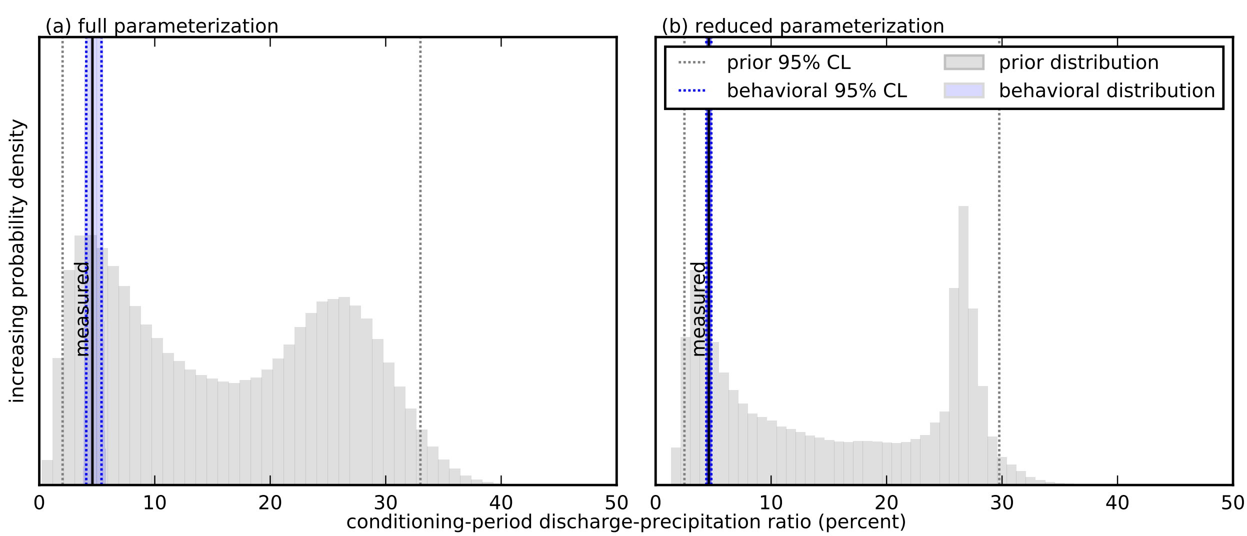

Figure 5. Quantity of interest QOI-2: Simulated conditioning period (pre-treatment) streamflow as a percentage of precipitation. The effects of the conditioning process can be seen as large reduction in the range of the behavioral distribution compared to the prior distribution. The prior and behavioral distributions for model parameterizations bracket the measured value.

