



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

Jeremy White¹, Victoria Stengel¹, Samuel Rendon¹, and John Banta¹

¹U.S. Geological Survey, Austin TX, 78754

Correspondence to: Jeremy White (jwhite@usgs.gov)

Abstract. Computer models of hydrologic systems are frequently used to investigate the hydrologic response of land-use 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-use change. Specifically, we apply the soil water assessment tool (SWAT) model to a 1.4 km² watershed in south Texas to investigate the simulated hydrologic response of brush management (the mechanical removal of woody plants), a discrete land-use change. The watershed was previously 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, 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 “behavioral” in that they reproduce daily streamflow acceptably well according to Nash-Sutcliffe, percent bias and coefficient of determination. However, the total volumetric ET difference resulting from simulated brush management remains highly uncertain after conditioning to daily 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-use change simulations.

1 Introduction

Keywords

– brush management



- land-use change
- uncertainty analysis
- parameterization
- SWAT

5 Highlights

- simulated outcome of brush management, a land-use 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 streamflow data
- level of parameterization does affect uncertainty estimates in quantities of interest

10 An important use of computer models of hydrologic systems is simulation of the hydrologic response of land-use change (Fohrer et al., 2001; DeFries and Eshleman, 2004); many modeling analyses have been undertaken in attempt to better understand how changes in land-use may change the timing and quantity of runoff, recharge, and evapotranspiration (See Schilling et al. (2014); Ahn and Merwade (2017); Chu et al. (2010), among others). Given the uncertainties that exist in nearly every hydrologic model input, the potential exists for the simulated outcomes to be highly uncertain, even after conditioning
15 to streamflow data. Given this potential uncertainty in model outcomes, uncertainty quantification in the simulated results of land-use 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). Here we investigate how parameterization may
20 affect the uncertainty quantification process when simulating a discrete, vegetative land-use 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 of water (by plant
25 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).

To that end, many hydrologic modeling analyses have been completed to evaluate the feasibility of brush management to decrease the quantity of water transpired within a basin. (Ben Wu et al., 2001; Lemberg et al., 2002; Brown and Raines, 2002;
30 Afinowicz et al., 2005; Bumgarner and Thompson, 2012; Harwell et al., 2016). However, to date (2016), 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 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-use changes, such as brush management, the soil water assessment tool (SWAT) (Arnold et al., 1998) was applied to a 1.4 km² watershed in South Texas. The watershed has been the focus of previous investigations (Banta and Slattery, 2011); estimates of precipitation, streamflow, and ET are available. The objectives of this study are to 1) verify to 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, including those outputs used in the conditioning process as well as those outputs that capture the simulated effects of brush management.

1.1 Hydrologic Setting

The brush-management simulation described herein is applied to a 1.4 km² 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 the watershed analyzed in this study is referred to as the “treatment watershed” in Banta and Slattery (2011)).

Briefly, the watershed generally has gentle slopes (less than 5 percent) with steeper slopes in the stream channel ravines. The clay and clay loam soils overlie the Trinity aquifer outcrop, a regional karst aquifer system. Prior to treatment, the study area was largely dominated by ashe juniper (*Juniperus ashei*). After brush management, native grasses naturally re-established in their place.

Ashe juniper transpires large quantities of water and its dense canopy captures more water as interception storage compared to herbaceous land cover (Archer et al., 2011). As such, brush management focused on the removal of ashe juniper has been studied and implemented at the Honeycreek State Natural Area (Banta and Slattery, 2011). For the watershed studied in this analysis, approximately 40% of the land covered by predominately ashe juniper was mechanically cleared during calendar year 2004. Following ashe juniper removal, the land returned to a native rangeland land cover type.

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 analysis.



2.1 Datasets

Three datasets are needed to apply the ArcSWAT tool (Winchell et al., 2007) to discretize the watershed into hydrologic response units (HRUs) and subsequently construct the SWAT model inputs for the watershed of interest:

- digital elevation model: The 10m national elevation dataset (NED) (Maune et al., 2007)
- 5 – 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 programmatically within the ArcSWAT tool to find unique land slope/soil/land cover combinations across the watershed. These unique combinations ultimately became HRUs in the SWAT model. Note the NED digital elevation model for the watershed was smoothed with a 4-pixel width averaging kernel to remove apparent artifacts.

- 10 As part of a previous study evaluating the effects of brush management at the Honey Creek State Natural Area, daily total precipitation and evapotranspiration (ET), and average daily streamflow were measured during 2001 through 2010 (Figure 2) (Banta and Slattery, 2011). These precipitation data were used as inputs to the SWAT model while the ET and streamflow data were used for conditioning and verification (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 averaged together
- 15 to develop the precipitation input dataset. For additional discussion of the methodology used to collect the input datasets, see Banta and Slattery (2011). 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 due to instrumentation issues (Banta and Slattery, 2011).

2.2 ArcSWAT

- 20 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 (SWAT parameter IEVENT=3) (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.

- 25 The application of the ArcSWAT tool with the previously-described datasets resulted in a model with a single subbasin covering the 1.4 km² watershed with 47 distinct HRUs (Figure 1). A summary of the HRU characteristics is included in the supplementary material.

2.3 Model Configurations

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



- **conditioning period:** 1 Jan 2002 to 31 Dec 2003; pre-treatment watershed conditions; daily streamflow data from this period were used for conditioning the model inputs.
- **forecast period:** 1 Jan 2005 to 31 Dec 2010; post-treatment watershed conditions; used for verification and forecasting the long-term water budget effects of simulated brush management.

5 Note that 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.

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

10 Here, two distinct SWAT model datasets were constructed to simulate the pre-treatment (conditioning period) and post-treatment (forecast period) watershed conditions. The only difference between the two models are the inputs to HRUs 18, 20, 22, 32; all other inputs remain identical. Together, HRUs 18, 20, 22, 32 represent approximately 40% of the watershed area, which represents the area of watershed that was converted from evergreen forest (e.g., ashe juniper) to rangeland by brush-management activities during 2004 (Banta and Slattery, 2011). The only differences in the SWAT model input files of HRUs
15 18, 20, 22, and 32 between the two models are related to how brush-management operations change two aspects of the SWAT model:

- 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

We modified the maximum canopy storage and the plant growth aspects of HRUs 18, 20, 22, and 32 since these inputs
20 directly affect the available precipitation for partitioning and simulated ET processes, respectively. In the pre-treatment model, these model inputs were specified to represent ashe juniper land cover for HRUs 18, 20, 22, 32, while 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 Parameterization section for detailed description of how the CANMX variable, as well as variables related to various components of the simulated
25 growth cycle, were parameterized in the modeling analysis. See the SWAT theory (Neitsch et al., 2011) and input-output (Arnold et al., 2012a) documentation for more information on these inputs.

