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# Investigating Parameter Sensitivity for Management in Snow-Driven Watersheds

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**Abstract:** Recent projections of environmental change have shown possible variation to temperature and precipitation patterns due to climate change. In snowmelt-dominated watersheds, adapting to such environmental changes requires a detailed understanding of hydrological processes in addition to historical snow cover and streamflow data. Snow models are often incorporated as an additional component of hydrological modeling studies that inform research and operations management. However, previous research and parameter estimation approaches using snow models assume that parameters have a single optimal value and that each parameter is sensitive. This paper demonstrates that an improved understanding of snow model parameter sensitivity can aid in key decisions for water management in these basins. This study uses Sobol's sensitivity analysis method combined with a multi-objective optimization calibration to determine a set of sensitive parameters for a snow model and obtain parameter sets that perform well with respect to multiple calibration objectives. The calibration results provide an ensemble of possible hydrological outcomes that can help management decisions. Data from four Natural Resource Conservation Service SNOTEL sites in Colorado were chosen to demonstrate the approach.

**Keywords:** Parameter sensitivity; calibration; snow model; multiobjective evolutionary algorithm.

## 1. INTRODUCTION

As much as 75 percent of water supplies in the western United States are derived from snowmelt (USGS, 2014), and snowmelt-dominated watersheds are especially sensitive to changes in temperature and precipitation (Barnett et al., 2005). There are major implications in snowmelt-dominated watersheds that can result from even the least severe climate change scenario. These implications include large reduction in snowpack, insufficient reservoir storage to handle the projected shift in streamflows, and increased frequency and severity of droughts (Barnett et al. 2005; Mote et al., 2005).

Although there might be a consensus that temperature and precipitation patterns will be modified under a changing climate, it is still an open question how these changes will propagate to impacts on water management. In order to adapt to these changes, managers must be able to model detailed hydrological processes under perturbed input conditions. Wagener (2007) highlights the need for an understanding of parameter sensitivity (i.e., how changes in the parameters lead to changes in the model performance), which is a step toward finding relationships between regional watershed characteristics and model parameters. Our work in this study seeks to contribute to the body of work that has investigated model behavior, particularly for predicting snowmelt. For example, Koskela et al. (2012) hypothesized that additional snow data in a hydrological model coupled with a simple degree-day snow model would provide enough new information to identify model parameters, precipitation uncertainty, and model uncertainty. However, the authors determined the additional data did not provide new information that could replace parameter uncertainty, implying that a more complex model is not necessarily more accurate.

In addition to parameter sensitivity, model calibration is an important aspect of using hydrological models, finding the optimal 'fit' between model output and observed data. By calibrating the model parameters, models can be used for predictive purposes. Additionally, model calibration can be complimented by sensitivity analysis (van Werkhoven et al. 2009), since calibration gives the best values of parameters (whereas sensitivity analysis often only shows that a parameter is important but does not suggest its optimal value). Because there exists multiple (sometimes conflicting) measures of model fit, calibration is often performed with respect to multiple objectives, employing multiobjective evolutionary algorithms (MOEAs) to find multiple parameter values that balance the objectives (Efstratiadis and Koutsoyiannis, 2010). An example study is Manandhar et al. (2013), which successfully calibrated and evaluated a hydrological model integrated with a simple degree-day snow accumulation/melt model using the Nash-Sutcliffe Efficiency (NSE) coefficient and the volume bias (VB), comparing the snow cover pattern in the model-generated snow cover map with a satellite-captured map.

This paper represents a preliminary analysis of a popular snow model often used in water management in the U.S. We combine global sensitivity analysis using Sobol' variance decomposition with multiobjective calibration using an advanced MOEA. The snow model considered is SNOW-17, an index model using air temperature to determine the energy exchange between the snow-air interface, which has been successfully applied at point locations to simulate the accumulation and melting of snow cover to a rainfall/runoff model (Anderson, 2006). The goal of this paper is to determine the most sensitive model parameters in SNOW-17 and calibrate it for several representative sites. This research is therefore a first step toward improved understanding of snow model parameter sensitivity to help aid key decisions for water management in snow-dominated basins.

