UNDERSTANDING SCALE IMPACTS OF HETEROGENEITY AND TOPOGRAPHY ON WATER AND ENERGY FLUXES IN MOUNTAIN MEADOWS USING A FULLY-INTEGRATED HYDROLOGIC MODEL

by

Sarah Trutner
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Golden, Colorado

Date ______________________________

Signed: ______________________________
Sarah Trutner

Signed: ______________________________
Dr. Reed Maxwell
Thesis Advisor

Golden, Colorado

Date ______________________________

Signed: ______________________________
Dr. Jonathan Sharp
HSE Director
ABSTRACT

Mountain watersheds and their subsystems are critical sources of water for much of the Western U.S. The ability to predict their behavior in response to perturbations such as climate change, grazing, mining, and pumping is becoming increasingly important. Land cover, subsurface, and topographic heterogeneity have all been shown to control infiltration rates, subsurface flow, soil moisture, and energy flux distributions. Many hydrologic models operate at scales which do not capture the variability of these parameters, often because of limited availability of computational resources and high-resolution data. The effects of these small-scale heterogeneities on local water-energy balances are thus largely unknown. This work examines the influence of small-scale heterogeneity in an alpine meadow microcatchment (250m x 300m) within the East River watershed near Crested Butte, CO, using the integrated groundwater-surface water model, ParFlow-CLM. Topography for the simulation was derived from LiDAR data taken at 0.5m resolution, and plant functional types were assigned based on remote sensing data flown for the area. A suite of ParFlow simulations were run to evaluate the impact of a systematic loss of information on integrated hydrologic response. The importance of microtopography was studied using simulations with different grid resolutions. The sensitivity of land cover was studied using homogeneous and heterogeneous representations of plant functional type and the role of subsurface heterogeneity on states and fluxes was explored using correlated, Gaussian random fields to represent the spatial distribution of soil. Output comparisons have shown that land cover heterogeneity plays an important role in controlling water and energy fluxes, such as snowmelt and ET, while topography and soil heterogeneity control water distribution within the model, as well as outflow and total storage.
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CHAPTER 1: INTRODUCTION

Predicting the behavior of natural systems is an increasingly important skill for proper management of resources and stewardship of the environment. Natural systems often involve a complex chain of responses to equally complex perturbations, and predicting those responses can be an important tool for informing our behavior and choices. One of the best tools we have for quantifying and predicting the effects of complex perturbations on a system is numerical modeling. Models allow us to understand the physical behavior of a system, simulate that behavior in more detail than is usually feasible with just instrumentation and fieldwork, study how the system might respond to perturbations that we cannot physically create, and isolate aspects of both potential perturbations and the physical system that normally cannot be separated. Hydrologic models in particular focus on understanding and predicting the behavior of the water balance in a domain, which allows us to understand how that behavior may change under a given set of conditions.

There are multiple issues facing mountain watersheds today whose effects require hydrologic modeling to understand, such as climate change, mountain pine beetle infestation, grazing, and mining. Predicting how mountainous watersheds will be impacted by these perturbations, especially with respect to all their potential uncertainties, is one particularly important and complex problem facing hydrologic modelers. Many attempts have been made to answer these questions using models (Bearup et al., 2014; Cristea et al., 2014; Rasmussen et al., 2014; Foster et al., 2016; Pribulick et al., 2016).

Understanding the effects of future perturbations on mountain headwaters and their subsystems is a difficult process, as both the perturbation and the system have the potential for a great deal of complexity and uncertainty. With respect to climate change in particular, a great deal of effort has been focused on understanding the effects that changes in temperature and precipitation will have as those changes intensify. Some studies have attempted to isolate precipitation and temperature impacts from each other, or only focus on temperature effects (Barnett et al., 2005; Foster et al., 2016; Pribulick et al., 2016). Other potential impacts involve atmospheric effects, such as atmosphere-ocean circulation or the impact of aerosols, and local effects, such as heterogeneity and evapotranspiration, abbreviated from here on as ET (Barnett et
al., 2005). It has been argued (Barnett et al., 2005) that changes in ET may not have a large effect on water resources under climate change because a drying environment would limit its actual effects in any case. However, the effects of ET on baseflow during late summer are worth considering due to potential effects on summer water availability, which may be significant (Goulden and Bales, 2014). Additionally, recent work has shown that plant water sources for transpiration shift toward deeper groundwater during the dry season (Gou et al., 2018), supporting the need to further understand this process and the complications it may present for late-summer groundwater resources.