2.4 Parameterization

Herein, we refer to the subjective and necessary process of selecting model inputs to treat as adjustable in the conditioning process as parameterization. It is a critical part of any modeling analysis and has received considerable attention in the literature
30 (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



investigate the importance of parameterization for obtaining robust and reliable simulated brush-management outcomes by evaluating two parameterization designs:

- **reduced parameterization** uses the 12 model inputs listed on Table 1 of Arnold et al. (2012b) as the most cited SWAT model inputs chosen for calibration/conditioning when simulating surface-water runoff and baseflow processes (Table 1). This parameterization is, therefore, representative of many SWAT modeling analyses in the literature. For the reduced parameterization model, inputs are adjusted at the subbasin scale - all 47 HRUs receive the same value for each of these 12 model inputs.
- **full parameterization** includes 1,305 model inputs. It builds on the 12 parameters of the reduced parameterization by adding 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, including additional soil properties, and inputs that govern the simulation of plant growth. 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 the Supplementary Material for a listing of the full parameterization.

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 changes. Therefore, CANMX potentially exhibits a strong control of the simulated outcomes of brush management. We chose to treat the CANMX input differently than other SWAT inputs:

- 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
- 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 and post-treatment models to receive the same parameter values. Since 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 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.

CANMX is not treated as uncertain in the reduced parameterization as it is not commonly treated as adjustable (Arnold et al., 2012b). The parameters *canmx_v*, *canmxfac_07* and *canmxfac_15* are specified values of 13.0 mm, 0.625 (8.13 mm) and 0.25 (3.25 mm), respectively, which corresponds to the midpoint of the respective parameter ranges.

These two parameterizations represent two different approaches to hydrologic modeling. As such, we include both of these parameterizations in the analysis to facilitate a comparison of how these parameterization approaches perform in the context of brush-management modeling analyses.



The specified parameter ranges from a multivariate uniform distribution that we treat as the Prior parameter distribution, which 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.

5 Using the pre- and post-treatment models and the two parameterizations, the following steps represent a single model forward run:

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. Populate these tables with the base input values from the ArcSWAT process for both the pre- and post-treatment models.
- 10 2. for each “value”-type basin-scale parameter, replace the values in the base tables for each corresponding column with the parameter value, assigning all HRUs the same value
3. for each “multiplier”-type basin-scale parameter, multiply the corresponding column of the base tables by the parameter value, scaling all HRUs by the same value
4. apply *canmx_v*, *canmxfac_07* and *canmxfac_15* parameters to the CANMX column of both base tables according to the
15 land-use type of each HRU using the previously-described relation between these parameters.
5. for each “multiplier”-type HRU-scale parameter, multiply the corresponding row-column location in the base tables by the parameter value, scaling only a single entry in the table
6. translate the base tables into the appropriate SWAT input files for both the pre-treatment and post-treatment models
7. run the pre-treatment model for the time period 2001 through 2010 (pre-treatment model outputs are needed from 2005-
20 2010 for calculation of brush-management quantities of interest)
8. run the post-treatment model for the time period 2004 through 2010
9. post-process both model runs to formulate brush-management quantities of interest and conditioning measures

2.5 Evaluation of Brush Management Simulations

We use uncertainty quantification techniques to investigate how well the previously-described SWAT model simulates the
25 effects of brush management on long-term water budget components. Specifically, we use Monte Carlo analysis in conjunction with GLUE-based (Beven and Binley, 1992) conditioning to construct prior and behavioral distributions of parameters and several model outputs that are important to simulating the outcomes of brush management. These important outputs, which we term quantities of interest (QOIs), 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
- 5 – **QOI-5:** volumetric forecast-period difference between the simulated treated and untreated watershed

The work of Banta and Slattery (2011) includes daily estimates of ET and streamflow 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 the 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.

2.6 Monte Carlo and GLUE

Monte Carlo analysis (MC) (Tarantola, 2005) was used to investigate how SWAT model input uncertainty influences brush-management QOIs. MC was chosen because it employs few assumptions and because the forward model run time is relatively short. Furthermore, the GLUE method of Beven and Binley (1992) was used to condition the MC prior ensembles into behavioral ensembles. The combined MC-GLUE analysis provides estimates of parameter and QOI uncertainty, as well as estimates of the worth of the conditioning data to reduce QOI uncertainty.

To perform the MC analysis, a one-million parameter set ensemble was drawn using the prior, uniform distribution 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 upper and lower bound of each parameter). Once the prior parameter ensemble was constructed, the SWEEP utility of the PEST++ software suite 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. 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 prior ensemble was modified so that the value of parameters not included in reduced parameterization were fixed at the midpoint of the associated range. The resulting prior ensemble was then 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. Following Moriasi et al. (2007), we selected the following conditioning measures, which are based on daily mean streamflow, to form the behavioral ensemble:

- **CM-1** conditioning-period (pre-treatment) Nash-Sutcliffe efficiency > 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 streamflow (Moriasi et al., 2007). Realizations in the each of prior ensembles that satisfied all three of these criteria are designated as “behavioral” and, taken together, comprise the reduced and full parameterization behavioral ensembles, respectively. The behavioral ensembles represent parameter realizations that respect the Prior but that also reproduce daily average stream flow acceptably well according to the three conditioning measures. That is, each parameter set in the full- and reduced-parameterization ensembles can be considered “calibrated” in that each of these parameter sets fit the data.

2.7 Global Sensitivity Analysis

Given the drastic 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 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) with 20 discretization points across the range of each parameter.

3 Results

The application of the GSA method of Morris (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 MC-GLUE analysis reveals a relatively large discrepancy in the estimated range of QOI-5 between the full and reduced 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 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).

5 3.2 Monte Carlo

The Monte Carlo and associated GLUE-based conditioning process (MC-GLUE) yielded 7,155 and 6,846 realizations that comprise the behavioral ensembles for the reduced and full parameterizations, respectively. These behavioral realizations reproduce the pre-treatment daily streamflow data acceptably well according to the three conditioning measures. The prior and behavioral relation among the three conditioning measures for both 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 conditioning measures, while the off-diagonal panes show the relation between conditioning measures. Parameter realizations within the hatched boxes on Figure 3 collectively form the behavioral ensembles for both the full- and reduced-parameterization.

3.2.1 Verification QOIs

15 The prior and behavioral ensembles of reduced and full parameterizations bracket, at the 95% confidence level, the measured value for verification QOI-1, QOI-2 and QOI-3 (Figures 4, 5, and 6). However, the measured value for QOI-4, volumetric forecast-period (post-treatment) streamflow-precipitation ratio, was not captured by either behavioral distribution or the prior distribution of the reduced parameterization (Figure 7).

In general, for both 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 indicates the conditioning process has not changed uncertainty that exists in model simulated ET. However, QOIs related to streamflow (QOI-2 and QOI-4) have markedly different behavioral distributions compared to priors, indicating considerable conditioning of streamflow-sensitive parameters.

25 3.2.2 forecast QOI

The prior uncertainty in the QOI-5, the simulated total forecast-period ET difference between the treated and untreated watershed, was substantially larger for the full parameterization compared to the reduced parameterization (Figure 8): the full parameterization model yielded a prior uncertainty that ranged from approximately -7.5% to +0.5% while the reduced parameterization prior uncertainty ranged from approximately -4.1% to -2.1%. 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.