## 2. BACKGROUND

### 2.1 Model Description

SNOW-17 is a conceptual snow accumulation and ablation model first described by Anderson (1973) as a component of the U.S. National Weather Service (NWS) River Forecast System for use in river forecasting. The NWS has used SNOW-17 for decades to create short- and long-term stream flow predictions across the nation. SNOW-17 is an index model using air temperature as the only index to determine the energy exchange across the snow-air interface. The only other input variable is precipitation (Anderson, 2006). As mentioned by He et al. (2011), although SNOW-17 has been used in an operational environment for decades, comprehensive sensitivity analyses of the model parameters are infrequent.

### 2.2 Sensitivity Analysis

Sensitivity analysis seeks to find which parameters are most important in determining a model's response. The Sobol' sensitivity analysis method used in this research is a global method which varies all of the model's parameters in predefined regions to quantify the parameter interactions. The sensitivity of each parameter or parameter interaction is assessed based on its contribution to the total model output variance. First order, second order, and total order effects are calculated from the Sobol' analysis. In the interest of space, we will not discuss the first order and second order effects. The total order effect is the most comprehensive measure of a parameter's sensitivity because it represents the summation of all variance contribution involving that parameter (Tang et al., 2006). For more information on Sobol's method see Sobol' (1993).

Saltelli (2002) introduced a new strategy for the computation of total order sensitivity indices that required 50% less model evaluations than the previous method. This study uses an implementation within the MOEAFramework (http://www.moeaframework.org), to implement Sobol', which employs the Saltelli strategy and has been used in prior studies (see Hadka and Reed 2012). Thus, the default number of re-samples in the MOEAFramework for the bootstrapping is 1,000. This results in a total of 18,000 model simulations, each consisting of different parameter sets, which were performed for each sensitivity analysis experiment.

### 2.3 Multi-Objective Evolutionary Algorithms

MOEAs are often used for multi-objective calibration of hydrological models (Efstratiadis and Koutsoyiannis, 2010). The approach uses multiple measures of model performance to fit the model parameters. MOEAs are population-based search heuristics that use a process analogous to natural selection to find solutions that balance conflicting objectives. Because the optimization process does not use weights between the objectives, it allows the user to find their own preferences between objectives (e.g., different calibration measures). In order for an MOEA to be successful, an MOEA should be able to solve problems from different domains and allow for control of the precision of the solution set in order to generate a reasonable number of solutions. We use the Borg MOEA in this work, an adaptive MOEA framework that uses multiple variation operators to modify itself based on problem properties (Hadka and Reed, 2013). Recent diagnostic tests of several state of the art algorithms have shown the superior performance of the Borg MOEA framework (Hadka and Reed, 2012; Reed et al., 2013).

### 2.4 Objective Functions

Model performance in this study is quantified using several quantitative performance metrics, chosen to reflect typical practice in hydrological studies. The objective functions are used both in the sensitivity analysis (see section 2.2) and calibration (section 2.3). Each objective function uses observed and modelled data of snow water equivalent (SWE). Please note that other objective functions could be employed in a study such as this; objective functions should be chosen to meet the modelling goals of a study; in some cases, results of a Sobol' analysis can be used to choose objectives (Kasprzyk et al. 2012). The first objective function is a commonly used statistic metric, root mean squared error (RMSE), which is defined as

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(x_{1,t} - x_{2,t})^2}{n}}$$

where $n$ is the number of timesteps, $x_{1,t}$ is the modelled snow water equivalent in timestep $t$, $x_{2,t}$ is the observed SWE in timestep $t$. Because it uses the squared difference between modelled and observed data, the RMSE assists with fitting high SWE portions of the graph (van Werkhoven et al., 2009).

The second objective function, is the Nash-Sutcliffe (NSE) index, which is another statistical metric based on least squares method, and is defined as

$$NSE = 1 - \frac{\sum_{t=1}^{n}(x_{2,t} - x_{1,t})^2}{\sum_{t=1}^{n}(x_{2,t} - \overline{x_2})^2}$$

where $\overline{x_2}$ is the mean observed SWE, and other variables are as defined previously. NSE efficiencies can range from –(infinity) to 1, and an efficiency of 1 corresponds to a perfect match of modelled to observed SWE. NSE is an often used calibration metric, and its values are helpful because a NSE of less than 0 indicates that "the model is no better than using the observed mean as a predictor" (Gupta et al., 2009).