Different models are set up with a wide range of detail, accuracy, and integration, depending on their purpose and the modeler’s computational, data, and time limitations. Many natural processes occur at small scales or in very specific times and places (Dwivedi et al., 2017), which means that these limitations may cause a model to miss an important part of the system it represents and introduce uncertainty or bias in its outputs. In theory, giving a model more detailed and more accurate data should improve its results. However, every model has a cutoff from diminishing returns at which more detail is either not necessary to include or not feasible. There are still some questions about where this cutoff might be, and how much more useful a large or detailed model is than its less detailed counterparts. Several studies have attempted to address this uncertainty, either in scaling or in the representation of heterogeneity (Wood et al., 1988; Maxwell, 2010; Atchley and Maxwell, 2011; Condon et al., 2013; Foster, 2018).

Ongoing projects such as the Watershed Function Scientific Focus Area (SFA), led by Lawrence Berkeley National Laboratory, also seek to answer questions about how to accurately predict the effects of perturbations such as climate change on the availability of water and other resources. The Watershed Function SFA focuses on the East River watershed, a representative mountain watershed in the Colorado Rockies. One question that the SFA focuses on is how much fine-scale representation of hydrologic and biogeochemical processes in models can improve understanding and prediction of those processes. To this end, a great deal of high-resolution remote sensing data (described in more detail in the following sections) has been collected in this watershed (Hubbard et al., 2018), and shared among researchers of many different fields.

This study focuses on a small, meadow-dominated site within the East River watershed, referred to as the Bradley site. Meadows are both an important and a fragile subsystem in
mountain watersheds. Mountain meadows tend to slow drainage rates near headwater streams, creating a relatively shallow water table and wetter conditions overall (Patton and Judd, 2007). These conditions encourage the growth of riparian herbs and grasses, as opposed to shrubs and trees, which are more suited to dry conditions and lower water tables (Berlow et al., 2002; Patton and Judd, 2007). They have also been observed to provide habitat and forage for a diverse array of species, such as various herbs and grasses, deer and elk, insects, and birds (Patton and Judd, 2007). Additionally, wet meadows have been shown to have a significant stabilizing effect on their associated stream banks, both by slowing erosion of stream bank sections and keeping failed sections attached to the bank (Micheli and Kirchner, 2002). Meadows are also highly sensitive to changes in climate, land use, and water availability. Long periods of decreased groundwater flow can lower the water table, reducing the benefits of meadows and accelerating loss of meadow area by incursion of shrubs and trees (Berlow et al., 2002; Patton and Judd, 2007; Lowry et al., 2010). The importance of meadow ecosystems to mountain watersheds and their sensitivity to perturbations makes this site useful for a study of this type.

The goal of this study is to examine the small-scale effects of topographic resolution and heterogeneity in land cover and soil representations. By quantifying how losing information from each of these inputs changes water and energy fluxes near the land surface, this study can help inform future hydrologic modelers of the level of detail necessary to answer their questions with as little bias as possible from their model inputs.
CHAPTER 2: METHODS

2.1 Study Site and Data Sources

The East River watershed is located near Crested Butte, CO, and encompasses the Rocky Mountain Biological Laboratory (RMBL). It is a tributary to the Upper Colorado River and is representative of the Colorado River headwaters basins (Markstrom et al., 2012), making it a convenient study site for understanding the behavior and sensitivity of the regions that ultimately supply water to much of the western United States. The watershed as a whole is about 300 km². It encompasses a 1,420 m range of elevation with an average elevation of 3266 m and contains a variety of subsystems within its boundaries (Hubbard et al., 2018).

Data for this study was aggregated from existing East River studies and projects, including remote sensing data (Hubbard et al., 2018; Falco et al., 2018) and estimates of plant classifications and soil parameters used in a recently built 10 m-resolution model of the East River (Foster, 2018).

The microcatchment of interest in this study, referred to as the Bradley site, is a small, meadow-dominated site close to the river in the northern area of the watershed (see Figure 2.1 on page 5). The model domain encompassing the microcatchment is about 260 m by 330 m and only contains about a 53 m range of elevation, making it a much smaller and more topographically homogeneous domain than the East River as a whole. The area within the model itself varies slightly with resolution; however, it is always just under 50,000 m². It does not contain any permanent streams, so water movement through the area largely consists of intermittent streams and groundwater flow.