The behavioral uncertainty in QOI-5 yielded by the full parameterization is similar to the prior, but shifted slightly towards positive values, ranging from -6.2 to +0.5 (Figure 8 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. Conversely, QOI-5 behavioral uncertainty from the reduced parameterization is substantially different than the prior and included values only in the range -2.5 to -2.0. We attribute the differences in QOI-5 distributions between the full and reduced 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.

10 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 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 unprecedented result. Harwell et al. (2016) showed a net decrease in surface-water yield following simulated brush-management activities for one of their simulated subbasins. Furthermore, the range of outcomes yielded for QOI-5 is an important result for resource managers in hydrologic settings similar to the one herein: modeling alone may not be able to provide the level of confidence needed to support a risk-based decision to undertake costly brush management. Furthermore, we have demonstrated that conditioning/calibration of a hydrologic model to daily streamflow data does not necessarily increase the reliability of forecasts made with the model.

20 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 the importance of robust uncertainty quantification to support simulations of brush management, and, more generally, simulating the hydrologic outcomes of land use change. Without uncertainty quantification, the results of simulating brush management are simply a single point on the behavioral distributions, which conveys no information related to the reliability of the model results. Given the cost associated with watershed- and basin-scale brush management, it is critical to provide a conservative and robust estimate of uncertainty in the modeled outcomes of brush management; an estimate of the possible ineffectiveness of brush management is likely more valuable than a "best-fit" modeled outcome of brush management.

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 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 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
5 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., 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-use 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 other practitioners may
10 choose different prior distributions and/or ranges for these parameters, we doubt any practitioners would state these model inputs are known with absolute certainty.

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 simulate brush management with SWAT. In this study, brush management is simulated by modifying the maximum canopy storage and inputs
15 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. However, if a different strategy is selected, and a realistic estimate of uncertainty is included in the implementation of the strategy, it is likely the simulated outcome of brush management will be similar to the results found herein.

5 Conclusions

20 An analysis of the ability of the SWAT model to forecast how brush management affects 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 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,
25 Monte Carlo and GLUE analyses were used to estimate the uncertainty of brush-management QOIs for the reduced and full parameterization schemes, respectively.

The 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
30 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 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 obviously 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.

5 6 Code availability

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

7 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 (<http://pubs.usgs.gov/sir/2011/5226/>)

10 The model archive for this analysis includes all 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:

- ESRI ArcMAP 10.2.2 project that includes the ArcSWAT version 2012.10.2.18 project used to create the base model
- base SWAT2012 input files generated by the ArcSWAT tool
- PEST++ interface files including python pre- and post-processing scripts
- 15 – comma-separated value files of parameters and QOIs for prior ensembles of both the full and reduced parameterizations

Supplementary Material include:

- HRU summary table
- parameter description table
- GSA method of Morris top 5 list
- 20 – GSA method of Morris summary table

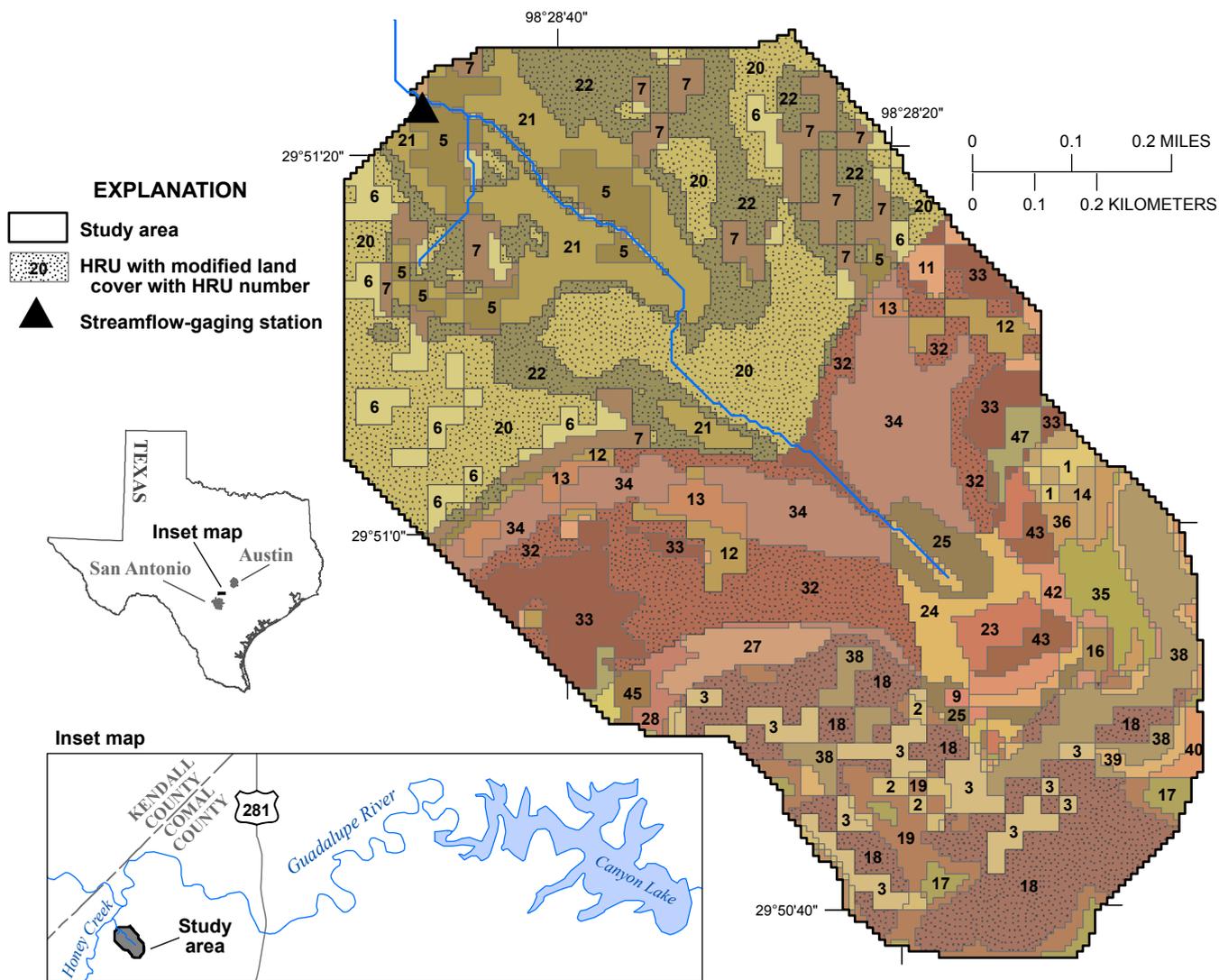


Figure 1. Study area and watershed location. The 47 HRUs yielded by the ArcSWAT tool (Winchell et al., 2007). The model inputs of HRUs 18, 20, 22, and 32 were modified to simulate the brush-management activities.