The third objective function is Fortin, which is built around the relative deviation between observed and calculated SWE, and was developed by Fortin et. al. (1971). Fortin is defined as

$$Fortin = \frac{1}{n} \cdot \sum_{t=1}^{n} \left| \left[ \left( \frac{x_{1,t} - x_{2,t}}{x_{2,t}} \right) \left( 1 + \frac{\left| x_{2,t} - \overline{x_2} \right|}{\overline{x_2}} \right) \right] \right|$$

The expression tends toward 0 as the modelled SWE tends toward the observed SWE. In a comparison of several objective functions by Servat and Dezetter (1991), the Fortin objective function was identified as robust compared to a suite of other objective functions.

## 3. COMPUTATIONAL EXPERIMENT

Our computational experiment seeks to understand controls on the popular SNOW-17 model, using Sobol' sensitivity analysis and MOEA calibration of the model for several representative sites in Colorado. The inputs of SNOW-17 are precipitation (millimeters, mm) and temperature (degrees Celsius, °C). This model is comprised of eight main parameters: snow correction factor (SCF) (S), average wind function during rain or snow (UADJ), base temperature above which melt typically occurs (MBASE), maximum melt factor during non-rain periods (MFMAX) as mm per degree Celsius, minimum melt factor during non-rain periods (MFMIN), model parameter for deep snowpack areas (TIPM), maximum negative melt factor (NMF), and percent liquid water holding capacity (PLWHC) as a percent. The output is daily snow water equivalent (SWE).

The eight model parameters were all included in the Sobol' analysis. The ranges for all of the parameters were chosen based on calibration information provided in Anderson (2002), representing reasonable upper and lower bounds that could be expected at snowmelt dominated sites. Table 1 summarizes the ranges used for each parameter. By default, the MOEA Framework used to conduct the Sobol' analysis employs bootstrap analysis using confidence intervals within the MOEA Framework.

**Table 1.** Parameter Ranges for Sobol' Sensitivity Analysis

| **Parameters** | **S (%)** | **UADJ (mm/mb)** | **MBASE (°C)** | **MFMAX (mm/°C)** | **MFMIN (mm/°C)** | **TIPM** | **NMF (mm/°C)** | **PLWHC (%)** |
|---|---|---|---|---|---|---|---|---|
| **Lower Bound** | 0.9 | 0.05 | 0.0 | 0.5 | 0.1 | 0.05 | 0.05 | 0.02 |
| **Upper Bound** | 1.6 | 0.2 | 2.0 | 2.2 | 0.5 | 0.2 | 0.3 | 0.3 |

The sensitivity analysis was conducted using temperature, precipitation, and observed SWE data for the 2010 through 2012 water years from four different SNOTEL locations in Colorado (Copper Mountain, Vail Mountain, Beaver Creek Village, and Michigan Creek) in order to analyze variability of parameter sensitivities among different locations.

The second part of this research involved using the Borg MOEA with three objective functions (RMSE, NSE, Fortin) and the eight parameters from the SNOW-17 model to generate optimal parameter sets for the four different SNOTEL sites. The default parameterization of the Borg MOEA framework was used, which is justified based on comparative studies that show Borg's good performance over its parameter range (e.g. Reed et al. (2013)). In this study, the algorithm was run for a single trial of 10,000 function evaluations for each site. Future work will investigate Borg's performance over multiple seeds and for a longer run time, where termination criteria will be chosen based on visualizations of the algorithm's performance. Several epsilon values were tested, but the final epsilon resolution for each objective was chosen as 0.1.