2.2 ParFlow-CLM

All simulations were run using ParFlow, a fully integrated, physically based, surface-subsurface hydrologic model. Unlike many other hydrologic models, it is capable of solving both surface and subsurface flow simultaneously, with the kinematic wave approximation to simulate overland flow and the three-dimensional, mixed form of Richards’ equation to simulate variably saturated subsurface flow (Ashby and Falgout, 1996; Jones and Woodward, 2001; Kollet and Maxwell, 2006; Maxwell, 2013). In this study, ParFlow was coupled with the land surface model CLM, which simulates the behavior of various plant functional types down to the root zone along
with meteorological forcing data (Maxwell and Miller, 2005; Kollet and Maxwell, 2008). When the two models are combined, ParFlow-CLM is capable of solving for water and energy fluxes in simulations with detailed atmospheric inputs, heterogeneous land cover, detailed topography, and variable subsurface conditions. These capabilities make ParFlow-CLM well-suited for a study focused on the small-scale hydrologic impacts of heterogeneity.

Figure 2.1: A view of the Bradley site from Google Earth. While the site is located next to the East River, it does not contain any permanent streams of its own. However, plant type changes due to more consistent shallow groundwater are visible within both the study site and the surrounding area.

Another important aspect of ParFlow-CLM its ability to model plant water use and evapotranspiration. Based on the plant functional type specified for every surface cell in the model, CLM specifies parameters to describe the physical properties of the plants in that cell (Maxwell and Miller, 2005). These properties are then taken into account when calculating evapotranspiration and latent heat fluxes. The fact that ParFlow-CLM can integrate subsurface flow, surface flow, ET, and atmospheric inputs in one model is what makes it possible to focus on the relationships between them, since the behavior of each component of the model is
evaluated along with all other components and every input has the potential to effect every aspect of the water and energy budgets.

2.3 Digital Elevation Model (DEM) and Slope Processing

The DEM for the domain was initially cropped from 0.5m-resolution LiDAR data over the whole East River watershed (Wainwright and Williams, 2017; Hubbard et al., 2018). Slope processing was done using a method modified by Condon and Maxwell (2019) from the “priority flood” algorithm (Wang and Liu, 2006; Barnes et al., 2014; Zhou et al., 2016). This algorithm processes a given DEM to ensure that every cell drains outward to the border and fills any depressions in the DEM that prevent cells from draining. It then calculates the slopes in the x and y directions, and outputs them in a format that can easily be converted for use by ParFlow. Other processing options exist in the algorithm, those used here include setting a primary and secondary slope direction in each cell and limiting all slopes to a maximum of 0.5 for ease of computation in ParFlow.

Figure 2.2: An elevation map of the domain used in the model, with the Bradley site outline included.
2.4 Land Cover Data

Initial estimates of land cover type and soil parameters were taken from an existing 100 m model of the East River watershed (Foster, 2018). Additionally, high-resolution multispectral data from the Worldview-2 satellite were combined with LiDAR DEMs and plant height data to map out information about plant species and volume. The collective data were then used to create a plant classification map at 2m resolution, similar to the methods used in other sites in the East River (Falco et al., 2018). This method was able to provide a detailed, accurate, and comprehensive plant distribution map (Figure 2.3). The 100 m model assigns essentially the entire area to meadow land cover, so a homogeneous meadow domain is one of the datasets to be compared within this study as a reasonable model representation. However, it can be seen from the 2m land cover map, and from Figure 2.1, that this homogeneity is not the reality of the domain.

![2m Remote Sensing Land Cover](image)

Figure 2.3: The land cover dataset created using remote sensing data for the area. The plant functional types used in the model are visible here and include evergreens, riparian shrubs, meadow, and bare soil. The homogeneous land cover dataset, by comparison, is entirely meadow.
2.5 Meteorologic Forcing Data

ParFlow-CLM requires the input of hourly meteorologic forcing data, including incoming longwave and shortwave radiation, precipitation, air temperature and pressure, wind speed and direction, and humidity (Maxwell and Miller, 2005). For this study, the necessary data are used from a combined CASTNET and SNOTEL dataset taken in water year 2006, which has been used in a previous study by Pribulick et al. (2016).