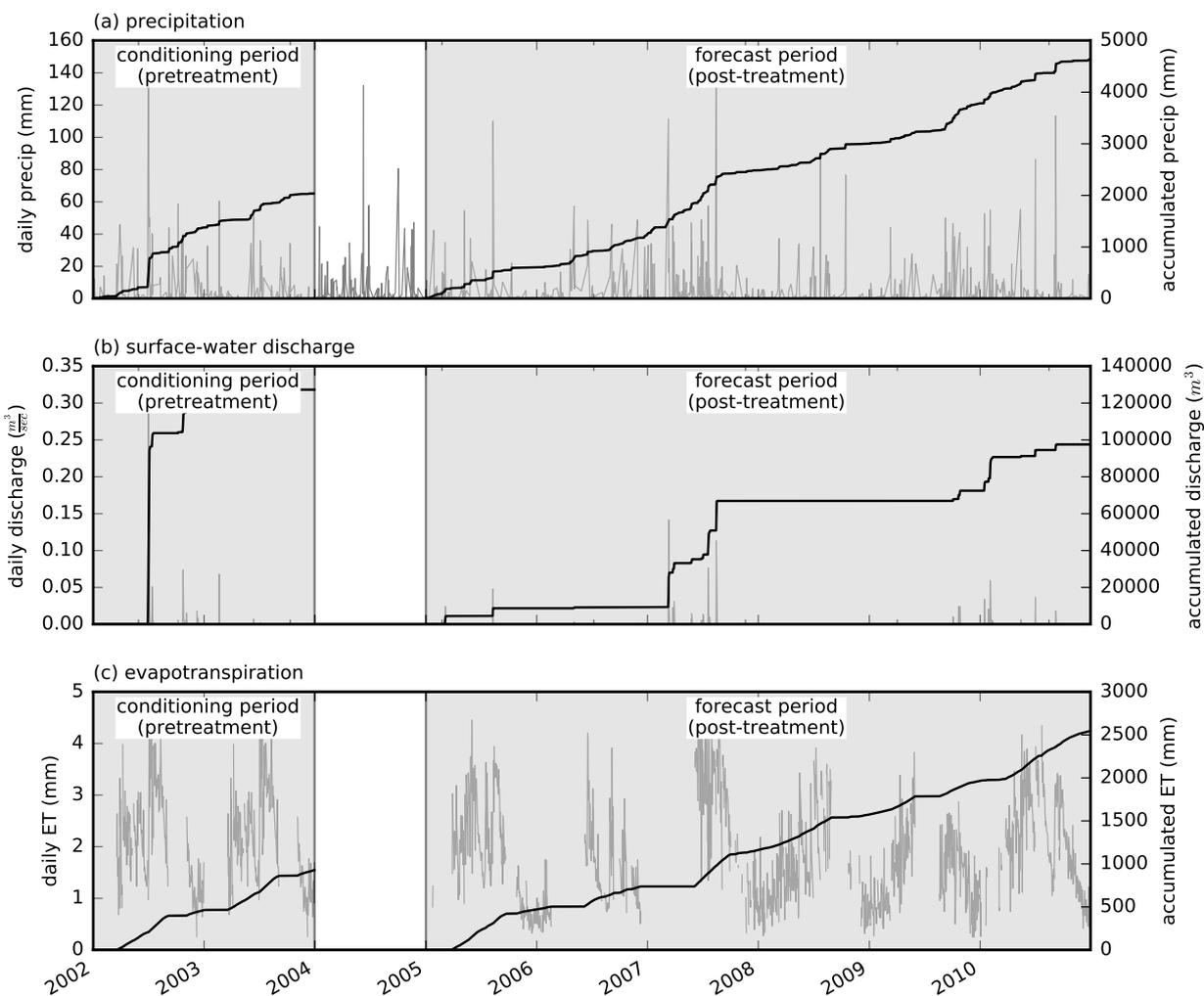


Figure 2. Summary of (a) precipitation, (b) streamflow, and (c) evapotranspiration used in the modeling analysis. Accumulated values for the conditioning and forecast period are shown in heavy black lines. Precipitation, streamflow and evapotranspiration estimates are from Banta and Slattery (2011).