## 4. RESULTS

### 4.1 SOBOL' ANALYSIS

This study used Sobol' sensitivity analysis to determine individual parameter sensitivities of eight parameters used in SNOW-17. Results, which are presented as total order indices, provide a broad picture of model behaviour since they estimate the effect of the individual parameters and their interactions with other parameters. A sensitivity threshold, t, is often set, such that parameters with sensitivity indices above t are considered sensitive. For example, van Werkhoven et al. (2009) explored several values of t including 0.05, 0.1, 0.2, and 0.3. A t value of 0.05 was chosen for this study. Additionally, sensitivity values greater than 0.8 indicate that a parameter controls the model's response. Table 2 summarizes the total order indices for the three objective functions for each location. Numerical instabilities (truncation errors, and Monte Carlo approximation errors) led to some sensitivity indices of less than 0; these values are reported as 0 with an asterisk in the table.

**Table 2.** Total-Order Effects Resulting from Sobol's Sensitivity Analysis

| Objective Function | S | UADJ | MBASE | MFMAX | MFMIN | TIPM | NMF | PLWHC |
|---|---|---|---|---|---|---|---|---|
| **Copper Mountain (site #415, elevation =3215.64 m)** | | | | | | | | |
| RMSE | 0.8962 | 0.0006 | 0.0751 | 0.2038 | 0.0024 | 0.0026 | 0.0021 | 0.0222 |
| NSE | 0.8690 | 0* | 0.0724 | 0.2673 | 0.0016 | 0.0040 | 0.00002 | 0.0399 |
| FORTIN | 0.9109 | 0.00006 | 0.0515 | 0.1352 | 0.0047 | 0.0013 | 0.0008 | 0.0145 |
| **Vail Mountain (site #842, elevation =3139.44 m)** | | | | | | | | |
| RMSE | 0.8393 | 0.0020 | 0.1181 | 0.4217 | 0.0132 | 0.0034 | 0.0059 | 0.0407 |
| NSE | 0.8437 | 0* | 0.1139 | 0.4658 | 0.0134 | 0.0055 | 0.0014 | 0.0662 |
| FORTIN | 0.8989 | 0.00009 | 0.0662 | 0.2387 | 0.0166 | 0.0022 | 0.0037 | 0.0270 |
| **Beaver Creek Village (site #1041, elevation =2590.80 m)** | | | | | | | | |
| RMSE | 0.3835 | 0.0046 | 0.2146 | 0.7076 | 0.0293 | 0.0078 | 0.0072 | 0.0263 |
| NSE | 0.8134 | 0* | 0.1154 | 0.3080 | 0.0237 | 0.0025 | 0.0030 | 0.0360 |
| FORTIN | 0.3665 | 0.0026 | 0.2264 | 0.6834 | 0.0315 | 0.0054 | 0.0042 | 0.0304 |
| **Michigan Creek (site #937, elevation = 3230.88 m)** | | | | | | | | |
| RMSE | 0.8702 | 0.0010 | 0.1225 | 0.2517 | 0.0143 | 0.0030 | 0.0060 | 0.0245 |
| NSE | 0.8356 | 0* | 0.1299 | 0.3140 | 0.0168 | 0.0044 | 0.0034 | 0.0447 |
| FORTIN | 0.8877 | 0.0001 | 0.0753 | 0.1685 | 0.0155 | 0.0016 | 0.0026 | 0.0151 |

The data depict that S is by far the most dominant parameter within SNOW-17. The MBASE and MFMAX parameters also demonstrate significance with total order indices exceeding 0.05. The data also portray that Beaver Creek Village has total order indices that differ from the other three locations. One explanation may be that the precipitation data for Beaver Creek was more accurate than the other three sites, and thus the snow correction factor had less of an influence on the model output. Results are slightly different across objectives, showing the usefulness of including multiple objectives in the study; these objectives are also used in the calibration in the next section.

