SENSITIVITY AND MODEL REDUCTION OF SIMULATED SNOW PROCESSES:
CONTRASTING OBSERVATIONAL AND PARAMETER UNCERTAINTY
TO IMPROVE PREDICTION

by
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ABSTRACT

The hydrology of high-elevation, mountainous regions is poorly represented in Earth Systems Models (ESMs). In addition to regulating downstream water delivery, these ecosystems play an important role in the storage and land-atmosphere exchange of water. Water balances are sensitive to the amount of water stored in the snowpack (snow water equivalent, SWE), as much of Colorado’s water supply is derived from snowmelt. In an effort to resolve this hydrologic gap in ESMs, this study seeks to better understand how uncertainty in both model parameters and forcing affect simulated snow processes. To better understand parameter uncertainty and assess model performance, this study conducts a sensitivity analysis, using active subspaces, on model inputs (meteorological forcing and static parameters) for both evergreen needleleaf and bare ground land cover types. Observations from an AmeriFlux tower at the Niwot Ridge research site are used to force an integrated single-column hydrologic model, ParFlow-CLM. This study found that trees can mute the effects of sublimation causing the evergreen needleleaf model to be sensitive primarily to hydrologic forcing; humidity in the winter, radiation and air temperature in the summer months. However, bare ground simulations were most sensitive to snow parameters along with radiation as these are unblocked by canopy. The bare ground model is most sensitive to overall changes to the linear combination of input parameters, which means radiation observations and snow parameterizations are of great importance for obtaining accurate hydrologic model results. Humidity measurements are also important, but the change in SWE of the evergreen needleleaf simulations was less than that of the bare ground simulations.
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CHAPTER 1
INTRODUCTION

Approximately one-sixth of the world’s population live in snowmelt-dominated regions and rely on snowmelt for their water supply (Barnett et al., 2005). Snow is a critical component of the hydrologic cycle in mountain headwaters systems, with melting snow providing seventy percent of the western United States’ water supply (Chang et al., 1987). In fact, eighty-five percent of streamflow for the Colorado River comes from snowmelt in the Colorado headwaters region and the majority of Colorado’s water supply is from snow fall and subsequent melt in the mountains (Ikeda et al. 2010, Barnett et al., 2005). Though snow is a vital piece of the hydrologic cycle, hydrologic models have little ability to accurately capture snowmelt in highly heterogeneous mountain systems largely because of lack of available data in mountainous regions (Bales et al., 2006). Most hydrologic models use datasets with coarse spatial resolution and the extrapolation of point data across a large region, which cannot capture the inherent heterogeneity of these systems (Lundquist, 2010; Dettinger, 2004). Yet, accurate characterization of this heterogeneity is invaluable for accurately modeling snowpack in these mountainous regions.

Given that the variability in snow parameters and forcing affect the modeled output of snow process, such as SWE, it is imperative that the model physics are correctly understood. One way to better understand snow model physics in mountain systems is through sensitivity analysis. Sensitivity analysis considers the uncertainty that is introduced during the process of collecting meteorological data or parameterizing models and extrapolating across a heterogeneous region. It is important to understand how these uncertainties affect model output in order to understand why the model is producing a certain result, along with determining the accuracy of that result. With regard to modeling snow water equivalent, some studies have evaluated the differences between models and their snow formulations, but few studies have conducted a sensitivity analysis for these snow formulations and parameters (Chen et al., 2014).

Studies that have conducted a sensitivity analysis on snow parameters in heterogeneous mountain regions find that the topographic characteristics and snow albedo parameterizations play a large role in determining the snow-covered area and
SWE model outputs (Engel et al., 2017; Houle et al., 2016). This emphasizes the need for further sensitivity analysis into the snow parameters as well as the forcing parameters—which are driven, in part, by topographic heterogeneity—in order to better understand the model process linked to SWE calculation.
CHAPTER 2
METHODS

This study conducts a sensitivity analysis on 900 model simulations with varying land cover type, meteorological and snow model parameters. This allows for a better understanding of how each of land cover types, forcing variables, and snow parameters contributes to the modeled output of snow water equivalent.

2.1 Integrated Hydrologic Model

Using an integrated and coupled model for this work allows for modeling the feedbacks of surface and sub-surface processes simultaneously, including groundwater, soil moisture, and atmospheric variables, all of which are important to snow accumulation and melt (Dai et al, 2003; Dickenson et al., 1993; Domine, 2011). This study uses ParFlow-CLM (PF-CLM), a fully-integrated, coupled hydrologic model (Figure 2.1a). ParFlow solves the three-dimensional Richards equation for subsurface flow and the shallow water equations for the surface flow (Jones and Woodward, 2001; Kollet and Maxwell, 2006). CLM simulates the surface energy and water balances and passes this information to ParFlow, allowing for communication between all layers of the model (Maxwell and Miller, 2005). ParFlow-CLM has been used to analyze many different hydrologic problems relating to surface water-groundwater interactions, atmospheric interactions, residence times, and land cover-groundwater interactions (Condon et al., 2015; Maxwell and Condon, 2016; Gilbert et al., 2017; Maxwell et al., 2016; Bearup et al., 2016; Pribulick et al., 2016; Rihani et al., 2010).

