MODELING WILDFIRE IMPACT ON HYDROLOGIC PROCESSES
USING A PRECIPITATION-RUNOFF MODEL

by

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A thesis submitted to the Faculty and the Board of Trustees of the Colorado School of Mines in partial fulfillment of the requirements for the degree of Master of Science (Civil and Environmental Engineering).

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ABSTRACT

As large magnitude wildfires persist across the western United States, understanding their impact on hydrologic behavior and predicting regional streamflow response is increasingly important. Peak flows, sediment flows, and debris flows in burned watersheds are often addressed, but wildfires also alter the timing and overall volume of runoff, making the prediction of post-fire streamflow critical for water resources management. Six wildfire-impacted watersheds in the western United States are modeled using the Precipitation Runoff Modeling System (PRMS), a distributed-parameter, physical process based watershed model. Two change detection modeling approaches are applied in order to better understand post-fire changes and their related processes. First, the model is used to determine if each watershed shows significant changes in flow regimes following each wildfire. Second, post-fire parameterization is examined using a generalized likelihood uncertainty estimation (GLUE) approach and a national-scale sensitivity analysis. Three of the six watersheds showed significant increases in the difference between observed and modeled daily streamflow following the wildfire. For these watersheds, the parameterization analysis using PRMS revealed that changes in immediate surface runoff processes are best represented through preferential flow and imperviousness, and changes in evapotranspiration can be best represented through soil zone capacities.
# TABLE OF CONTENTS

ABSTRACT............................................................................................................................... iii

LIST OF FIGURES...................................................................................................................... vi

LIST OF TABLES......................................................................................................................... vii

ACKNOWLEDGEMENTS............................................................................................................. viii

CHAPTER 1    INTRODUCTION .................................................................................................. 1

1.1 Watershed Impacts ........................................................................................................... 1

1.2 Post-wildfire Modeling ..................................................................................................... 3

1.3 The Precipitation Runoff Modeling System ................................................................. 4

1.4 The National Hydrologic Model .................................................................................... 6

1.5 Study Objectives ............................................................................................................. 7

CHAPTER 2    STUDY AREAS AND MODEL SETUP ................................................................ 8

2.1 Burned Area Determination ........................................................................................... 8

2.2 Identification of Case Study Watersheds ...................................................................... 9

2.3 Description of Case Study Watersheds ....................................................................... 11

2.4 Identification of Burned National HRUs ................................................................. 15

2.5 Model Calibration Methods ....................................................................................... 16

2.5.1 General Calibration Scheme ................................................................................. 16

2.5.2 Model Forcing ...................................................................................................... 20

2.6 Calibration Results ...................................................................................................... 20

2.6.1 Station Distribution Methods .............................................................................. 21

2.6.2 PRISM Method .................................................................................................. 22

CHAPTER 3    CHANGE DETECTION ...................................................................................... 24

3.1 The Change Detection Method .................................................................................... 24

3.2 Study Methods ............................................................................................................. 25
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.3</td>
<td>Results</td>
<td>26</td>
</tr>
<tr>
<td>CHAPTER 4</td>
<td>POST-FIRE PARAMETERIZATION</td>
<td>32</td>
</tr>
<tr>
<td>4.1</td>
<td>Case Study Watershed Parameterization</td>
<td>33</td>
</tr>
<tr>
<td>4.1.1</td>
<td>Methods</td>
<td>33</td>
</tr>
<tr>
<td>4.1.2</td>
<td>Results</td>
<td>35</td>
</tr>
<tr>
<td>4.2</td>
<td>Evapotranspiration</td>
<td>40</td>
</tr>
<tr>
<td>4.2.1</td>
<td>National Model Vegetation and Evapotranspiration Response</td>
<td>40</td>
</tr>
<tr>
<td>4.2.2</td>
<td>National Model Vegetation and Evapotranspiration Sensitivity</td>
<td>41</td>
</tr>
<tr>
<td>CHAPTER 5</td>
<td>CONCLUSIONS</td>
<td>45</td>
</tr>
<tr>
<td>REFERENCES</td>
<td></td>
<td>47</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

Figure 1.1       Hydrologic Process modeled in PRMS (from Markstrom et al. 2015).............................. 5

Figure 2.1     Areas considered as study area watersheds. (a) All GAGES II watersheds in the NHM with over 25% total burn. (b) Those GAGES II with no significant dams. (c) Those watersheds selected as case study watershed based on performance with a calibration scheme ........................................................................................ ...... 10