2.6 Model Simulations

With all of these datasets collected, several different models with varying dataset combinations were run to isolate the effects of heterogeneity and scaling in various aspects of the domain. Two land cover datasets (Falco et al., 2018; Foster, 2018) currently exist for this domain, and the difference in level of detail between them is significant. Foster’s model was run at 100 m resolution and covered the entire East River watershed; however, due to the coarser resolution, the land cover at the scale of the Bradley site could not be captured in detail. As a result, the general locations of meadow and tree cover are correct, but the boundaries between them are imprecise, and the assigned category within the model domain is entirely meadow. The land cover data developed by Falco et al. (2018) shows a much higher level of detail and includes the locations of other plant functional types, such as riparian shrubs (Figure 2.3). These two land cover datasets were compared within this model domain in order to explore the importance of land cover detail to modeling plant water use and evapotranspiration.

Additionally, two different versions of soil permeability were compared. Several studies have shown the importance of soil heterogeneity for infiltration rates and land-atmosphere fluxes (e.g. Maxwell, 2010; Atchley and Maxwell, 2011). The effects of soil and land cover heterogeneity have the potential to change model outputs in different ways, and this study presents an opportunity to compare those effects at high resolutions. Foster’s (2018) model included a representation of soil types and associated parameters over the East River, and the parameter values given at this site were used for the homogeneous soil input. The permeability and correlation length associated with the given soil type were then also used to create a random field of permeability values (Figure 2.4) with the same geometric mean as the homogeneous permeability value. This random field was used as the heterogeneous soil dataset.
Figure 2.4: Heterogeneous soil permeability at 2 m resolution (left) and 5 m resolution (right) for the topmost layer only. Soil permeability varies in 3 dimensions. Both sample from the same, 3-dimensional distribution function, so any difference between the two distributions is due only to resolution.

Since 0.5 m-resolution topography data is available for this area, we were able to examine the effects of different topographic representations at high resolution. Along with the soil and land cover representations, two different topographic resolutions were also compared for this study. The 0.5 m topography data was aggregated into 2 m and 5 m resolution, and x- and y-slopes for both resolutions were calculated from their corresponding topographic datasets. The results of each slope calculation are shown in Figure 2.5.

Regardless of horizontal resolution, all simulation domains were 5 m deep, with a vertical resolution of 0.1 m, for a total of 50 cell layers in the subsurface. Additionally, the sides and bottom of each domain were set as no-flow boundaries through which water could neither enter nor leave the model. The only exception was the side boundary in the southernmost 5% of the domain (near the outlet), which were allowed to have an annual outward flux of roughly 10% of the total annual precipitation. This flux allowed some water to exit the simulations through the subsurface; otherwise, water would only leave the model from the surface, as runoff or ET.
Figure 2.5: Slope inputs for both the 2 m and 5 m topographic resolutions. 2 m model x-slope (top left) and y-slope (top right) and 5 m model x-slope (bottom left) and y-slope (bottom right) inputs are shown. Positive values (in blue) point left for the x-slopes and down for the y-slopes.

For this study, six total models were run: four at the 5m resolution, and two at the 2m resolution. The 5m models included all four combinations of homogeneous and heterogeneous land cover and soil data in order to isolate the effects of changing just one dataset. Assuming similar effects from isolating either land cover or soil changes, the 2m models were chosen to be entirely heterogeneous (both land cover and soil) and entirely homogeneous, so that the two models could be compared to their 5m counterparts. The simulations are summarized in
Table 2.1. Each simulation was spun up, or allowed to reach a dynamic equilibrium, before any output data was collected so that biases from changing conditions would not affect the results. Spin ups were conducted by first using a constant precipitation minus evapotranspiration (or P-ET) value based on average values for the region to allow the domain to reach a steady state. Then, simulations were run repetitively with the annual forcing data as an input until the total storage in the simulation from the end of one year to the end of the next changed by less than 1%. The first year that met this condition, even after rounding the percent change, was used as the simulation year.

Table 2.1: Setup of simulations run for this study. There were two options for each input changed: land cover (heterogeneous and homogeneous), soil (heterogeneous and homogeneous), and topographic resolution (2m and 5m), and six of the eight total options were run and compared.