Figure 2.1 ParFlow-CLM: (a) conceptual diagram of sophisticated surface and subsurface model interactions; (b) conceptual diagram of CLM snow processes.
2.2 ParFlow-CLM Model Physics

ParFlow-CLM contains a robust physical representation of snow processes, the focus of this study. CLM contains up to five snow layers and calculates snow degradation and accumulation based on albedo, snow age, snow metamorphism, and temperature (Dickenson et al., 1993). As precipitation falls, the canopy intercepts some of the precipitation until the default canopy capacity of 0.1mm is reached, at which point the precipitation falls to the ground. The fraction of precipitation that falls as direct throughfall is determined by:

\[ q_{TF} = P * \left( -e^{-0.5 \cdot (L_{AI}^E + S_{AI}^E)} \right) \]  

(2.1)

where \( P \) is precipitation, \( L_{AI}^E \) is exposed leaf area index and \( S_{AI}^E \) is exposed stem area index. The fraction of precipitation that falls as rain varies linearly with air temperature as:

\[ F_{ifall} = \begin{cases} 
0 & T_{air} \leq T_{frz} \\
-54.632 + 0.2 \cdot T_{air} & T_{frz} < T_{air} \leq T_{frz} + 2 \\
0.4 & T_{frz} + 2 < T_{air}
\end{cases} \]  

(2.2)

where the rest of the precipitation falls as snow, with \( T_{frz} \) being 273.16K. The depth of new snow is based on the density of fresh snow calculated from the Alta relationship (Anderson, 1976; Giddings and LaChapelle, 1961).

\[ \rho_{snow} = \begin{cases} 
50 & T_{air} \leq T_{frz} - 15 \\
50 + 1.7 \cdot (T_{air} - T_{frz} + 15)^{1.5} & T_{frz} - 15 < T_{air} \leq T_{frz} + 2 \\
189 & T_{frz} + 2 < T_{air}
\end{cases} \]  

(2.3)

When precipitation falls to the ground as snow, it is added to the already existing snow layers increasing snow depth and SWE. If no snow is present on the ground, a new snow layer is formed when the snow depth exceeds 0.01m.

Shortwave radiation is split between direct and diffuse shortwave radiation (\( SW_{t,dir}, SW_{t,dif} \)) and the corresponding albedos are used to calculate the shortwave radiation absorbed by the surface by:

\[ SW_{abs} = SW_{t,dir} * (1 - \alpha_{dir}) + SW_{t,dif} * (1 - \alpha_{dif}) \]  

(2.4)

Snow albedo is calculated separately for direct and diffuse solar radiation for either the visible or near-infrared waveband. Snow albedo also decays with age due to the accumulation of dust and dirt along with increasing grain size (Warren and Wiscombe, 1980; Dickenson et al., 1993).
The albedo of new snow ($\alpha_{\lambda, new}$) is waveband-specific with a default of 0.95 for visible (snal0) and 0.65 for near-infrared wavebands (snal1). The empirical decay constant with age ($C_\lambda$) is 0.5 for visible (cons) and 0.2 for near-infrared (conn) wavebands (Dickenson et al., 1993). Non-dimensional snow age ($\tau_{snow}$) is estimated by accounting for three processes that will alter snow albedo:

1) change in grain size with vapor diffusion as the snowpack ripens, approximating the vapor pressure using surface temperature ($T_g$) as:

$$A_1 = e^{\frac{1}{50000} \frac{T_g}{T_{trz}} \frac{1}{T_R}} ,$$

2) increase in effective grain size near freezing approximated as:

$$A_2 = A_1^{10} ,$$

3) the darkening of snow due to the deposition of soot or dirt (age3), which is assumed to be 0.3. The change in snow age over a time step of $dt$, ($\Delta \tau_{snow}$) combines these three age-effects:

$$\Delta \tau_{snow} = 10^{-6} \cdot \Delta t \cdot (A_1 + A_2 + A_3)$$

which is then added to the current snow age to obtain the snow age for the next time step. Snow albedo is then further corrected for solar zenith angle, which describes the angle of the sun perpendicular to the surface for a given time, latitude, and longitude using equation:

$$c_{ff} = \frac{\frac{1}{s_i} \frac{1}{1 + \cos\text{zen}^2 + s_i}}{s_i} ,$$

where $c_{ff}$ is the snow albedo correction factor for a zenith angle greater than sixty degrees, $\cos\text{zen}$ is the cosine solar zenith angle for the next time step, and $s_i$ is a factor that helps control albedo zenith dependence.
2.3 Study Site

The study site is the Niwot Ridge Long Term Ecological Research site, which lies in the Rocky Mountains near Nederland, CO, 65 km north-west of Denver (Figure 2.2). Niwot Ridge houses an AmeriFlux eddy covariance (flux) tower that has been collecting data since 1998 and is located at 3050m elevation. This flux tower data is used to drive the model. The surrounding subalpine forest is about 97 years old and in a state of aggradation after recovering from early twentieth century logging (Monson et al., 2002). The site was established in 1980 and is representative of alpine ecosystems in the southern Rocky Mountains (Blanken, 1998-). Due to the long-term and well-curated data record, this site is an ideal location for sensitivity analysis.

Figure 2.2  Niwot Ridge Long Term Ecological Research site. The star in the inset shows location of the AmeriFlux eddy covariance tower.

2.4 Model Design

While sensitivity analyses have been performed using large-scale, three-dimensional models, it is computationally expensive because these models can contain millions of parameters (Condon et al., 2013). Therefore, this study uses a single-column approach to understand the physics and constraints of the snow processes of PF-CLM. This approach decreases input parameters and computational expense. Modeling one water year at a single-column scale takes about twenty minutes on a laptop and still accounts for all the processes needed to run a sensitivity analysis. The domain
represented here is a single-column with dimensions of 1 m$^3$ and five subsurface layers. The site vegetation is characterized by evergreen needleleaf. This study uses a one-dimensional meteorological forcing comprised of incoming shortwave and longwave radiation, air temperature, wind speed, atmospheric pressure, and specific humidity from the flux tower at Niwot Ridge for water year 2014. The precipitation data used in this study comes from the U.S. Climate Reference Network (USCRN), which is a network of climate monitoring stations across the United States (Diamond et al., 2013). This data was obtained from the Boulder 14W gage, which is about one kilometer from the AmeriFlux site and has been collecting data since 2003. This precipitation is used rather than the AmeriFlux precipitation data due to a flux tower precipitation gage malfunction after year 2011. Water year 2014 was chosen for the baseline run as the modeled SWE most accurately estimates the observed SWE from the AmeriFlux site (Figure 2.3).