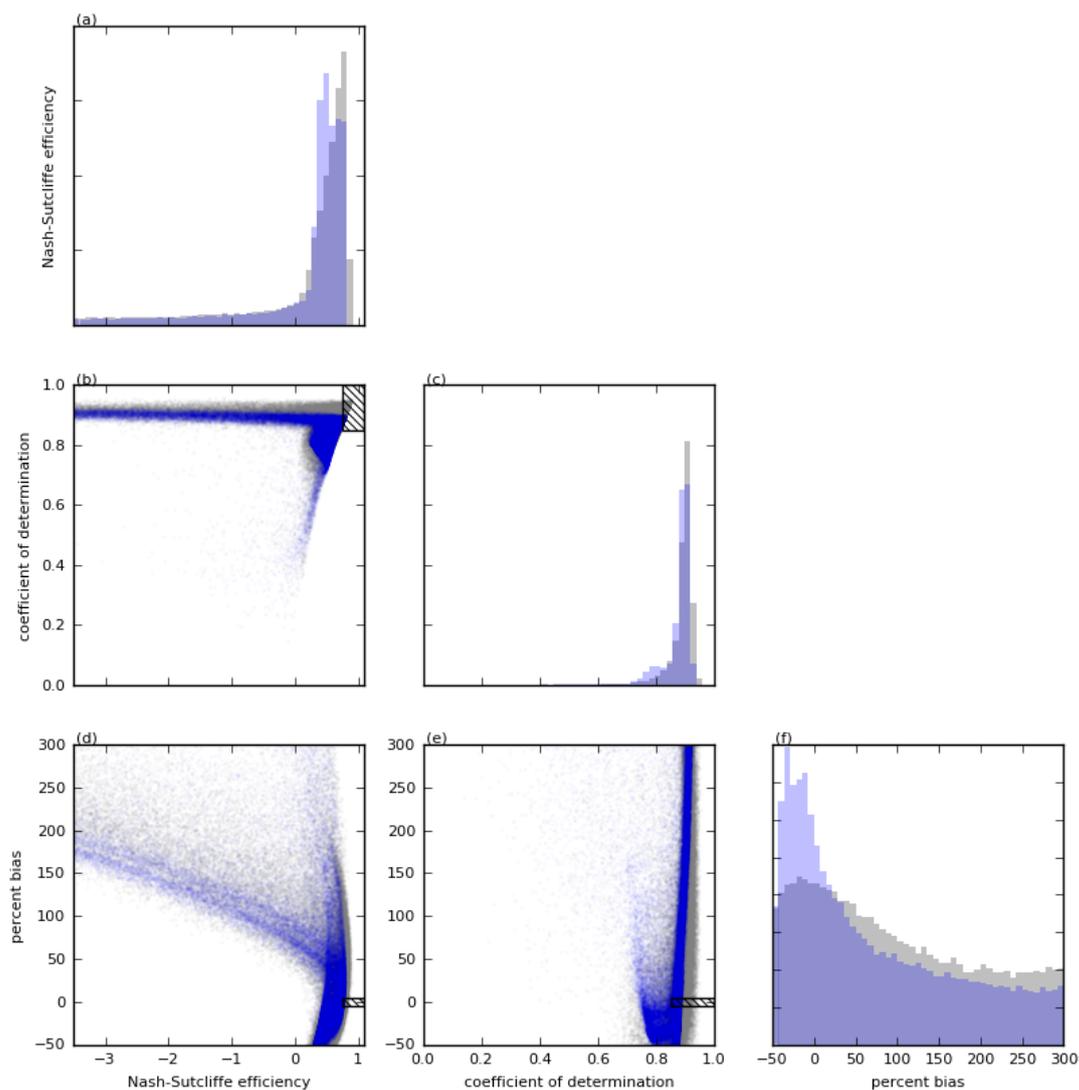


Figure 3. Values of conditioning measures for the full (gray) and reduced (blue) parameterizations. The diagonal panes ((a), (b), and (c)) show distribution of each conditioning measure; the off-diagonal panes ((b), (d) and (e)) show the relation between respective conditioning measures. The hatched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

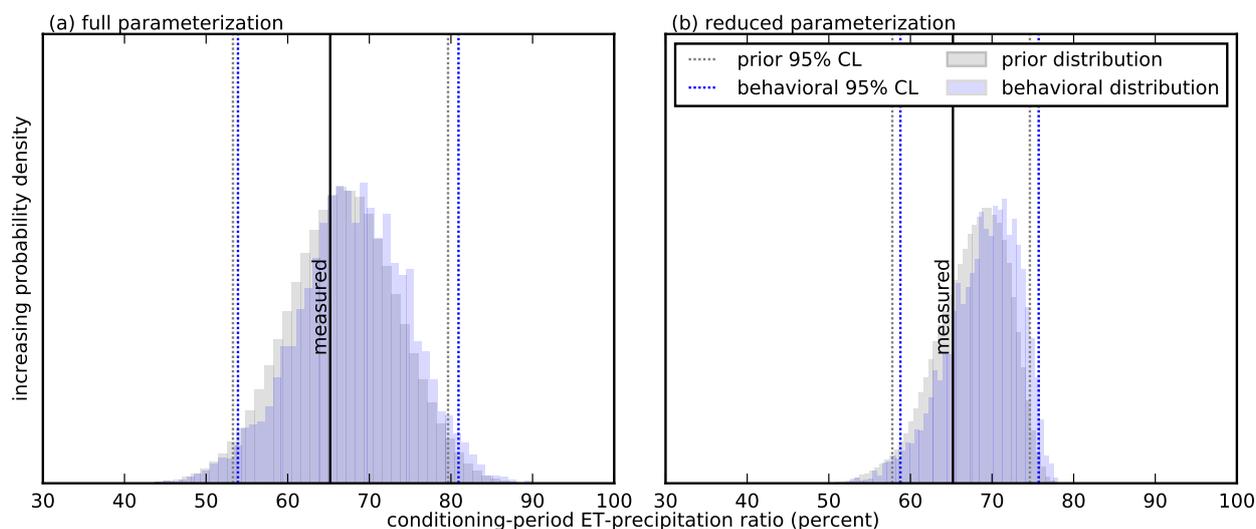


Figure 4. Quantity of interest QOI-1: Simulated conditioning period (pre-treatment) ET as a percentage of precipitation. The prior and behavioral distributions of both model parameterizations capture the measured value. However, the conditioning process has little affect on uncertainty as the behavioral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

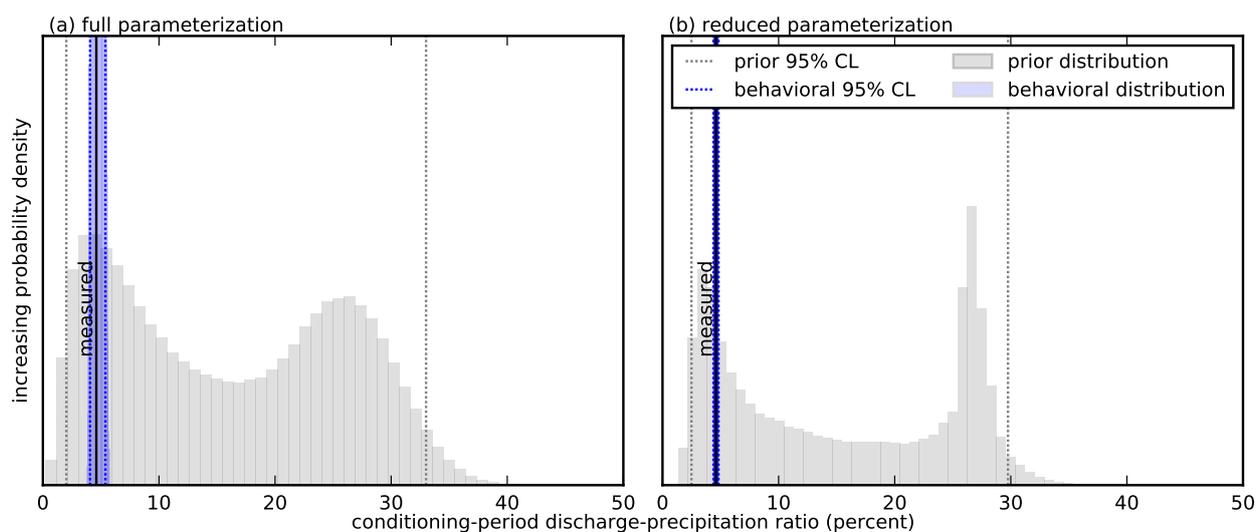


Figure 5. Quantity of interest QOI-2: Simulated conditioning period (pre-treatment) streamflow as a percentage of precipitation. The effects of the conditioning process can be seen as large reduction in the range of the behavioral distribution compared to the prior distribution. The prior and behavioral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