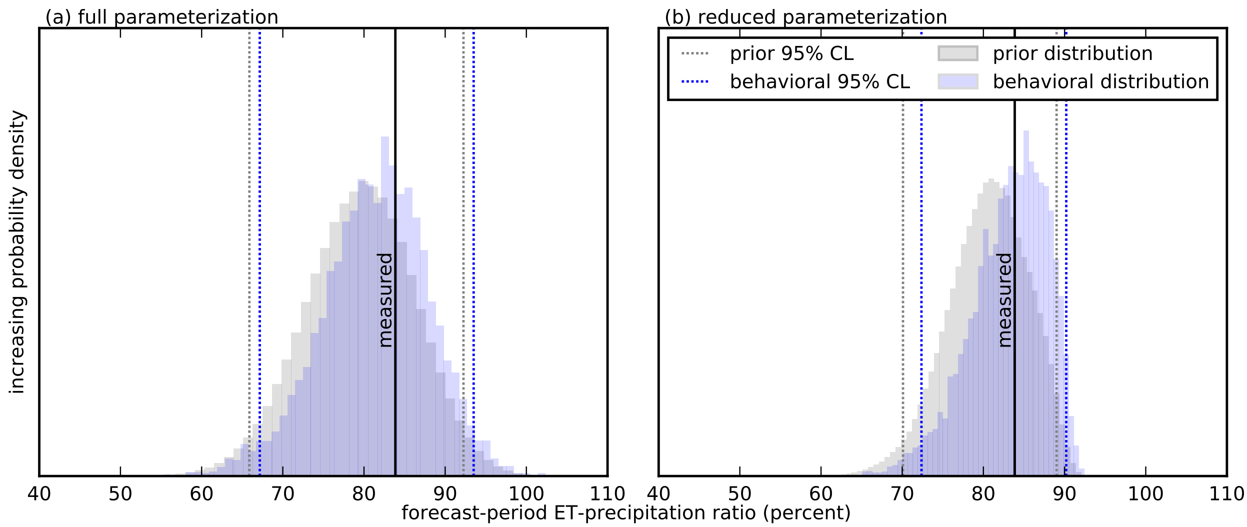

Figure 6. Quantity of interest QOI-3: Simulated forecast period (post-treatment) ET as a percentage of precipitation. All 95% confidence intervals ~~capture~~ bracket the measured value. However, the conditioning process has done little to decrease uncertainty as the behavioral distributions are similar to the prior distributions for both model parameterizations.

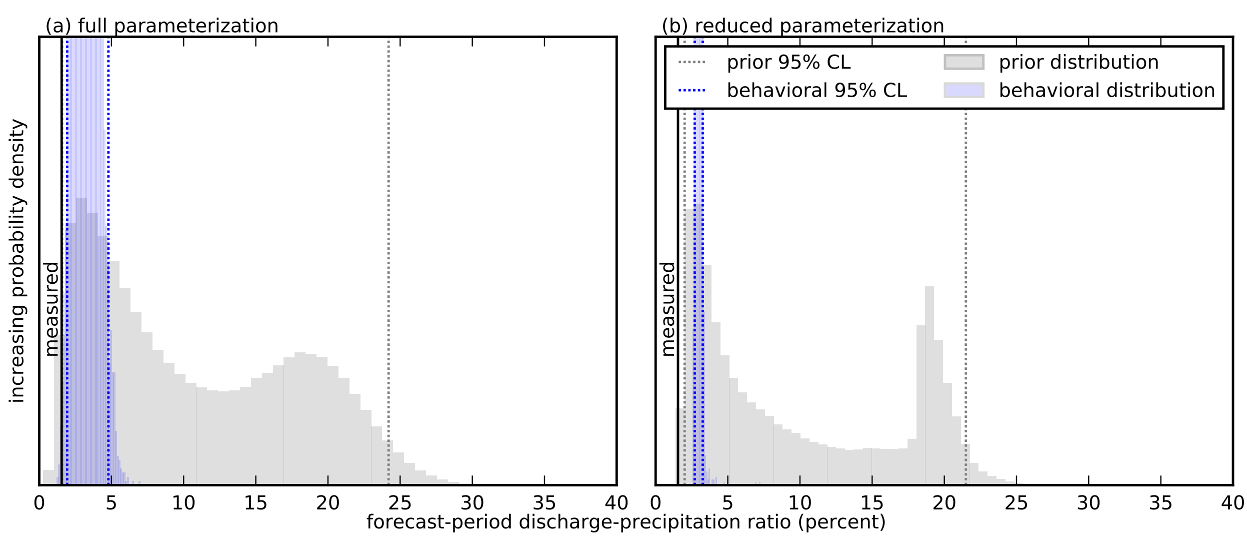

Figure 7. Quantity of interest QOI-4: Simulated forecast period (post-treatment) streamflow as a percentage of precipitation. Both the parameterizations appear to have been “overfit” with respect to this QOI as both behavioral distributions do not ~~capture~~ bracket the measured value at the 95% confidence level.