Figure 2.3  Modeled SWE output using ParFlow-CLM with the AmeriFlux observation measurement of SWE for water year 2014.
2.5 Active Subspaces Methodology

This study employs the active subspaces method of sensitivity analysis. Active subspaces globally compares the relationship of the ParFlow-CLM input parameters and the forcing parameters with the quantity of interest (model output). This method identifies the important directions in the fourteen-dimensional input space along which the output changes more than in the orthogonal directions. The active subspace is a span of a set of directions composed of a set of weights defining a linear combination of the inputs. The active subspace is usually derived by the gradient of the input parameters. ParFlow-CLM, however, does not access this gradient and must substitute an algorithm to define the single most important direction in the input space, since a finite difference approximation would be too computationally expensive. Therefore, we chose to use a linear model to approximate these gradients. The normalized gradient of the linear model gives the single most important direction in the fourteen-dimensional input space. The steps used to compute the active subspace are as follows:

1. Draw a sufficiently large number of independent samples from a range of values for each input parameter with the range of values centering on the baseline value.
2. For each sample, run the simulation and compute the quantity of interest.
3. Use a least-squares fit linear model to compute the coefficients of that linear model.
4. Compute the normalized gradient of the linear model.
5. Plot the linear combination of inputs against the quantity of interest.

This approach is valid if the active subspace is one-dimensional and the output is monotonic with respect to the input. This can be verified by the sufficient summary plot (SSP). The SSP (step 5) reveals whether the relationship between the quantity of interest and the combination of input parameters (the active variable) fits a univariate, scalar-value function fit, such as linear, quadratic, or cubic. Each point on the SSP corresponds to the inputs and output from one model realization. This takes the fourteen-dimensional input space, identifies the direction in which the fourteen parameters create a line, and plots this linear combination against the output, thus
collapsing the fourteen-dimensional space to a one-dimensional space (Constantine, 2015).

The weights of the linear combination of the inputs reveal to which parameters the model is most sensitive. Input parameters with weights of larger magnitudes are more important because a change in these parameters causes a greater change in the output than other input parameters. A negative weight means an increase in the input parameter results in a decrease in the output and a positive weight means an increase in the input parameter results in an increase in the output (Jefferson et al., 2015).

2.6 Active Subspaces on Model Parameters

The meteorological forcing and the physical snow parameters embedded in the model control SWE. Shortwave radiation (sw) and longwave radiation (lw) in the direction toward Earth’s surface, precipitation (precip), air temperature (airt), wind speed from west-to-east (windu) and from south-to-north (windv), atmospheric pressure (press), and specific humidity (hum) form the meteorological forcing. The value for snow decay due to accumulation of particles (age3), visible and near-infrared albedo of new snow (snal0 and snal1, respectively) (Eq. 5a, Eq. 5b), decay constant for visible and near-infrared albedo of snow (cons and conn, respectively) (Eq. 5a, Eq. 5b), and the factor that controls albedo zenith dependence (sl) (Eq. 9) comprise some of the important snow parameter values embedded in the model. By understanding how modifying these input parameters affects the quantities of interest of this study—output of peak SWE, monthly averaged SWE, timing of melt, and timing of peak SWE—the PF-CLM inputs are better constrained leading to more accurate model results that can be scaled to coarser resolution models. Additionally, running a sensitivity analysis on the snow and forcing parameters allows for a sensitivity comparison between values based on field data and values embedded in the model.

Using the accuracy measurements from the manuals for the instruments that collect the meteorological data and the literature surrounding snow parameters in hydrologic models (RM Young, 2000; Vaisla, 2016; Campbell Scientific, 2011; CS105; Hollinger and Richardson, 2005; Warren and Wiscombe, 1980; Warren, 1980; Grenfell et al., 1994; Dickenson et al., 1993; Bonan et al., 2002), we chose a range of values
from which to sample each parameter for this sensitivity analysis (Table 2.1). Three hundred values were sampled from the parameter ranges using a Monte Carlo method. Each year of forcing for each forcing parameter was then multiplied by one of the 300 randomly selected values from the ranges shown in Table 2.1, so as to keep the timing of the meteorological events consistent to the baseline as well as to keep the method consistent between parameters with differing units of measure. Also, the active subspaces method becomes infeasible to conduct if using too many parameters due to computational expense. For example, instead of using a set of eight forcing parameters for each hour of the year for three hundred simulations (21,024,000 variables) this study was conducted on the multiplier value (300 simulations for eight forcing parameters equals 2,400 variables) of the forcing parameters. The sampled values from the snow parameter ranges shown in Table 2.1 completely replaced the baseline parameters in the 300 model runs.
Table 2.1 ParFlow-CLM snow and forcing parameters.