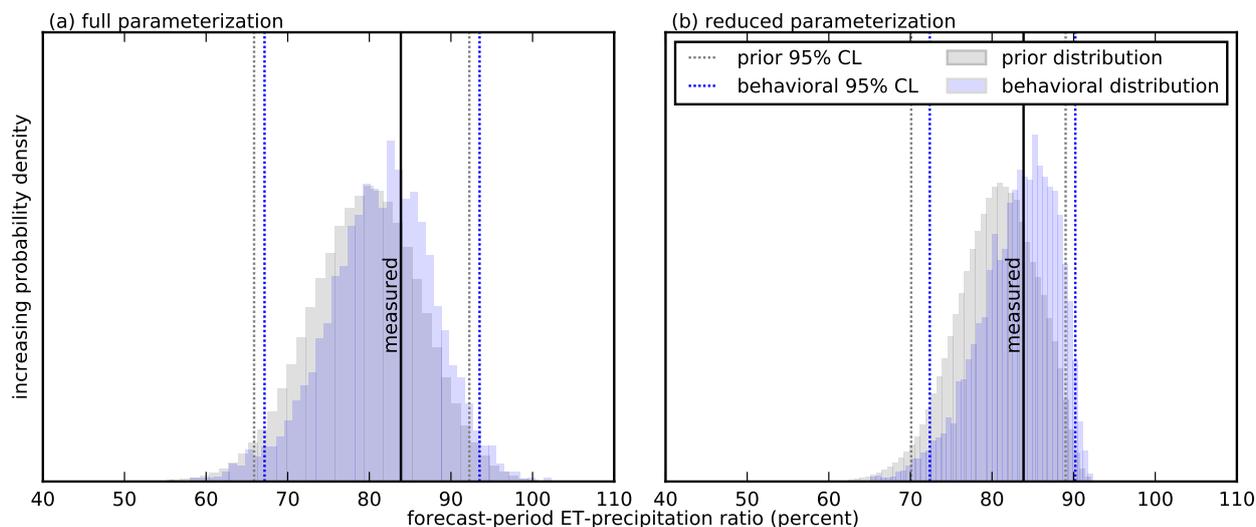


Figure 6. Quantity of interest QOI-3: Simulated forecast period (post-treatment) ET as a percentage of precipitation. All 95% confidence intervals capture the measured value. However, the conditioning process has done little to decrease uncertainty as the behavioral distributions are similar to the prior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

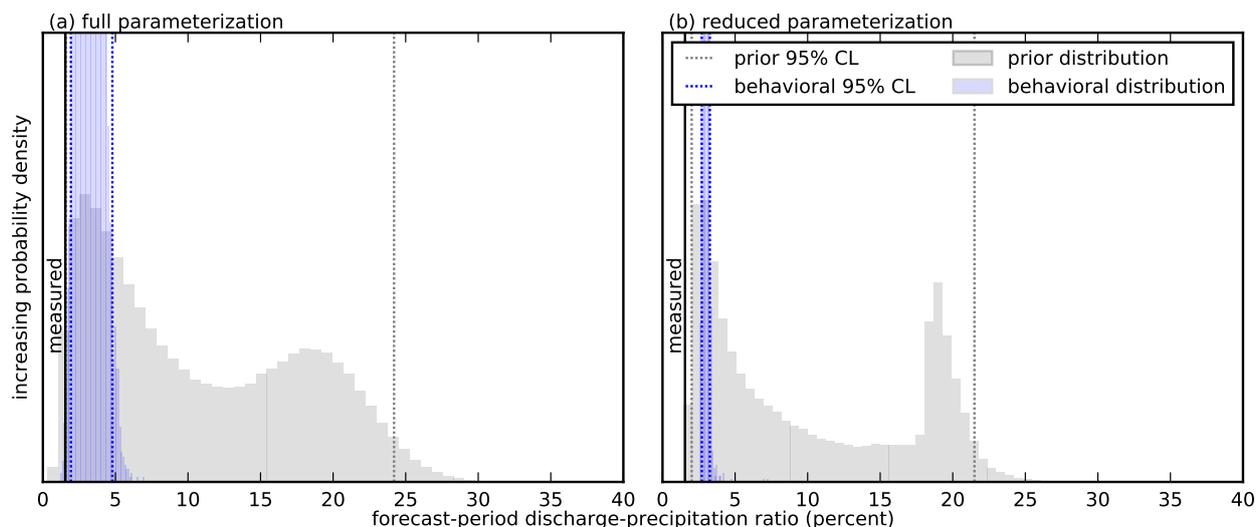


Figure 7. Quantity of interest QOI-4: Simulated forecast period (post-treatment) streamflow as a percentage of precipitation. Both the parameterizations appear to have been “overfit” with respect to this QOI as both behavioral distributions do not capture the measured value.

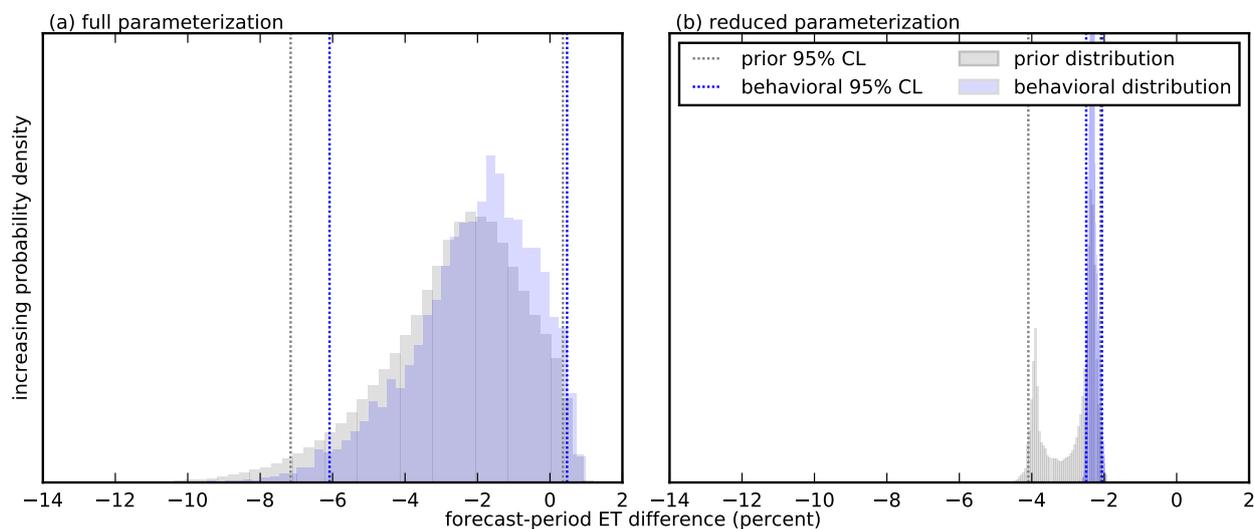


Figure 8. Quantity of interest QOI-5: Simulated difference in total forecast period (post-treatment) ET volume as a result of brush management. Negative values indicate a decrease in ET as a result of brush management. The reduce parameterization yields a much narrower confidence interval compared to 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	type	lower bound	upper bound	description (with units if applicable)
alpha_bf_v	value	0.10	0.50	subbasin baseflow alpha factor ($\frac{1}{\text{days}}$)
cn2_r	multiplier	0.50	1.50	subbasin soil moisture condition II curve number
epco_v	value	0.50	0.98	subbasin plant uptake compensation factor
esco_v	value	0.50	0.98	subbasin soil evaporation compensation factor
gw_delay_v	value	10.00	300.00	subbasin groundwater delay time (days)
gw_revap_v	value	0.02	0.40	subbasin groundwater 'revap' coefficient
gwqmn_v	value	500	4000	subbasin groundwater threshold return flow depth (mm)
ov_n_r	multiplier	0.50	1.50	subbasin overland flow Manning's 'n'
rchrp_dp_v	value	0.25	0.75	subbasin deep aquifer percolation factor
revapmn_v	value	100	1000	subbasin groundwater threshold 'revap' depth (mm)
sol_awc_l_r	multiplier	1.00	5.00	subbasin soil available water capacity ($\frac{\text{mm}}{\text{mm}}$)
surlag_v	value	2.00	12.00	subbasin surface runoff lag coefficient

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.