Figure 2.2      HRU delineation and burn severities for the case study watershed ...................................... 14

Figure 2.3      Burned National HRUs ....................................................................................................... 15

Figure 2.4      Nash-Sutcliff Efficiency for all NHM basins for which the general calibration scheme was applied ........................................................................................................... 16

Figure 3.1       Annual volume comparisons. Watersheds in the top row showed a statistically significant increase in daily flow residuals ................................................................. 30

Figure 3.2      Monthly volume comparisons. Watersheds in the top row showed a statistically significant increase in daily flow residuals ................................................................. 31

Figure 4.1     Surface runoff parameter ranges of the top 50 behavior models in the GLUE analysis for each watershed for each time period ........................................................................ 36

Figure 4.2     Interception parameter ranges of the top 50 behavior models in the GLUE analysis for each watershed for each time period ........................................................................ 38

Figure 4.3      Evapotranspiration parameter ranges of the top 50 behavior models in the GLUE analysis for each watershed for each time period .......................................................... 39

Figure 4.4      Solar radiation parameter ranges of the top 50 behavior models in the GLUE analysis for each watershed for each time period ................................................................. 39

Figure 4.5     Comparison of ensemble mean time series for remote sensing products, NDVI and PRMS actual evapotranspiration for all burned national HRUs ....................................... 42

Figure 4.6     Method used by PRMS to calculate evapotranspiration based on soil zone saturation for each soil type ........................................................................................................... 43

Figure 4.7     Sensitivity of actual evapotranspiration to soil_moist_max. (Left) the first 100 HRUs are shown for simplicity. (Right) HRUs are categorized by aridity index and the ensemble mean for each range is shown. ................................................................. 44
### LIST OF TABLES

Table 1.1  Datasets used in the parameterization of the National Hydrologic Model .......................... 7

Table 2.1  Characteristics of the Case Study Watersheds .................................................................. 14

Table 2.2  Case study watershed burn severities ............................................................................... 15

Table 2.3  Parameters and descriptions for each step in the general calibration scheme .................... 18

Table 2.4  Sensitive parameters for each basin. The calibration only utilized those parameters which were sensitive or not included in the sensitivity analysis................................................... 19

Table 2.5  Statistics to compare calibration using each of the alternative forcing methods. The bold columns indicate the forcing option used as a final calibration.................................................. 21

Table 3.1 Wilcoxon Rank-sum test P-values for a statistically significant increase in daily residual streamflow for each cumulative time period following each wildfire .................. 27

Table 4.1  Wildfire-related parameters and processes ....................................................................... 32

Table 4.2  NSE values for the least likely GLUE model ....................................................................... 34

Table 4.3  Percent bias values for the least likely GLUE model ............................................................ 34

Table 4.4  RMSE (cfs) for the least likely GLUE model......................................................................... 34
ACKNOWLEDGEMENTS

I would like to thank my committee members for their guidance and expertise. My thesis advisor, Dr. Terri Hogue, provided valuable academic and moral support. Special thanks also go to Dr. Lauren Hay, Dr. Steve Markstrom, and R. Steve Regan from the Modeling of Watershed Systems (MOWS) group with the United States Geological Survey (USGS) for providing help with technical aspects of PRMS and the National Hydrologic Model, providing tools for model analysis, and for their guidance in the research process. I would also like to thank the MOWS group and the USGS for financial support.
CHAPTER 1
INTRODUCTION

Wildfires have been a persistent issue in the western United States. The frequency and magnitude of wildfires has increased in recent years (Dennison et al. 2014), and large wildfires are projected to continue to increase, especially in hot and dry regions (Stavros et al. 2014). This increase has commonly been attributed to regional drought and temperature shifts associated with climate change (Westerling et al. 2006), as well as land use change and fire suppression practices. Current wildfire regimes are changing and are likely different from those seen historically. For example, Zhao et al. (2015) found that wildfires in the northern Rocky Mountains occur less frequently but at a higher burn severity than before these areas were extensively settled. Costly damages to infrastructure are only temporarily postponed by fire suppression practices, which are also expensive. In 2015 alone, 2.1 Billion dollars were spent on fire suppression (National Interagency Fire Center 2016), and many uncontrolled fires still occurred.