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CHAPTER 3: RESULTS

3.1 Storage and Water Table Depth

Storage and water table depth are similarly affected by all three model input changes. Figure 3.1 shows that the total storage (normalized by area) of the heterogeneous 2 m simulation is consistently the lowest. Changing the resolution to 5 m results in a storage gain of about 3.8 cm over the domain area, and loss of all heterogeneity results in a gain of about 4.3 cm at 2 m resolution and 3.7 cm at 5 m resolution, most of which is associated with the loss in soil heterogeneity specifically.

For water table depth, the results are similar. As seen in Figure 3.2, changing the resolution from 2 m to 5 m results in a water table elevation gain of about 16.1 cm for the heterogeneous simulations, and a gain of 13.9 cm for the homogeneous simulations. Loss of heterogeneity, meanwhile, results in an elevation gain of 16.6 cm for the 2 m simulations, and 14.4 cm for the 5 m, most of which is again due to the change from heterogeneous to homogeneous soil. Overall, loss of topographic resolution and of both types of heterogeneity increase the overall storage within the model and raise the water table depth, and the difference is fairly consistent throughout the simulation year.

Effects of various inputs can also be seen in the annually averaged outputs from each simulation. Here, each cell value represents the annual average of the output values in that location. The fully heterogeneous model outputs are shown first, with the others (homogeneous land cover, soil, or both) shown as difference plots to demonstrate the effects of the loss of heterogeneity. Again, results are similar between the storage (Figure 3.3 on page 15 and Figure 3.4 on page 16) and water table (Figure 3.5 on page 17) datasets; a loss of soil heterogeneity appears to decrease the amount of water stored in certain areas around the edges of the domain and simultaneously increase the amount of water stored near the middle. A loss of land cover heterogeneity has a much smaller effect; however, there is again a slight increase in water storage and water table elevation near the middle, near where the small stand of evergreens is located.
Figure 3.1: Effects on daily total water storage from changing model inputs. Removing heterogeneity and decreasing the resolution from 2 m to 5 m both increase the overall storage in the model. Note that storage is normalized by area and expressed as a depth of water over the model, since the 5 m and 2 m resolution domains have slightly different surface areas.
Figure 3.2: Effects on daily average water table depth from changing model inputs. Results here are plotted as negative elevations below the surface, so a higher value indicates a shallower water table.
Figure 3.3: Annual-averaged storage results for 5 m heterogeneous (top left), with difference plots for 5 m heterogeneous land cover (top right), 5 m heterogeneous soil (bottom left) and 5 m homogeneous (bottom right).
Figure 3.4: Annual-averaged storage results for 2 m heterogeneous simulation (left) and the differences in storage from switching to a 2 m homogeneous simulation (right).

3.2 Soil Moisture

Soil moisture appears to be heavily dependent on near-surface permeability, and its spatial distribution over the year illustrates the effect of soil heterogeneity. Along with the overall surface patterns in the heterogeneous model that are removed along with soil heterogeneity, the moisture around the small stream near the center of the model expands when soil permeability is heterogeneous. While there is a slight increase in soil moisture close to where some of the trees and shrubs would be located, removing land cover heterogeneity does not seem to have a dramatic effect on the spatial distribution of moisture. See Figure 3.6 on page 18.

3.3 Outflow

Land cover heterogeneity also had the largest effect on modeled outflow, as replacing it with homogeneity raised the total runoff by 5.6-5.7%. There is also a small period of higher flow just after the peak flow, in April, in the simulations with heterogeneous land cover that does not appear in the homogeneous simulations. Removing soil heterogeneity had a small effect in the opposite direction of the overall land cover effect, decreasing the total runoff by 0.5-0.6%. Lowering resolution from 2 m to 5 m had a similar effect to soil, decreasing the total runoff by 0.5-0.7%. See Figure 3.7 on page 19.
Figure 3.5: Annual-averaged water table depth for 5 m heterogeneous (top left), with difference plots for 5 m heterogeneous land cover (top right), 5 m heterogeneous soil (bottom left) and 5 m homogeneous (bottom right). Note that here, the color scale is flipped so that blue means a decrease in water table depth, or an increase in water table elevation.
Figure 3.6: Annual average soil moisture outputs from 5 m heterogeneous (top left), with difference plots for 5 m heterogeneous land cover (top right), 5 m heterogeneous soil (bottom left) and 5 m homogeneous (bottom right).
Figure 3.7: Effects of changing model inputs on total outflow. Land cover seems to have the biggest effect, adding extra outflow from late snowmelt but also showing lower peak and baseline flows.
3.4 Latent Heat Flux