Competing interests. The authors declare that they have no conflict of interest.

Disclaimer. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government

Acknowledgements. The authors would like to recognize Kyle Douglas-Mankin, as well as additional reviewers, whose insightful comments
5 improved the manuscript.



References

- Abbaspour, K., Johnson, C., and Van Genuchten, M. T.: Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure, *Vadose Zone Journal*, 3, 1340–1352, 2004.
- Abbaspour, K. C.: SWAT-CUP SWAT calibration and uncertainty programs, Texas A & M University, 2015.
- 5 Afinowicz, J. D., Munster, C. L., and Wilcox, B. P.: Modeling effects of brush management on the rangeland water budget: Edwards PLATEAU, Texas, *Journal of the American Water Resources Association*, 41, 181, 2005.
- Ahn, K.-H. and Merwade, V.: The effect of land cover change on duration and severity of high and low flows, *Hydrological Processes*, 31, 133–149, doi:10.1002/hyp.10981, <http://dx.doi.org/10.1002/hyp.10981>, hYP-15-0997.R4, 2017.
- Archer, S., Davies, K. W., Fulbright, T. E., McDaniel, K. C., Wilcox, B. P., Predick, K., and Briske, D.: Brush management as a rangeland conservation strategy: A critical evaluation, *Conservation benefits of rangeland practices*. Washington, DC, USA: US Department of Agriculture Natural Resources Conservation Service, pp. 105–170, 2011.
- Arnold, J., Kiniry, J., Srinivasan, R., Williams, J., Haney, E., and Neitsch, S.: Soil Water Assessment Tool Input/Output Documentation, College Station, TX, <http://swat.tamu.edu/media/69296/SWAT-IO-Documentation-2012.pdf>, 2012a.
- Arnold, J. G., Srinivasan, R., Mutiah, R. S., and Williams, J. R.: Large area hydrologic modeling and assessment part I: Model development, *Journal of the American Water Resources Association*, 34, 73–89, doi:10.1111/j.1752-1688.1998.tb05961.x, <http://dx.doi.org/10.1111/j.1752-1688.1998.tb05961.x>, 1998.
- 15 Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R., Van Griensven, A., Van Liew, M. W., et al.: SWAT: Model use, calibration, and validation, *Transactions of the ASABE*, 55, 1491–1508, 2012b.
- Banta, J. and Slaterry, R.: Effects of brush management on the hydrologic budget and water quality in and adjacent to Honey Creek State Natural Area, Comal County, Texas, 2001–10, U.S Geological Survey Scientific Investigations Report, 2011, 2011.
- 20 Ben Wu, X., Redeker, E. J., and Thurow, T. L.: Vegetation and water yield dynamics in an Edwards Plateau watershed, *Journal of Range Management*, pp. 98–105, 2001.
- Beven, K. and Binley, A.: The future of distributed models: Model calibration and uncertainty prediction, *Hydrological Processes*, 6, 279–298, doi:10.1002/hyp.3360060305, <http://dx.doi.org/10.1002/hyp.3360060305>, 1992.
- 25 Brown, D. and Raines, T.: Simulation of Flow and Effects of Best-Management Practices in the Upper Seco Creek Basin, South-Central Texas, 1991 – 98, U.S. Geological Survey Scientific Investigation Report, 02-4249, 2002.
- Bumgarner, J. and Thompson, F.: Simulation of streamflow and the effects of brush management on water yields in the Upper Guadalupe River Watershed, South-Central Texas, 1995 – 2010, U.S. Geological Survey Scientific Investigation Report, 2012-5051, 2012.
- Chu, H.-J., Lin, Y.-P., Huang, C.-W., Hsu, C.-Y., and Chen, H.-Y.: Modelling the hydrologic effects of dynamic land-use change using a distributed hydrologic model and a spatial land-use allocation model, *Hydrological Processes*, 24, 2538–2554, doi:10.1002/hyp.7667, <http://dx.doi.org/10.1002/hyp.7667>, 2010.
- 30 Cibin, R., Sudheer, K. P., and Chaubey, I.: Sensitivity and identifiability of stream flow generation parameters of the SWAT model, *Hydrological Processes*, 24, 1133–1148, doi:10.1002/hyp.7568, <http://dx.doi.org/10.1002/hyp.7568>, 2010.
- DeFries, R. and Eshleman, K. N.: Land-use change and hydrologic processes: a major focus for the future, *Hydrological Processes*, 18, 2183–2186, doi:10.1002/hyp.5584, <http://dx.doi.org/10.1002/hyp.5584>, 2004.
- 35 Douglas-Mankin, K., Srinivasan, R., and Arnold, J.: Soil and Water Assessment Tool (SWAT) model: Current developments and applications, *Transactions of the ASABE*, 53, 1423–1431, 2010.