The increasing frequency and magnitude of wildfires results in higher risk to infrastructure and human lives. Wildfires frequently occur near the wildland-urban interface (WUI), where human presence increases the ignition rates and fuel available Mercer and Prestemon (2005). Housing at the WUI is vulnerable to the fire, and the communities may be prone to flooding and debris flows after the fire. The WUI has been growing, and is future projected growth is the highest in mountainous areas of the western United States (Theobald and Romme 2007). Thus, it is critical to continue to examine the effects of wildfires for future development and management of fire-prone areas at the WUI.

1.1. Watershed Impacts

An understanding of the ways in which wildfires affect specific processes is critical to implementing post-wildfire hydrologic changes in computer models. There are several ways that hydrologic processes are altered after wildfires. These changes have been documented through field-scale studies using wildfires and prescribed fires, as well as lab-scale studies to examine changes to soil properties (Certini 2005).The current study focuses on the physical changes that affect runoff generation
utilizing an operational hydrologic, though physical changes are closely related with chemical and microbial effects. For simplicity, hydrologic affects have been categorized as soil effects and vegetation effects.

Vegetation combustion causes primary immediate and long-term effect after wildfires. Vegetation can be affected differently depending on the severity of the fire and the pre-fire conditions. For low severity burn areas, the understory vegetation is often burned while the older trees are more resilient and may survive. For high severity burns, all vegetation is burned, either clearing the canopy or leaving dead trees standing. Changes in vegetation can affect both hydrologic processes and energy budgeting. First, reduction in canopy thickness can allow less precipitation interception, therefore allowing more precipitation to reach the soil surface and less water to be evaporated from the canopy. Second, reduction of vegetation density can lead to less evapotranspiration (Bales et al. 2011), and dead vegetation will no longer transpire. Finally, the reductions in understory, canopy, and vegetation density can increase the amount of short-wave radiation which penetrates the canopy and reaches the soil surface or the snowpack.

While the immediate impacts to the vegetation are important, the vegetation recovery must also be considered. Recovery of vegetation is dependent on a variety of factors, including the types of vegetation, the climate, and treatments of the area during both the pre-fire and post-fire period (Kinoshita and Hogue, 2011). Some studies have attempted to attribute vegetation recovery to a variety of factors. For example, Casady, Leeuwen, and Marsh (2009) found that higher elevations recovered more quickly, perhaps due to higher water availability. Arnan, Rodrigo, and Retana (2007) found that plants which re-seed recover more quickly than plants which re-sprout in Mediterranean ecosystems, and the slower recovery of re-sprouters allow for new opportunistic species to occupy the area during recovery. Similarly, Kinoshita and Hogue (2011) found that grasses and other short-term vegetation appear immediately after fire in Mediterranean ecosystems, but the original vegetation takes longer to recover. So, recovery may often involve changes of vegetative species and may ultimately never return to pre-fire conditions. This presents difficulty in physically-based modeling, because predictions of hydrologic recovery rely on predictions of vegetation recovery. Therefore, the current study examines recovery based
on hydrologic regimes and general vegetation characteristics, rather than detailed analysis of the types of vegetation present.

The heat of a wildfire of moderate or high severity can cause physio-chemical changes in the soil that create water repellency layer at the top of the soil (Beyers et al. 2005). This effect is easily reproducible at the lab scale and has been commonly cited as a primary mechanism for increased runoff generation. However, other physical changes are observed, including increased bulk density and ash deposition into the void space resulting in soil sealing (Certini 2005). Though it may be difficult to determine which soil effects are primarily responsible for increased runoff, some have attempted. For example, Larsen et al. (2009) found removal of surface cover to be more significant for generating runoff than hydrophobicity and soil sealing at the plot scale. For the purposes of the current study, specific attribution is avoided by considering the effects of hydrophobicity, soil sealing, ash layer deposition, and cover removal without specific attribution.

1.2. Post-wildfire Modeling

After wildfires, downstream communities are often concerned about increases in peak flows, erosion, sediment transport, and debris flows. Peak flows may be the principal concern, because they serve as a driver for erosion, sediment flows, and debris flows. Several methods exist to model peak flows after wildfires, and are frequently employed immediately following a wildfire to inform mitigation practices which may be necessary. Kinoshita, Hogue, and Napper (2014) evaluated five of the most common of these methods across watersheds in the western United States and found differences in the performance of each model depending on the watershed characteristics and climate.