Both land cover and soil heterogeneity had an effect on the water and energy fluxes in the model (Figure 3.8). Between the 5 meter-resolution simulations, changing from heterogeneous to homogeneous land cover lowered the average latent heat flux of the simulation by 14.2-16.3%. By contrast, changing from heterogeneous to homogeneous soil raised the average latent heat flux by about 1.2-1.5%. Additionally, decreasing the resolution from 2 m to 5 m raised the average latent heat flux by 2.0-2.3%, giving topography changes a similar effect to soil changes. Note that monthly averages will be used instead of daily for latent heat and ET results due to daily averages containing significant short-term variation and noise.

![Monthly Average Latent Heat](image)

Figure 3.8: Monthly averaged latent heat flux, showing the effect of adding soil or land cover heterogeneity or raising topographic resolution. For latent heat fluxes, the most significant effect is associated with changes between heterogeneous and homogeneous land cover.
Along with the varying dependencies on all three inputs in the monthly averaged outputs, latent heat also has a spatial distribution that is dependent on both land cover and soil heterogeneity, although its soil response is much lower. In the annual-averaged results, shown in Figure 3.9 below, the water use by trees and shrubs is up to about 3x higher than the background average latent heat flux. The spatial change in latent heat flux due to loss of soil heterogeneity varies, which is likely why the monthly averaged output difference is so small.

Figure 3.9: Spatial distribution of latent heat in 5m heterogeneous (top left), with difference plots for 5m heterogeneous land cover (top right), 5m heterogeneous soil (bottom left) and 5m homogeneous (bottom right).
3.5 Evaporation

Ground evaporation depends more evenly on all three compared factors—land cover, soil, and topography. Unlike most of the previous results, there is no single input change that dominates the output response. Slight timing changes in lower evaporation during November and December and higher evaporation during February and March are associated with changes in land cover, with the heterogeneous models showing slightly later minima and maxima than the homogeneous models (Figure 3.10).

![Monthly Evaporation](image.png)

Figure 3.10: Monthly total evaporation results from all six simulations. All input changes have a small effect on overall results. Slight timing changes can also be seen between homogeneous and heterogeneous land cover.

The spatial distribution of evaporation is again mediated by both land cover and soil heterogeneity (Figure 3.11 and Figure 3.12). When land cover heterogeneity is lost, there is an increase in evaporation in the cells containing riparian shrubs and a variable decrease around the

22
cells containing evergreens. When soil heterogeneity is lost, there is a smaller, variable response over most of the domain, with an increase in the area of high evaporation values due to shallow water/moist soil.

Figure 3.11: Annual-averaged evaporation outputs for 5m heterogeneous (top left), with difference plots for 5m heterogeneous land cover (top right), 5m heterogeneous soil (bottom left) and 5m homogeneous (bottom right).
3.6 Transpiration

Transpiration is almost entirely mediated by land cover heterogeneity (Figure 3.13). In the monthly totals, the 5 m simulation with only heterogeneous land cover has a slight increase in its maximum from both of the fully heterogeneous simulations. Otherwise, the simulations with and without heterogeneous land cover plot almost exactly on top of each other, and neither soil nor topographic resolution seems to have a noticeable effect on transpiration through time.

Annual transpiration totals demonstrate very similar results (Figure 3.14). The spatial distribution of transpiration in the initial 5 m heterogeneous simulation demonstrates that transpiration in the model is dominated by trees and shrubs. When heterogeneous land cover is removed, the difference in transpiration is also dominated entirely by the locations of the larger plants, and any difference in soil contribution is difficult to see. When heterogeneous soil is removed and the impact of soil is isolated, there is a slight increase in transpiration in some cells containing trees and shrubs, but not anywhere else in the domain.
Figure 3.13: Monthly averaged transpiration results for all six simulations. The results are split into two groups based on land cover representation, with not much difference within each group.
Figure 3.14: Annual-averaged transpiration outputs for 5m heterogeneous (top left), with difference plots for 5m heterogeneous land cover (top right), 5m heterogeneous soil (bottom left) and 5m homogeneous (bottom right). Soil heterogeneity has a very minimal contribution to transpiration overall, relative to land cover.
3.7 Snow Water Equivalent (SWE)

Snowmelt is also slowed in the simulations with heterogeneous land cover (Figure 3.15), and spatial data shows that SWE is present in the model longer in the cells with trees and shrubs present (Figure 3.16). This is likely due to the shading effect from the increased leaf area index of the trees and shrubs replacing meadow cells. There are small differences in values between all the simulations, but shows that each simulation with heterogeneous land cover has the first snow-free day 26 days after each with homogeneous land cover.