### 4.2 Multiobjective Model Calibration

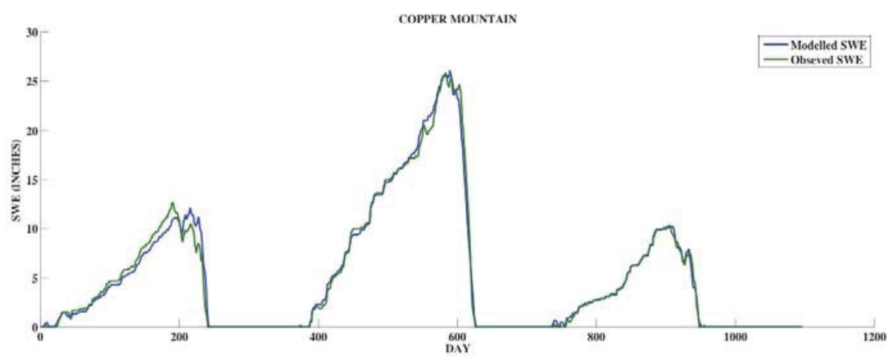
Although Sobol' analysis is valuable in understanding the most important model parameters, it does not give a sense for what the best numerical value for each parameter is, as well as how the model's parameters change when trying to fit different calibration objectives. Therefore, the second phase of this study used an MOEA framework (Borg) to model tradeoffs among the model parameters for the different locations. For all four locations, the tradeoffs between parameters collapsed to a single parameter set. This result suggests that there is no conflict between RMSE, NSE, and Fortin for each site. Our tests showed that this result is true even for smaller epsilon values. Table 3 summarizes the optimal parameter values for each location. Table 4 summarizes the objective function values associated with the optimal parameter sets. Figure 1 portrays graphs of the observed SWE and modelled SWE using the optimal parameter set for each site. Figure 1 shows that the optimal parameter set for each site produces modelled SWE values that very closely match the observed SWE values.

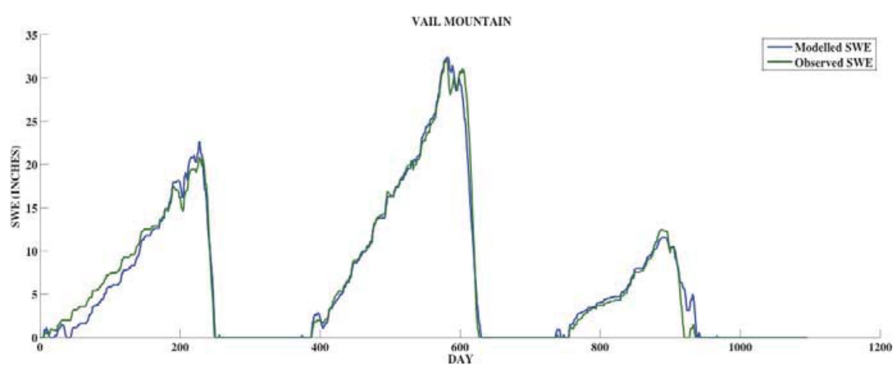
**Table 3.** Borg Optimal Parameter Values

| S | UADJ | MBASE | MFMAX | MFMIN | TIPM | NMF | PLWHC |
|---|---|---|---|---|---|---|---|
| **Copper Mountain (site #415, elevation =3215.64 m)** | | | | | | | |
| 0.9767 | 0.0500 | 0.6070 | 0.6989 | 0.2496 | 0.1844 | 0.2245 | 0.1710 |
| **Vail Mountain (site #842, elevation =3139.44 m)** | | | | | | | |
| 1.079 | 0.0502 | 1.180 | 0.8305 | 0.5000 | 0.0505 | 0.2231 | 0.0200 |
| **Beaver Creek Village (site #1041, elevation =2590.80 m)** | | | | | | | |
| 1.033 | 0.0500 | 1.998 | 0.6842 | 0.3149 | 0.0530 | 0.2173 | 0.1254 |
| **Michigan Creek (site #937, elevation = 3230.88 m)** | | | | | | | |
| 0.9000 | 0.0500 | 1.802 | 0.8448 | 0.1394 | 0.0953 | 0.1961 | 0.0248 |

**Table 4.** Objective Function Values Associated with Optimal Parameter Sets

| RMSE | NSE | Fortin |
|---|---|---|
| **Copper Mountain (site #415, elevation =3215.64 m)** | | |
| 0.6202 | 0.9908 | 0.0621 |
| **Vail Mountain (site #842, elevation =3139.44 m)** | | |
| 1.0467 | 0.9837 | 0.0879 |
| **Beaver Creek Village (site #1041, elevation =2590.80 m)** | | |
| 0.5201 | 0.9824 | 0.0821 |
| **Michigan Creek (site #937, elevation = 3230.88 m)** | | |
| 0.4786 | 0.9882 | 0.0776 |