| Variable | Value | CLM File | Units | Definition | Used in | Min   | Max   |
|----------|-------|----------|-------|------------|---------|-------|-------|
| age3     | 0.3   | clm_snowage.F90 |       | set value for snow decay due to accumulation of particles | age3=0.3 | 0.1000 | 0.5000 |
| snal0    | 0.95  | clm_snowalb.F90 |       | vis albedo of new snow | albs = snal0*(1.-cons*age) | 0.7000 | 0.9900 |
| snal1    | 0.65  | clm_snowalb.F90 |       | nir albedo of new snow | albl = snal1*(1.-conn*age) | 0.0000 | 0.7000 |
| cons     | 0.2   | clm_snowalb.F90 |       | constant for visible snow albedo calculation | albs = snal0*(1.-cons*age) | 0.1000 | 0.3000 |
| conn     | 0.5   | clm_snowalb.F90 |       | constant for nir snow albedo calculation | albl = snal1*(1.-conn*age) | 0.4000 | 0.6000 |
| sl       | 2     | clm_snowalb.F90 |       | factor that helps control albedo zenith dependence | \( \text{off} = \frac{((1+1./sl)/(1.+\max(dble(0.001),\cos\text{zen})*2.*sl)^2)}{1./sl} \) | 1.0000 | 3.0000 |
| sw       |       |          | W/m²  | shortwave radiation down (solar) | forcing | 0.9000 | 1.1000 |
| lw       |       |          | W/m²  | longwave radiation down (IR) | forcing | 0.9000 | 1.1000 |
| precip   |       |          | mm/s  | precipitation | forcing | 0.9990 | 1.0010 |
| airt     |       |          | K     | temperature | forcing | 0.9993 | 1.0007 |
| press    |       |          | Pa    | atmospheric pressure | forcing | 0.9993 | 1.0007 |
| hum      |       |          | g/kg  | specific humidity/ measures RH | forcing | 0.9700 | 1.0300 |
| windu    |       |          | m/s   | wind speed by direction | forcing | 0.9900 | 1.0100 |
| windv    |       |          | m/s   | wind speed by direction | forcing | 0.9900 | 1.0100 |
CHAPTER 3
RESULTS

After perturbing both the snow parameters and the forcing and computing the active subspace on 600 simulations, we observed the relationships between the input parameters and quantities of interest: monthly-averaged SWE, peak SWE, time of total melt, and time of peak SWE (Figure 3.1). We then ran an additional set of 300 simulations only changing the snow parameters and keeping the forcing consistent with the baseline and using bare ground land cover to better determine the sensitivity of the model to the snow parameters. The model sensitivities change depending on land cover and on the quantity of interest.

Figure 3.1  Conceptual figure defining the quantities of interest on a baseline model output.

3.1 Effect of Land Cover on SWE

SWE is also controlled by land cover type (Figure 3.2). Though Niwot Ridge is classified as evergreen needleleaf, running the baseline scenario with bare ground results in different magnitude and timing of SWE over water year 2014; the bare ground scenario has less SWE than the evergreen needleleaf scenario. This is validated by the
ground temperature model outputs (Figure 3.3). The ground temperature refers to the top of the snowpack when snow is present. This ground temperature remains frozen longer in the evergreen needleleaf baseline simulation than for the bare ground baseline simulation. The bare ground simulation also reaches greater ground temperatures than the needleleaf simulation, resulting in a warmer snowpack where snow will melt more quickly. Since SWE is controlled by land cover type as well as the input parameters mentioned above, we ran a set of 300 simulations using land cover type evergreen needleleaf and a set of 300 simulations using bare ground to better understand the relationships between SWE, land cover type, and PF-CLM input parameters.

**Baseline: Evergreen Needleleaf vs Bare Ground**

![Graph](image_url)

Figure 3.2 Modeled SWE for water year 2014 using evergreen needleleaf and bare ground land cover types.
Figure 3.3 Modeled ground temperature for water year 2014 using evergreen needleleaf and bare ground land cover types.

3.2 Monthly Averaged SWE

Figure 3.4 shows the weights of each parameter by month and the model outputs with respect to the active variable. August and July are missing from this figure, as SWE is zero in these months for all 300 simulations. As stated above, the larger the magnitude of the weights, the more important the parameter. A positive weight means the output increases with an increase in input and a negative weight means the output decreases with an increase input.

The results of the evergreen needleleaf simulations show ParFlow-CLM is most sensitive to changes in longwave radiation and air temperature throughout the water year (Figure 3.4). For every month, the weights of these parameters are greater than 0.25. However, some sensitivities vary with month. Humidity is an important parameter in the months of snow accumulation, while it has a weight of less than 0.25 for May, June, and September when snow is generally melting. The ParFlow-CLM evergreen needleleaf simulations are insensitive to the snow parameters for every month.
The months most sensitive to changes in input parameters as a whole are April, May, and June, shown by the larger slopes on the sufficient summary plot. This means the linear combination of weights of parameters is greater in these months than the others. Snowmelt occurs during these months leading to an overall greater sensitivity when the weights are linearly combined than in the other months.

![Figure 3.4](image-url) Active subspace results plot for monthly-averaged SWE for the evergreen needleleaf simulations.

The results for the bare ground simulations reveal very different sensitivity relationships from month to month than the evergreen needleleaf (Figure 3.5). The model with bare ground is sensitive to longwave radiation in every month, just as the evergreen needleleaf simulations. Shortwave radiation is also an important parameter in every month, except September. The bare ground simulations are sensitive to the near-infrared albedo coefficients throughout the year and the visible albedo coefficients in the winter and spring months (Table 3.1).
The months most sensitive to change of the input parameters are January, February, March, April, and May, revealing that the bare ground simulations as a whole are more sensitive to change in the input parameters than the evergreen needleleaf simulations as there is more variation within each month and more months showing noteworthy variation. March and April are again the most sensitive months.

Figure 3.5  Active subspace results plot for monthly-averaged SWE for the bare ground simulations.

Figure 3.6 shows the same results as Figure 3.5, but for scenarios where the snow parameters are perturbed and the forcing is consistent with the baseline case. This focus on the snow parameters reveals the dependence of the model to forcing parameters versus snow parameters. Figure 3.6 shows the snow parameters have similar weights as the previous bare ground run; however, parameters snal0 and snal1 have much higher weights for every month, with September exhibiting a higher inverse weight. Furthermore, the range of maximum SWE for each month is smaller when only the snow parameters are perturbed than when both the forcing and snow parameters
are perturbed. This difference in range and parameter weights can then be attributed to the perturbation of the forcing parameters.