![Daily Average SWE](image)

Figure 3.15: Changes in daily average SWE with changes in land cover, the only visible change. SWE inputs are roughly the same, but melting rates are slowed with heterogeneous land cover.

Land cover is also shown to have the largest effect on the spatial distribution of average SWE over the year. In the 5 m heterogeneous model, the higher average SWE values match the cells with the trees and shrubs. Switching to homogeneous land cover removes that signal and
lowers the average SWE in those cells by a maximum of about 20 mm. Switching to homogeneous soil has a small, varying effect throughout the domain.

Figure 3.16: Annual average SWE depths from 5m heterogeneous (top left), with difference plots for 5m heterogeneous land cover (top right), 5m heterogeneous soil (bottom left) and 5m homogeneous (bottom right).
4.1 Implications

Each input that was tested had a slightly different effect on model behavior. Land cover changes had the largest effect on surface fluxes, including latent heat, transpiration, SWE, and runoff. There are probable explanations for each of these effects. Trees and shrubs use significantly more water than herbs and grasses, so their inclusion dominates the transpiration signal and thus the latent heat flux, since transpiration accounts for more water and energy transfers than ground evaporation. The slight increase in transpiration from the 5 m heterogeneous land cover simulation above both of the fully heterogeneous simulations shown in Figure 3.13 may be related to the increase in water table depth from homogeneous soil shown in Figure 3.5. When heterogeneous soil was switched to homogeneous soil, the water table rose near the middle of the model, around where the stand of evergreens was located. That change may have given the trees increased access to soil water, allowing their water use and transpiration to increase slightly. SWE differences associated with land cover changes are likely due mostly to increased leaf area index from trees and shrubs, which probably slowed snowmelt in the spring by providing shade to their respective cell areas.

The combined input and output effects from SWE and transpiration changes may then have had the biggest effect on outflow. As shown in Figure 3.7, land cover heterogeneity was associated with lower outflow throughout the year, which was probably because that water was instead being taken up by plants. The temporary increase in flow just after the snowmelt peak (in April and early May) was likely from the last shaded snow melting from under the trees, days after all of the snow had vanished from the simulations with homogeneous land cover. Overall, the representation of land cover in this model had the biggest impact on water and energy fluxes into and out of the model.

However, representations of soil and topography have a significant effect on where and how water is stored within the model, generally more so than land cover effects. Soil moisture, water table depth, and subsurface storage are all significantly affected by both soil permeability and topography, both spatially and temporally, even though their effect on runoff is smaller. For
models that focus on the spatial distribution of water, accuracy in both of these inputs is likely important.

4.2 Model Limitations

While these simulation comparisons have their uses, they cannot reasonably be expected to closely match real behavior at the site for two reasons. First, the boundary conditions in the simulations are largely no-flow, and the assumed microcatchment boundaries do not actually encompass the whole area that contributes to it. Lowry et. al. (2010) note that, along with high spatial and temporal resolution being necessary to accurately recreate the hydrologic complexity of a mountain meadow, realistic boundary conditions are critical to the model’s success as well. Their solution was to link two models together and have a basin-scale hydrology model that provided spatially and temporally heterogeneous groundwater fluxes into their higher-resolution meadow model. Other models, such as aim to solve this problem with a combination of matching model boundaries with real watershed boundaries and generally being large enough that most of the model is not dramatically affected by the boundaries in any case. The Bradley model does not utilize any of these solutions; thus, it cannot reasonably be expected to closely match real observations, especially near the defined boundaries.