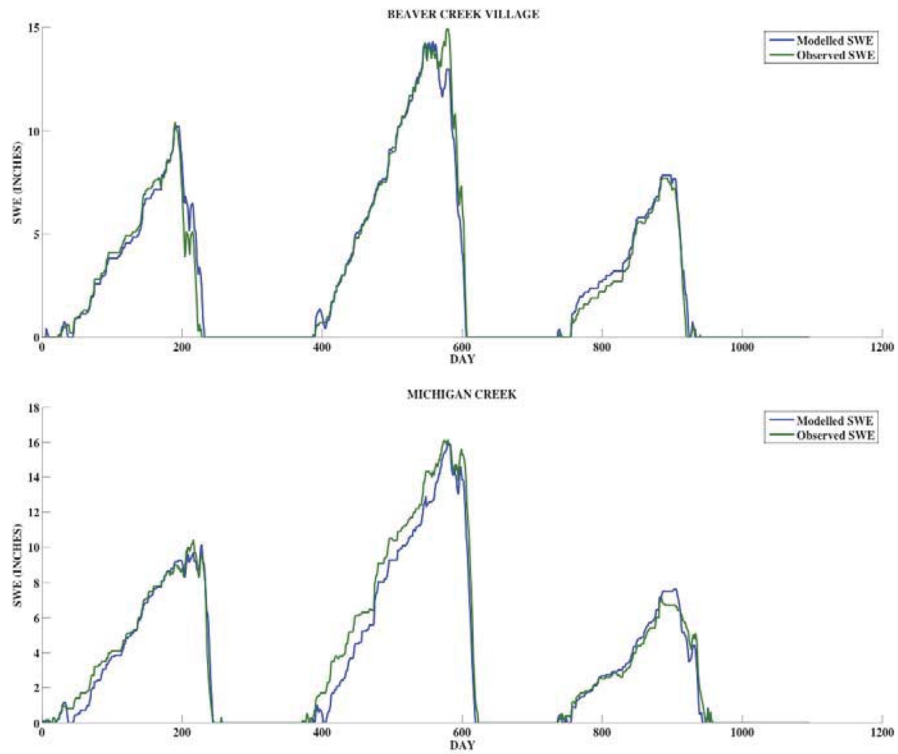



**Figure 1.** Modelled Versus Observed SWE

The modelled versus observed SWE for each site demonstrates that the optimal parameter sets produce generally good model fits to the observed SWE data. However, a short time period was used for the study data, and further investigation involving validation and calibration of the model is necessary. A comparison of wet, dry, and average precipitation years will also be useful in evaluating the goodness of fit when using the optimal model parameters. Similarly, future work can employ new objectives, such as quantifications of the fit to the cumulative "volume" of water throughout the year.

## 5. DISCUSSION AND CONCLUSIONS

The Sobol' sensitivity analysis demonstrated that parameter sensitivities varied among the objective functions, however, the same parameters remained sensitive across the objective functions and locations. These results demonstrate that all parameters within a model are not necessarily important. Following Koskela et al. (2012), if in a simple model such as SNOW-17 has insensitive parameters, one could conclude that additional data and/or increased model complexity do not necessarily result in improved model performance. Future work will determine if these results from SNOW-17 are generalizable to other modelling frameworks for these sites.

In the Borg optimizations, tradeoffs among objective functions collapsed to one optimal parameter set for each location. Several epsilon values were tested, but the tradeoffs among the objective functions also collapsed to one optimal parameter set for different epsilon values. This result implies that there is no tradeoff between performance for the chosen objective functions, but there could be additional tradeoffs if the set of objective functions was expanded. Our study therefore underscores the fact that objective functions should be chosen carefully to capture the modelling aspects that are desired by the user.

Throughout the research process, it was observed that modelled SWE performed poorly for model runs with poor parameter calibration. Using a poorly calibrated model for water management decisions could result in incorrect estimates of available water resources. . As climate changes and population increases, water resources planning becomes more important to ensure communities have a sustainable water supply. Accurate snow projections will provide insight regarding the possibility of extreme circumstances, and will improve managers' decision-making process for long-term water resources management.

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