Figure 3.6 Active subspace results plot for monthly-averaged SWE for the bare ground simulations with baseline forcing.

### 3.3 Peak SWE

Figure 3.7 shows the sensitivity of PF-CLM peak SWE with evergreen needleleaf land cover type. Similar to the monthly-averages of SWE, peak SWE is most sensitive to humidity and longwave radiation with air temperature being the only other parameter with a weight of magnitude greater than 0.25. Peak SWE ranges from 426.7mm to 457.9mm.
Table 3.1 Active subspace parameters with a weight of magnitude 0.25 or greater for the monthly averaged SWE quantity of interest.

| QOI     | Land Cover         | Snow Accumulation or Decay | Forcing Parameters | Snow Parameters |
|---------|--------------------|----------------------------|--------------------|-----------------|
|         |                    |                            | sw  lw  airt  hum  snal0  snal1 |                  |
| Oct SWE | Evergreen Needleleaf| accumulation                | x  x  x  x        |                 |
| Oct SWE | Bare Ground        | accumulation                | x  x              |                 |
| Nov SWE | Evergreen Needleleaf| accumulation                | x  x  x          |                 |
| Nov SWE | Bare Ground        | accumulation                | x  x              |                 |
| Dec SWE | Evergreen Needleleaf| accumulation                | x  x  x          |                 |
| Dec SWE | Bare Ground        | accumulation                | x  x              |                 |
| Jan SWE | Evergreen Needleleaf| accumulation                | x  x  x          |                 |
| Jan SWE | Bare Ground        | accumulation                | x  x              |                 |
| Feb SWE | Evergreen Needleleaf| accumulation                | x  x  x          |                 |
| Feb SWE | Bare Ground        | accumulation                | x  x              |                 |
| Mar SWE | Evergreen Needleleaf| accumulation                | x  x  x          |                 |
| Mar SWE | Bare Ground        | accumulation                | x  x              |                 |
| Apr SWE | Evergreen Needleleaf| decay                       | x  x  x          |                 |
| Apr SWE | Bare Ground        | decay                       | x  x              |                 |
| May SWE | Evergreen Needleleaf| decay                       | x  x  x          |                 |
| May SWE | Bare Ground        | decay                       | x  x              |                 |
| June SWE| Evergreen Needleleaf| decay                       | x  x  x          |                 |
| June SWE| Bare Ground        | decay                       | x  x              |                 |
| Sep SWE | Evergreen Needleleaf| accumulation                | x  x              |                 |
| Sep SWE | Bare Ground        | accumulation                | x                |                 |
Figure 3.7 Active subspace results plot for peak SWE of the evergreen needleleaf simulations.

Figure 3.8 shows the sensitivity of peak SWE to the parameters of the bare ground simulations. In these runs, PF-CLM is sensitive to both shortwave and longwave radiation as well as both the near-infrared and visible albedo coefficients (Table 3.2). Peak SWE for these runs varies from 151.3mm to 471.5mm. The ranges of modeled peak SWE are greater for the bare ground simulations than the evergreen needleleaf simulations revealing a greater sensitivity of the bare ground model to input parameters. The least-squares regression for the linear model in all simulations is 0.99, which means the variation in peak SWE can be explained by the linear combination of weights of the input parameters.
Figure 3.9 again shows the sensitivity of the model to perturbations in only the snow parameters. The range of peak SWE for these simulations is 179.1mm to 419.1mm. This is a smaller range than the bare ground runs that perturb all input parameters; however, it is not as small as the evergreen needleleaf runs. This indicates the difference in ranges of these simulations is due to the forcing parameters and land cover type.

Figure 3.8 Active subspace results plot for peak SWE of the bare ground simulations.

Figure 3.9 Active subspace results plot for peak SWE of the bare ground simulations with baseline forcing.
Table 3.2  Active subspace parameters with a weight of magnitude 0.25 or greater for the peak SWE quantity of interest.

| QOI             | Land Cover                  | Forcing Parameters | Snow Parameters |
|-----------------|-----------------------------|--------------------|-----------------|
|                 |                             | sw | lw | airt | hum | snal0 | snal1 |
| Peak SWE        | Evergreen Needleleaf        | x  | x  | x    |     |       |       |
| Peak SWE        | Bare Ground                 | x  | x  | x    |     |       |       |
| Peak SWE        | Bare Ground- only snow      |     |     | x    | x   |       |       |
|                 | changes                     |     |     |      |     |       |       |

3.4 Time of Total Melt

Figure 3.10 shows the sensitivity of time of total melt—the first time SWE reaches zero millimeters after peak SWE—for the evergreen needleleaf simulations. The longwave radiation and air temperature are most important, with the magnitude of shortwave radiation also being greater than 0.25 (Table 3.3). Time of total melt ranges from June 6, 2014 17:00 to June 13, 2014 12:00 MT.

The bare ground simulations show that radiation and the albedo coefficients are the most important parameters in peak SWE timing: an increase in radiation causes an earlier time of total melt and an increase in albedo coefficients causes a later time of melt (Figure 3.11). These are the same four parameters that were important for bare ground peak SWE. Time of total melt ranges from March 16, 2014 15:00 to June 8, 2014 12:00 MT. The time of total melt varies more in the bare ground simulation than the evergreen needleleaf, showing a greater sensitivity of bare ground to perturbations in the input parameters. Again, a change in the range of time of melt is seen when just the snow parameters are perturbed (Figure 3.12). The range of time of melt for this simulation is March 19, 2014 11:00 to May 31, 2014 12:00 MT. This reveals the change in ranges is due to land cover type and perturbation of forcing parameters.