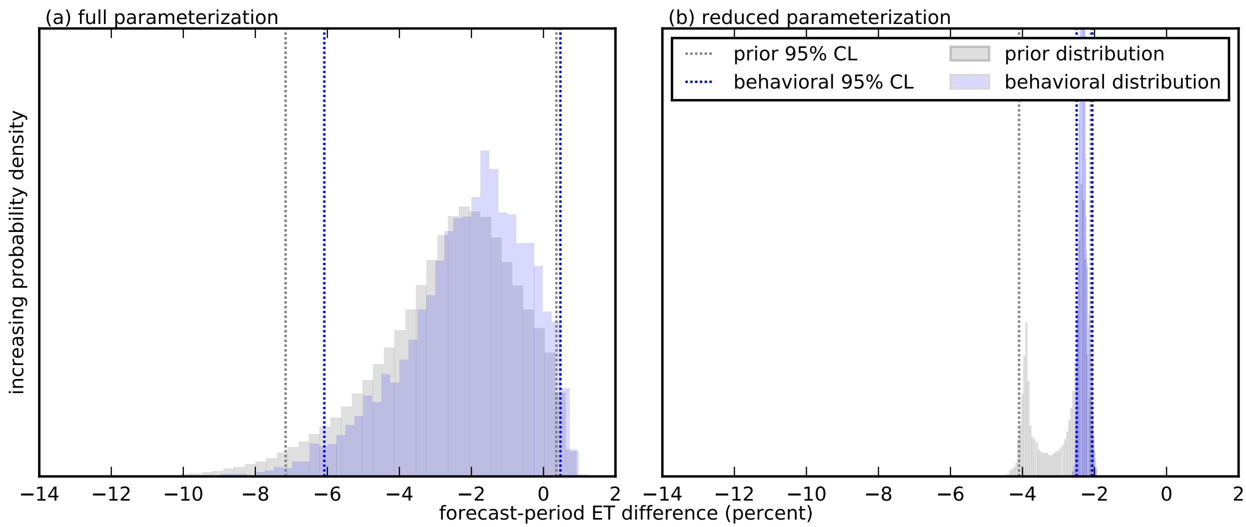

Figure 8. Quantity of interest QOI-5:Simulated difference in total forecast period (post-treatment) ET volume as a result of brush management. Negative values indicate a decrease in ET as a result of brush management. The reduce parameterization yields a much narrower confidence interval compared to the full parameterization.

Table 1. Summary of parameters used in the reduced parameterization. These 12 inputs were selected from Table 1 in Arnold et al. (2012b) and are adjusted at the sub-basin scale.

~~control file name~~ Parameter	~~type~~ Type	~~lower~~ Lower bound	~~upper bound~~ Upper Bound	~~description~~ Description (with units if applical
alpha_bf_v	value	0.10	0.50	subbasin baseflow alpha factor ($\frac{1}{day}$
cn2_r	multiplier	0.50	1.50	subbasin soil moisture condition II curve num
epco_v	value	0.50	0.98	subbasin plant uptake compensation fa
esco_v	value	0.50	0.98	subbasin soil evaporation compensation fa
gw_delay_v	value	10.00	300.00	subbasin groundwater delay time (da
gw_revap_v	value	0.02	0.40	subbasin groundwater 'revap' coeffic
gwqmn_v	value	500	4000	subbasin groundwater threshold return flow depth (n
ov_n_r	multiplier	0.50	1.50	subbasin overland flow Manning's
rchrg_dp_v	value	0.25	0.75	subbasin deep aquifer percolation fa
revapmn_v	value	100	1000	subbasin groundwater threshold 'revap' depth (n
sol_awc_1_r	multiplier	1.00	5.00	subbasin soil available water capacity ($\frac{mm}{mm}$mm
surlag_v	value	2.00	12.00	subbasin surface runoff lag coeffic

Author contributions. S. Rendon and V. Stengel gathered datasets and applied the ArcSWAT tool to prepared the SWAT model input files with help from J. Banta. J. White subjected the ArcSWAT model inputs files to the global sensitivity analysis and combined Monte Carlo GLUE analysis. J. White prepared the manuscript with contributions from all coauthors.

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