- Du, J., Rui, H., Zuo, T., Li, Q., Zheng, D., Chen, A., Xu, Y., and Xu, C.-Y.: Hydrological Simulation by SWAT Model with Fixed and Varied Parameterization Approaches Under Land Use Change, *Water Resources Management*, 27, 2823–2838, doi:10.1007/s11269-013-0317-0, <http://dx.doi.org/10.1007/s11269-013-0317-0>, 2013.
- Fohrer, N., Haverkamp, S., Eckhardt, K., and Frede, H.-G.: Hydrologic response to land use changes on the catchment scale, *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, 26, 577–582, 2001.
- Gassman, P. W., Sadeghi, A. M., and Srinivasan, R.: Applications of the SWAT model special section: overview and insights, *Journal of Environmental Quality*, 43, 1–8, 2014.
- Gitau, M. W. and Chaubey, I.: Regionalization of SWAT model parameters for use in ungauged watersheds, *Water*, 2, 849–871, 2010.
- Harwell, G. R., Stengel, V. G., and Bumgarner, J. R.: Simulation of streamflow and the effects of brush management on water yields in the Double Mountain Fork Brazos River watershed, western Texas 1994 - 2013, Tech. rep., U.S. Geological Survey, Reston, VA, doi:10.3133/sir20165032, <http://pubs.er.usgs.gov/publication/sir20165032>, 2016.
- Homer, C., Dewitz, J., Fry, J., Coan, M., Hossain, N., Larson, C., Herold, N., McKerrow, A., VanDriel, J., and Wickham, J.: Completion of the 2001 National Land Cover Database for the Conterminous United States, *Photogrammetric Engineering & Remote Sensing*, 73, 337–341, 2007.
- Jakeman, A. and Hornberger, G.: How much complexity is warranted in a rainfall-runoff model?, *Water resources research*, 29, 2637–2649, 1993.
- Jeong, J., Kannan, N., Arnold, J., Glick, R., Gosselink, L., and Srinivasan, R.: Development and integration of sub-hourly rainfall-runoff modeling capability within a watershed model, *Water Resources Management*, 24, 4505–4527, 2010.
- Kavetski, D., Kuczera, G., and Franks, S. W.: Bayesian analysis of input uncertainty in hydrological modeling: 2. Application, *Water Resources Research*, 42, 2006.
- Kuczera, G., Kavetski, D., Franks, S., and Thyer, M.: Towards a Bayesian total error analysis of conceptual rainfall-runoff models: Characterising model error using storm-dependent parameters, *Journal of Hydrology*, 331, 161–177, 2006.
- Lemberg, B., Mjelde, J. W., Conner, J. R., Griffin, R. C., Rosenthal, W. D., and Stuth, J. W.: An interdisciplinary approach to valuing water from brush control, *Journal of the American Water Resources Association*, 38, 409–422, doi:10.1111/j.1752-1688.2002.tb04326.x, <http://dx.doi.org/10.1111/j.1752-1688.2002.tb04326.x>, 2002.
- Leta, O. T., Nossent, J., Velez, C., Shrestha, N. K., van Griensven, A., and Bauwens, W.: Assessment of the different sources of uncertainty in a SWAT model of the River Slenne (Belgium), *Environmental Modelling and Software*, 68, 129 – 146, doi:<http://dx.doi.org/10.1016/j.envsoft.2015.02.010>, <http://www.sciencedirect.com/science/article/pii/S1364815215000596>, 2015.
- Malone, R. W., Yagow, G., Baffaut, C., Gitau, M. W., Qi, Z., Amatya, D. M., Parajuli, P. B., Bonta, J. V., and Green, T. R.: Parameterization guidelines and considerations for hydrologic models, *Transactions of the ASABE*, 58, 1681–1703, 2015.
- Maune, D., for Photogrammetry, A. S., and Sensing, R.: *Digital Elevation Model Technologies and Applications: The DEM Users Manual*, American Society for Photogrammetry and Remote Sensing, <https://books.google.com/books?id=IbwsAQAAAJ>, 2007.
- Mein, R. G. and Larson, C. L.: Modeling infiltration during a steady rain, *Water resources research*, 9, 384–394, 1973.
- Migliaccio, K. W. and Chaubey, I.: Spatial distributions and stochastic parameter influences on SWAT flow and sediment predictions, *Journal of hydrologic engineering*, 13, 258–269, 2008.
- Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., and Veith, T. L.: Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, *Transactions of the ASABE*, 50, 885–900, 2007.



- Morris, M. D.: Factorial Sampling Plans for Preliminary Computational Experiments, *Technometrics*, 33, 161–174, doi:10.1080/00401706.1991.10484804, 1991.
- Neitsch, S., Arnold, J., Kiniry, J., and Williams, J.: Soil Water Assessment Tool Theoretical Documentation, College Station, TX, <http://swat.tamu.edu/media/99192/swat2009-theory.pdf>, 2011.
- 5 Renard, B., Kavetski, D., Leblois, E., Thyer, M., Kuczera, G., and Franks, S. W.: Toward a reliable decomposition of predictive uncertainty in hydrological modeling: Characterizing rainfall errors using conditional simulation, *Water Resources Research*, 47, n/a–n/a, doi:10.1029/2011WR010643, <http://dx.doi.org/10.1029/2011WR010643>, w11516, 2011.
- Romanowicz, A. A., Vancloster, M., Rounsevell, M., and La Junesse, I.: Sensitivity of the SWAT model to the soil and land use data parameterisation: a case study in the Thyle catchment, Belgium, *Ecological Modelling*, 187, 27–39, 2005.
- 10 Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., Behringer, D., Hou, Y.-T., Chuang, H.-y., Iredell, M., et al.: The NCEP climate forecast system version 2, *Journal of Climate*, 27, 2185–2208, 2014.
- Schilling, K. E., Gassman, P. W., Kling, C. L., Campbell, T., Jha, M. K., Wolter, C. F., and Arnold, J. G.: The potential for agricultural land use change to reduce flood risk in a large watershed, *Hydrological Processes*, 28, 3314–3325, doi:10.1002/hyp.9865, <http://dx.doi.org/10.1002/hyp.9865>, 2014.
- 15 Sexton, A., Shirmohammadi, A., Sadeghi, A., and Montas, H.: Impact of parameter uncertainty on critical SWAT output simulations, *Transactions of the ASABE*, 54, 461–471, 2011.
- Staff, S. S.: Natural Resources Conservation Service, United States Department of Agriculture. Soil Survey Geographic (SSURGO) Database, <https://sdmdataaccess.sc.egov.usda.gov>, 2016.
- Tarantola, A.: Inverse problem theory and methods for model parameter estimation, *SIAM*, 2005.
- 20 Tennesen, M.: When Juniper and Woody Plants Invade, *Water May Retreat*, *Science*, 322, 1630–1631, 2008.
- U.S. Department of Agriculture, N. R. C. S.: National Conservation Practice Standard Code 314, U.S. Department of Agriculture, p. 4, 2009.
- Welter, D., White, J., Doherty, J., and Hunt, R.: PEST++ Version 3, a Parameter ESTimation and uncertainty analysis software suite optimized for large environmental models, U.S. Geological Survey Techniques and Methods Report, 7-C12, 54, 2015.
- White, J. T., Doherty, J. E., and Hughes, J. D.: Quantifying the predictive consequences of model error with linear subspace analysis, *Water Resources Research*, 50, 1152–1173, doi:10.1002/2013WR014767, <http://dx.doi.org/10.1002/2013WR014767>, 2014.
- 25 White, J. T., Fienen, M. N., and Doherty, J. E.: A python framework for environmental model uncertainty analysis, *Environmental Modelling and Software*, 85, 217 – 228, doi:http://dx.doi.org/10.1016/j.envsoft.2016.08.017, <http://www.sciencedirect.com/science/article/pii/S1364815216305461>, 2016.
- Winchell, M., Srinivasan, R., Di Luzio, M., and Arnold, J.: ArcSWAT interface for SWAT2005 user’s guide, Texas Agricultural Experiment Station and United States Department of Agriculture, Temple, TX, 2007.
- 30 Zhang, J. L., Li, Y. P., Huang, G. H., Wang, C. X., and Cheng, G. H.: Evaluation of uncertainties in input data and parameters of hydrological model using a Bayesian framework: A case study of a snowmelt-precipitation-driven watershed, *Journal of Hydrometeorology*, 0, null, doi:10.1175/JHM-D-15-0236.1, <http://dx.doi.org/10.1175/JHM-D-15-0236.1>, 2016.
- Zhenyao, S., Lei, C., and Tao, C.: The influence of parameter distribution uncertainty on hydrological and sediment modeling: a case study of SWAT model applied to the Daning watershed of the Three Gorges Reservoir Region, China, *Stochastic environmental research and risk assessment*, 27, 235–251, 2013.