Table 3.3  Active subspace parameters with a weight of magnitude 0.25 or greater for the time of total melt quantity of interest.

| QOI             | Land Cover                  | Forcing Parameters | Snow Parameters |
|-----------------|-----------------------------|--------------------|-----------------|
|                 |                             | sw | lw | airt | hum | snal0 | snal1 |
| Time of Melt    | Evergreen Needleleaf        | x  | x  | x    |     |       |       |
| Time of Melt    | Bare Ground                 |     | x  | x    |     |       |       |
| Time of Melt    | Bare Ground- only snow      | x  | x  |      | x   |       |       |
|                 | changes                     |     |     |      |     |       |       |
Figure 3.11 Actives subspace results plot for time of total melt of the bare ground simulations.

Figure 3.10 Active subspace results plot for time of total melt of the evergreen needleleaf simulations.
Figure 3.12  Active subspace results plot for time of total melt of the bare ground simulations with baseline forcing.

3.5 Time of Peak SWE

Time of peak SWE is the last quantity of interest studied. However, neither the evergreen needleleaf nor the bare ground simulations allow us to use active subspaces to study the sensitivity of the timing of peak SWE to the input parameters. Figures 3.13, 3.14, and 3.15 do not show a univariate, scalar-value function fit of the time of peak SWE to the active variable, which is a requirement for computing the active subspaces (Constantine, 2015).
Figure 3.13: Active subspace results plot for time of peak SWE of the evergreen needleleaf simulations.

Figure 3.14: Active subspace results plot for time of peak SWE of the bare ground simulations.

Active Variable Weight
- sw
- lw
- precip
- airt
- windu
- windv
- press
- hum
- age3
- snal0
- snal1
- cons
- conn
- sl

Input Parameter
- -1.0
- -0.5
- 0.0
- 0.5
- 1.0

Time of Peak SWE (MT)

Land Cover: Evergreen Needleleaf

Land Cover: Bare Ground
Figure 3.15 Active subspace results plot for time of peak SWE of the bare ground simulations with baseline forcing.
CHAPTER 4
DISCUSSION

The sensitivity of model parameters varies with both quantity of interest and land cover type. This study shows that trees mitigate the effects of sublimation more than they cause snow interception. One might expect the increased sublimation from bare ground to cancel with the increased snowfall from little vegetation interception (Biederman et al., 2014) leading to a bare ground snowpack similar to that with trees. These results suggest, however, that sublimation causes a lower snowpack than lack of interception causes snow to accumulate. The effect of greater sublimation influence can be seen by the lower snowpack in the baseline bare ground simulation compared to the baseline evergreen needleleaf simulation.

The evergreen needleleaf land cover causes less shortwave radiation and wind to penetrate the snowpack. An increase in these two parameters causes an increase in sublimation (Biederman et al., 2014). However, since the effect of these processes are so minimal with evergreen needleleaf cover, a third parameter important to sublimation takes over—humidity. This is seen by an increased sensitivity to humidity in the months of snow accumulation (winter) and amount of peak SWE; an increase in humidity results in decreased sublimation and increased SWE. However, in the spring and summer months, the snowpack decreases, air temperatures increase, and humidity is no longer a driver of SWE since shortwave radiation is now large enough to take over the melting of snow. Humidity is not as important in the bare ground model because the absence of trees allows for radiation and wind to affect the snowpack.

The trees also dampen the effect of the snow parameters. CLM attributes a fractional vegetation cover of 0.8 to evergreen needleleaf land cover. This causes the model to become insensitive to snow albedo since such little shortwave radiation reaches the ground (Dickenson et al., 1993). However, the bare ground simulations are sensitive to the visible and near-infrared albedo coefficients as shortwave radiation can penetrate the snowpack.

The month with the lowest number of important parameters for both land cover types is September. This is due to September having the lowest average SWE since radiation and air temperatures are melting snow before it can accumulate in the
evergreen needleleaf model. The bare ground model is insensitive to snow parameters in September due to lack of snow.

Furthermore, the overall sensitivity of the bare ground model is greater than the evergreen needleleaf model shown by larger ranges of all quantities of interest. The difference in ranges between the bare ground and bare ground with baseline forcing simulations can be attributed to the influence of the forcing parameters.
CHAPTER 5
CONCLUSION

In this study, a single-column, integrated hydrologic model, ParFlow-CLM, is used to evaluate the sensitivity of four quantities of interest—monthly averaged SWE, peak SWE, time of total melt, and time of peak SWE—to the eight forcing parameters and six snow parameters using active subspaces. This allows for a global sensitivity analysis of fourteen parameters, which are then collapsed into a one-dimensional linear combination and compared to modeled output values (Constantine, 2015).

This study found that sublimation is the main driver of snow melt with humidity being the dominant input parameter, in the evergreen needleleaf model, throughout the winter months until radiation is strong enough to overcome humidity. The bare ground SWE is less than the evergreen needleleaf in the baseline runs and more sensitive overall to changes in the input parameters evidenced by greater ranges in the quantities of interest to change of the active variables than the evergreen needleleaf outputs. Due to no vegetation cover, the bare ground simulations are also sensitive to the visible and near-infrared albedo coefficients. Trees mitigate the effects of sublimation—by blocking wind and radiation—and also cause the model to be less sensitive to changes of the input parameters as a whole, with an especially decreased sensitivity to the snow parameters. This study reveals the importance of land cover type on the ParFlow-CLM snow model as well which physical processes the model deems important for evergreen needleleaf and bare ground land cover. This shows the importance of measuring radiation and humidity correctly in the field for all land cover types as well as creating correct albedo parameterizations for bare ground models.