Second, the subsurface representation is assumed or randomized rather than based off of any real measurements. It was not feasible to actually measure soil properties at each cell location, and the only soil dataset that covers the site area is homogeneous. For the heterogeneous subsurface represented in the model, the distribution of soil properties involved a great deal of guesswork and almost certainly do not correlate with the real study site. Additionally, the site was assumed to have an even soil depth of 5 m, underneath which was assumed to be impermeable bedrock, so the bottom boundary of the model is also incorrect. Overall, although understanding what level of detail best represents the real site is an important question and only reasonable options for representing the real site are compared here, reproducing the site’s behavior perfectly is not feasible here. Instead, this study is only intended to show the effects of scaling and detail on the behavior of the model and what that might mean for necessary levels of detail in the construction of future models.
In this study, three different inputs (topographic resolution, land cover, and soil permeability) were systematically changed in a small hydrologic model domain in order to compare their effects on the resulting simulations’ outputs. Six simulations were run and compared: 2 m-resolution, fully heterogeneous (land cover and soil); 2 m-resolution, fully homogeneous; and four 5 m-resolution simulations with every combination of heterogeneous and homogeneous land cover and soil. When the resulting outputs were compared, each input ended up having a slightly different effect on overall model outputs. Changing the land cover representation from heterogeneous to homogeneous was associated with the largest losses in transpiration and latent heat flux from the model, the largest gain in total outflow from the model, and a shorter snowmelt period in the spring. Changing soil permeability from heterogeneous to homogeneous dramatically changed the distribution of the water table depth, water storage within the model, and soil moisture at the surface. It also increased water table elevation and storage overall, and slightly decreased total outflow from the domain. Lowering resolution from 2 m to 5 m had a similar effect to the soil change in some cases, such as raising the water table, increasing storage, and lowering outflow. Changing the resolution also changed the image clarity of the spatial results, although it did not dramatically affect the spatial distribution of those results in the same way that changing the soil did.

The results shown here are only from one mountain meadow-dominated site. Similar studies performed at other sites may have different results, or show different interactions between the land cover, topography, and soil permeability that change with alternate model representations. For example, the effect of land cover changes on water table depth may be much more dramatic in situations where the affected area is not already saturated regardless of the scenario. In this study site, most of the trees and shrubs that were represented in the domain grew along the low-lying areas that already had shallow groundwater due to the topography of the site. Thus, whether they were present or absent, the water table would remain near the surface in those areas, and the soil would remain saturated, so very little change could be seen. In a model of an area with a deeper water table and fluxes dominated by groundwater loss rather than
runoff, changing the land cover likely would have a more dramatic effect on water storage in the simulated outputs.

Additionally, the results of this study show that topography and soil heterogeneity both exert some control over where water is stored in the model. It should be noted that the changes in the results due to losing information from either one of these inputs depended on the complexity of both. Specifically, the change in water table depth due to the loss of soil heterogeneity showed how different the water table distribution became when it was controlled only by topography. If the soil had been less dramatically heterogeneous, this change would have been much smaller. Additionally, if the topography had been much flatter, its control over water table distribution would have been much smaller as well, and the shift would likely also have been less dramatic. Thus, it appears that the spatial distribution of water in the simulations shown here depended both on soil and topography individually and on how important they were relative to each other. An area that has different topographic behavior and different soil variation may see some changes in their relative importance compared to the results of this study.

Unfortunately, although the topography for this domain is processed from real, high-resolution data from this site, the soil parameters are only based on typical values for the soil type found at the site rather than real field measurements. This decision was made because, although accurate site data is important, it is also generally infeasible to collect useful data on soil parameters at the resolutions at which the simulations were run. Improved understanding of how soil type influences soil parameters and their distribution, and possibly how geomorphology plays a role in small-scale soil permeability variations, could help future models like this one improve their understanding of soil behavior and their accuracy without needing to do infeasible amounts of field measurements.

For future hydrologic modeling purposes, these results show that which inputs to represent accurately depends largely on the purpose of the model, again keeping in mind that model domains with very different behavior than this one may have different responses to change. For understanding overall fluxes and downstream outputs, it appears that land cover is important to represent accurately, as glossing over the land cover heterogeneity in an area can dramatically change modeled ET, snowmelt timing, and outflow from what they should be. However, models that focus on spatial distribution of water storage should focus much more on accurately representing soil type and heterogeneity, along with topography. While regional
hydrologic models generally do not run at the scales shown here, the same is likely true to some degree at larger scales as well. In order to avoid input biases in model results, it is best to understand what questions a given model is designed to ask and focus efforts on the most relevant dataset(s) to create the most useful representation of the domain possible.
REFERENCES