Continuous watershed models are less commonly employed following wildfires, but can provide valuable information for water resources management. In addition to peak flows, wildfires can also alter the timing and total volume of streamflow, especially in watersheds that are dominated by snowmelt (Seibert, McDonnell, and Woodsmith 2010). Because wildfires often occur in water-scarce areas and in times of drought, water managers could benefit from predictions of streamflow timing and volume
changes following the fire. Thus, the current project seeks to provide a framework to apply a continuous, physically based watershed model to post-wildfire areas in order to inform water resources decisions.

Many of the models used to predict peak flows are empirical or conceptual runoff models. They include some basic geophysical parameters of the watershed, and have a few parameters that may be calibrated and changed to reflect the watershed condition after the fire. Because watershed disturbances can be highly variable depending on the fire, climate, and other factors, it is often straight-forward to use these types of models to account for a large array of changes with few parameters. Conversely, strictly physical watershed models may be difficult to parameterize in post-disturbance areas, because the changes that occur are complex. The current study applies the Precipitation Runoff Modeling System (PRMS), which is a physically based, continuous watershed model with some conceptually based parameters. Thus, specific post-fire processes may be targeted while maintaining some of the flexibility of an empirical or conceptual model.

1.3. The Precipitation Runoff Modeling System

The Precipitation Runoff Modeling System is a deterministic, distributed-parameter, physical-process hydrologic model (Markstrom et al. 2015). PRMS is run at a daily time-step, and is built on the framework of the modular modeling system. Each component of the energy and water budgets are modeled. A description of hydrologic processes shown in Figure 1.1. Daily precipitation, minimum temperature, and maximum temperature are required inputs. Optional daily inputs are solar radiation and potential evapotranspiration (PET). The user has a choice of modules for various components of the hydrologic cycle. For example, if daily PET is not specified as an input, it can be calculated using a Jensen-Haise, Hamon, Hargreaves-Samani, or Priestly-Taylor formulation, depending on the module selected.

A domain in PRMS consists of Hydrologic Response Units (HRUs) and stream segments. HRUs are the spatial unit used in the model, where each HRU is considered to be homogenous and has a distinct set of parameters. HRU layout can be gridded, or can be non-uniform and based on geographic properties and watershed boundary delineations. Each HRU contains reservoirs for which water balances are
performed. Calculations are performed for each HRU and flow is computed between HRUs. Runoff and interflow from HRUs flow into stream segments, where streamflow routing can be performed using various methods (Markstrom et al. 2015).

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![Hydrologic Process modeled in PRMS](image)

Figure 1.1. Hydrologic Process modeled in PRMS (from Markstrom et al. 2015).
PRMS can be coupled with MODFLOW using the Coupled Ground-Water and Surface-Water Flow model (GSFLOW) (Markstrom et al. 2008). When operated without MODFLOW, PRMS simulates flow to and from a groundwater reservoir. In the current study, the standalone version of PRMS is used in order to systematically and automatically parameterize a large number of study areas, with a primary focus on surface processes.

While no previous studies are available using PRMS for post-wildfire modeling, other studies using PRMS provided valuable information. Perhaps the most relevant of these studies focus on forest management. Nakama and Risley (1993) initially used PRMS to predict the effects of clear cutting in an Oregon Coastal Range basin by altering parameters related to vegetation density, imperviousness, interception storage, and soil zone capacities. Later, Risley (1994) applied this framework to ten additional nearby basins, including some paired watersheds. The results showed a slight increase in peak flows following timber harvesting, and a larger increase in the overall basin water yield.

1.4. The National Hydrologic Model

The Geospatial Fabric for National Hydrologic Modeling (Viger and Bock, 2014) is the basis for PRMS model parameterization over the continental United States (Viger 2014). This model is known as the National Hydrologic Model (NHM), and is available for watershed scale to national scale analysis. The geospatial fabric is delineated based on soil, land cover, topographic, geographic, subsurface, and surface depression parameters, using the datasets shown in Table 1.1. Delineation is also based on points of interest, which are stream locations of significance. Most of the gage locations in the USGS Gage II dataset (Falcone 2011) appear as points of interest in the NHM, and thus guide the delineation of HRUs and allow for independent models to be disjointed from the national model for each of these watersheds. In general, the HRUs delineated for the NHM are lower resolution than would typically be used for most applications where the modeler delineates HRUs and stream segments. For example, the median HRU size for the California region is 23 square kilometers. Overall, The NHM is a powerful tool for investigating a large number of study areas and generalizing model parameterization.
Table 1.1 Datasets used in the parameterization of the National Hydrologic Model