This study focused on two land cover types, however, conducting a similar sensitivity analysis on all ParFlow-CLM land cover types would lead to a better understanding of the role of land cover on snow processes in hydrologic models. Furthermore, conducting a sensitivity analysis on more pieces of the model (thermal processes, energy process, etc.) would lead to a deeper understanding of model physics and the sensitivity of all model parameters.

Through sensitivity analysis, the importance of the meteorological parameters, snow parameters, and land cover type to the important snow processes of hydrologic
models can be analyzed. Mountain snowpack melt accounts for the majority of the Colorado River water supply, the western United States' water supply, and one sixth of the water supply for the world's population (Ikeda et al., 2010; Chang et al., 1987; Barnett et al., 2005). This highlights the importance of modeling these processes correctly, which requires an understanding how model input parameters correspond with modeled snow water equivalent.
REFERENCES CITED

Anderson, E. A. (1976). A point energy and mass balance model of a snow cover. NOAA Technical Report NWS 19. http://doi.org/10.1016/S0074-6142(99)80039-4

Bales, R. C., Molotch, N. P., Painter, T. H., Dettinger, M. D., Rice, R., & Dozier, J. (2006). Mountain hydrology of the western United States. Water Resources Research, 42(8), 1–13. http://doi.org/10.1029/2005WR004387

Barnett, T. P., Adam, J. C., & Lettenmaier, D. P. (2005). Potential impacts of a warming climate on water availability in snow-dominated regions. Nature, 438(7066), 303–309. http://doi.org/10.1038/nature04141

Bearup, L.A., Maxwell, R.M. and McCray, J.E. (2016). Hillslope response to insect-induced land-cover change: an integrated model of end-member mixing. Ecohydrology, 9, 195-203, doi:10.1002/eco.1729

Biederman, J. A., Brooks, P. D., Harpold, A. A., Gochis, D. J., Gutmann, E., Reed, D. E., ... Ewers, B. E. (2014). Multiscale observations of snow accumulation and peak snowpack following widespread, insect-induced lodgepole pine mortality. Ecohydrology, 7(1), 150–162. http://doi.org/10.1002/eco.1342

Blanken, Peter,(1998-) AmeriFlux US-NR1 Niwot Ridge Forest (LTER NWT1), 10.17190/AMF/1246088

Bonan, G. B., Oleson, K. W., Vertenstein, M., Levis, S., Zeng, X., Dai, Y., … Yang, Z.-L. (2002). The land surface climatology of the NCAR land surface model coupled to the NCAR community climate model. Journal of Climate, 15(22), 3123–3149. http://doi.org/10.1175/1520-0442(2002)015<3123:TLSCOT>2.0.CO;2

Campbell Scientific Inc. (2011). CNR1 net radiometer

T.C Chang, A & Foster, James & Gloersen, P. (2018). Estimating snowpack parameters in the Colorado River basin

Chen, F., Barlage, M., Tewari, M., Rasmussen, R., Jin, J., Lettenmaier, D., ... Yang, Z. (2014). Journal of Geophysical Research: Atmospheres, 795–819. http://doi.org/10.1002/2014JD022167.Received

Condon, L. E., Maxwell, R. M., & Gangopadhyay, S. (2013). The impact of subsurface conceptualization on land energy fluxes. Advances in Water Resources, 60, 188–203. https://doi.org/10.1016/j.advwatres.2013.08.001
Condon, L.E., Hering, A.S. and Maxwell, R.M. (2015). Quantitative assessment of groundwater controls across major US river basins using a multi-model regression algorithm. *Advances in Water Resources*, 82, 106-123, doi:10.1016/j.advwatres.2015.04.008

Constantine, P.G., 2015. Active Subspaces: Emerging Ideas in Dimension Reduction for Parameter Studies. SIAM, Philadelphia

CS105/CS105MD Barometric Pressure Sensor. (n.d.)

Dai, Y., Zeng, X., Dickinson, R. E., Baker, I., Bonan, G. B., Bosilovich, M. G., ... Yang, Z. L. (2003). The common land model. *Bulletin of the American Meteorological Society*, 84(8), 1013–1023. http://doi.org/10.1175/BAMS-84-8-1013

Dettinger, M., Redmond, K., & Cayan, D. (2004). Winter Orographic Precipitation Ratios in the Sierra Nevada—Large-Scale Atmospheric Circulations and Hydrologic Consequences. *Journal of Hydrometeorology*, 5(6), 1102–1116. http://doi.org/10.1175/JHM-390.1

Diamond, H. J., Karl, T. R., Palecki, M. A., Baker, C. B., Bell, J. E., Leeper, R. D., ... Thorne, P. W. (2013). U.S. climate reference network after one decade of operations status and assessment. *Bulletin of the American Meteorological Society*, 94(4), 485–498. http://doi.org/10.1175/BAMS-D-12-00170.1

Dickinson, E., Henderson-Sellers, A., & Kennedy, J. (1993). Biosphere-atmosphere Transfer Scheme (BATS) Version 1e as Coupled to the NCAR Community Climate Model. *NCAR Tech. Rep. NCAR/TN-3871STR*, 72, (August), 77. http://doi.org/10.5065/D67W6959

Domine, F. (2011). Physical Properties of Snow, 859–863. http://doi.org/10.1007/978-90-481-2642-2_422

Engel, M., Notarnicola, C., Endrizzi, S., & Bertoldi, G. (2017). Snow model sensitivity analysis to understand spatial and temporal snow dynamics in a high-elevation catchment. *Hydrological Processes*, 31(23), 4151–4168. http://doi.org/10.1002/hyp.11314

Giddings, J.C., & LaChapelle, E. (1961). Diffusion Theory Applied to Radiant Energy Distribution and Albedo of Snow. *Journal of Geophysical Research*, 66(1), 181–189. http://doi.org/10.1029/JZ066i001p00181

Gilbert, J.M., Maxwell, R.M. and Gochis, D.J. (2017). Effects of water table configuration on the planetary boundary layer over the San Joaquin River watershed, *California*. *Journal of Hydrometeorology*, 18, 1471-1488, doi:10.1175/JHM-D-16-0134.1
Grenfell, T. C., Warren, S. G., & Mullen, P. C. (1994). Reflection of solar radiation by the Antarctic snow surface at ultraviolet, visible, and near-infrared wavelengths. *Journal of Geophysical Research, 99*(D9), 18669. http://doi.org/10.1029/94JD01484

Hollinger, D. Y., & Richardson, A. D. (2005). Uncertainty in eddy covariance measurements and its application to physiological models, (February), 873–885

Houle, E. S., Livneh, B., & Kasprzyk, J. R. (2017). Exploring snow model parameter sensitivity using Sobol variance decomposition. *Environmental Modelling and Software, 89*, 144–158. http://doi.org/10.1016/j.envsoft.2016.11.024

Ikeda, K., Rasmussen, R., Liu, C., Gochis, D., Yates, D., Chen, F., … Guttman, E. (2010). Simulation of seasonal snowfall over Colorado. *Atmospheric Research, 97*(4), 462–477. https://doi.org/10.1016/j.atmosres.2010.04.010

IPCC. (2014). Climate Change 2014 Synthesis Report Summary Chapter for Policymakers. *ipcc*, 31. http://doi.org/10.1017/CBO9781107415324

Jefferson, J.L., Gilbert, J.M., Constantine, P.G. and Maxwell, R.M. (2015). Active subspaces for sensitivity analysis and dimension reduction of an integrated hydrologic model. *Computers and Geosciences, 83*, 127-138, doi:10.1016/j.cageo.2015.07.001

Jones, Jim E., and Carol S. Woodward. 2001. “Newton-Krylov-Multigrid Solvers for Large-Scale, Highly Heterogeneous, Variably Saturated Flow Problems.” *Advances in Water Resources* 24: 763–74. doi:10.1016/S0309-1708(00)00075-0

Kollet, S. J., & Maxwell, R. M. (2006). Integrated surface-groundwater flow modeling: A free-surface overland flow boundary condition in a parallel groundwater flow model. *Advances in Water Resources, 29*(7), 945–958. http://doi.org/10.1016/j.advwatres.2005.08.006

Luce, C. H., Lopez-Bugos, V., & Holden, Z. (2014). *Water Resources Research, 7058–7066*. http://doi.org/10.1002/2014WR015454.Received

Lundquist, J. D., Minder, J. R., Neiman, P. J., & Sukovich, E. (2010). Relationships between Barrier Jet Heights, Orographic Precipitation Gradients, and Streamflow in the Northern Sierra Nevada. *Journal of Hydrometeorology, 11*(5), 1141–1156. http://doi.org/10.1175/2010JHM1264.1

Maxwell, R.M. and Condon, L.E. (2016). Connections between groundwater flow and transpiration partitioning. *Science, 353*(6297), 377-380. doi:10.1126/science.aaf7891

Maxwell, R.M., Condon, L.E., Kollet, S.J., Maher, K., Haggerty, R., and Forrester, M.M. (2016) The imprint of climate and geology on the residence times of
groundwater. Geophysical Research Letters, 43(2), 701-708, doi:10.1002/2015GL066916

Maxwell, R., & Miller, N. L. (2005). Development of a Coupled Land Surface and Groundwater Model. Journal of Hydrometeorology, 6, 233–247. http://doi.org/10.1175/JHM422.1

Monson, R. K., Turnipseed, A. A., Sparks, J. P., Harley, P. C., Scott-Denton, L. E., Sparks, K., & Huxman, T. E. (2002). Carbon sequestration in a high-elevation, subalpine forest. Global Change Biology, 8(5), 459-478. DOI: 10.1046/j.1365-2486.2002.00480.x

Pribulick, C.E., Foster, L.M., Bearup, L.A., Navarre-Sitchler, A.K., Williams, K.H., Carroll, R.W.H, and Maxwell, R.M. (2016). Contrasting the hydrologic response due to land cover and climate change in a mountain headwaters system. Ecohydrology, 9(8), 1431-1438, doi:10.1002/eco.1779

Rihani, J., Maxwell, R.M., and Chow, F.K. (2010). Coupling groundwater and land-surface processes: Idealized simulations to identify effects of terrain and subsurface heterogeneity on land surface energy fluxes. Water Resources Research 46, W12523, doi:10.1029/2010WR009111

R M Young Company. (2000). Wind monitor - SE model 09101 instructions, (231)

Shin, M. J., Guillaume, J. H. A., Croke, B. F. W., & Jakeman, A. J. (2013). Addressing ten questions about conceptual rainfall-runoff models with global sensitivity analyses in R. Journal of Hydrology, 503, 135–152. https://doi.org/10.1016/j.jhydrol.2013.08.047

Vaisla. (2016). USER’ S GUIDE Vaisala Humidity and Temperature Probes. Retrieved from www.vaisala.com

Warren, S. G. (1982). Optical Properties of Snow (Paper 1R1505). Reviews of Geophysics and Space Physics, 20(1), 67. http://doi.org/10.1029/RG020i001p00067

Wiscombe, W. J., & Warren, S. G. (1980). 1520-0469%281980%29037_2712%3Aamftsasa_2.0.co%3B2.pdf. Journal of the Atmospheric Sciences