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<th>Data Used</th>
<th>Reference</th>
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<td>Soil</td>
<td>Soil Survey Geographic Database (SSURGO)</td>
<td>(Soil Survey Staff, Natural Resources Conservation Service, and United States Department of Agriculture 2013)</td>
</tr>
<tr>
<td>Land Cover</td>
<td>National Land Cover Database (NLCD 2001)</td>
<td>(Homer et al. 2007)</td>
</tr>
<tr>
<td>Topographic</td>
<td>NHDPlus</td>
<td>(McKay et al. 2012)</td>
</tr>
<tr>
<td>Geography</td>
<td>Geospatial Fabric</td>
<td>(Viger 2014; Viger and Bock 2014)</td>
</tr>
<tr>
<td>Subsurface Flux</td>
<td>Global Hydrogeology and Permeability Map</td>
<td>(Gleeson et al. 2011)</td>
</tr>
<tr>
<td>Surface Depression</td>
<td>NHD High-res</td>
<td>(McKay et al. 2012; McDonald et al. 2012)</td>
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1.5. Study Objectives

The current study seeks to address post-wildfire watershed hydrology with a focus on overall flow regime and volume changes. The applications of this study will ultimately assist water resources managers in better estimates of basin yield and runoff timing in water scarce areas that have been affected by wildfires. To do this, PRMS is applied to various wildfire-affected areas in the western United States. The physically based nature of the model will also provide insight into actual changes in hydrologic process based on model parameterization. Specifically, this study seeks to address the questions in conjunction with three distinct objectives:

Detection - In what ways can post-fire hydrologic response be quantified using a rainfall-runoff model (PRMS)?

Prediction - How can the model be parameterized to replicate and predict changes in flow regimes due to wildfire in a way that makes physical sense?

Recovery – For how long after a wildfire can burn conditions be represented, and how should model parameterization change over time?

First, for the detection objective, the current study must qualify and quantify which post-wildfire changes are seen within the error of the model and model calibration. Then, an in-depth analysis into model parameterization will help to inform how to apply PRMS to wildfire-affected watersheds in the future in order to predict changes in streamflow. The recovery is then be examined based on the detection and parameterization changes through time after the wildfire.
CHAPTER 2
STUDY AREAS AND MODEL SETUP

A large number of study areas was desirable in order acquire a sufficient amount of data to generalize post-wildfire runoff can be modeling. Multiple burn areas across the western United States were considered. This study employed two distinct sets of study areas at (1) the watershed scale and (2) the HRU-scale.

At the watershed scale, six different watersheds were selected as case studies. These were watersheds that could easily be setup as stand-alone models with reasonable calibration success using NHM parameterization. Observed streamflow data are available for these watersheds, making it possible to quantify the model performance and the response of hydrologic processes to wildfire. These watersheds may also serve as an example to modelers who wish to apply PRMS to wildfire-affected areas in the future.

At the HRU scale, all available HRUs in the western United States that were affected by a wildfire after January 2000 are examined. No streamflow data are available for this study area set, but relevant data can be obtained through model sensitivity analysis and remote sensing products.

2.1. Burned Area Determination

The monitoring trends in burn severity (MTBS) fire database was used to identify and categorize burned areas. The MTBS projects maps the severity of all fires that occurred after 1984, and are greater than 500 acres in the eastern United States or are greater than 1000 acres in the western United States (Eidenshink et al. 2007). MTBS burn severity is assessed using two scenes from the LANDSAT satellites - one pre-fire scene and one post-fire scene. The normalized burn ratio (NBR) is calculated for each LANDSAT image. The NBR is the normalized as the difference between the near infrared band and the shortwave infrared band (Key and Benson 2005). Burn severity is calculated using the difference between the NBR of the two scenes (dNBR). Values of dNBR are grouped into specific ranges, and classified as unburned to very low, low, moderate, and high burn severity.
Because of the platform and bands used, the dNBR published in the MTBS burn severity product mostly reflects changes in chlorophyll and water content in the vegetation, especially the upper canopy (Miller and Thode 2007). As a result, the dNBR is commonly used to represent vegetation burn severity (Lentile et al. 2006), and does not necessarily imply the burn severity of the soil. For example, the BAER teams use dNBR as first estimation of vegetation burn severity for the Burned Area Reflectance Classification BARC products (Hudak et al. 2004). As a result, the burn severities in this study are likely to better inform processes such as interception and evaporation than those processes at the surface and in the soil zone. With consideration of these limitations, the current study evaluates both soil and vegetation effects using the dNBR classification from the MTBS products. It is appropriate for the purposes of this study given the ready availability of the MTBS data, the objective of generalizing post-fire response, and the reasonable assumption that higher soil burn severities will likely occur at sites with higher vegetation burn severities. In fact, some skeptics argue against the use of dNBR for vegetation burn classification, but see dNBR as a useful tool for those who wish to incorporate effects of both vegetation and soil burn severity (Safford et al. 2007).

2.2. Case Study Watersheds

All watersheds in the Geospatial Attributes of Gages for Evaluating Streamflow, version II (GAGES II) dataset were considered in selection of study watersheds for two main reasons. First, the majority of the GAGES II watershed streamflow gages are included as points of reference in the NHM, which allows for easy conversion to standalone models. Second, these watersheds have already undergone extensive verification to ensure there are quality data, a sufficient period of record, and have minimal disturbance. All study watersheds have at least 20 complete years of flow record or were operating when the database was constructed in 2009 (Falcone 2011).

All of the GAGES II watersheds that appear in the NHM were overlaid with all MTBS wildfires in order to determine those suitable for study. Case study watersheds were then selected as those that meet
three criteria: (1) At least 25% burned (any severity) (2) Are free of significant dams, and (3) Can be reasonably calibrated for a 10-year pre-fire calibration period.

To examine the extent of flow modification due to dams, the watersheds were divided into three categories based on data available in the GAGES II dataset at the time of publication (2009). The categorization is as follows:

- Dam category 1: No dams or diversions
- Dam category 2: No major dams or diversions
- Dam category 3: Major dams or diversions

The watersheds available based on each criterion are shown in Figure 2.1. While there were 52 watersheds in the western United States with more than 25 percent area burned, many did not meet the other two criteria. Only those watersheds classified in dam category 3 were removed from consideration, as those in dam category 2 may still allow much of the natural watershed response to be apparent at the outlet streamflow gage. Out of the six watersheds that met all criteria and were selected as case studies, only one was classified as dam category 2.

Figure 2.1 Areas considered as study area watersheds. (a) All GAGES II watersheds in the NHM with over 25% total burn. (b) Those GAGES II with no significant dams. (c) Those watersheds selected as case study watershed based on performance with a calibration scheme
The final six case study watersheds were selected based on their ability to be reasonably well calibrated using a general calibration scheme. The classification of a reasonable calibration is subjective, but in this case thresholds defined by Moriasi et al. (2007) are utilized for first consideration. Based on these thresholds, an automated calibration may be considered satisfactory if the Nash-Sutcliff Efficiency (NSE) is greater than 0.5 and the overall percent is bias within ±25 percent when comparing observed and simulated streamflow data. NSE represents the model’s ability to predict streamflow in comparison to the average observed streamflow value, and was thus used to represent the goodness of fit for the shape of the hydrograph and the daily flow variations. A unity NSE value indicates all of modeled flow values are exactly the same as all observed flow values, while an NSE of zero indicates that the average streamflow value is a better predictor than the model. Percent bias indicates the difference in the sum of all daily modeled and observed streamflow for the calibration period. In other words, this represents the difference in the total volume of water. Because the NSE threshold was relatively easy to achieve for models that also displayed an adequate percent bias, this study uses a more stringent NSE threshold of 0.6, while keeping the percent bias threshold of ±25 percent.

Use of somewhat lenient calibration criteria in this case is appropriate because of the relatively low resolution of HRU delineation in the national model. Modelers who apply PRMS to wildfire-affected watersheds in the future for specific water resources decisions may want to use higher resolution HRU delineation and apply more site-specific knowledge to the setup of the model.

2.3. Description of Case Study Watersheds

All of the case study watersheds selected are located in the state of California, except for Ash Canyon, which is in Nevada on the eastern slope of the Sierra Nevada Mountains. Many previous studies on post-fire runoff also utilize California watersheds, likely due to two reasons. First, many areas in California may be especially susceptible to wildfires because of the high population, the dry climate, and the history of fire suppression techniques. Second, the network of stream gages for relevant areas in California is more extensive than many other arid and semi-arid areas in the western United States. So,
while the case study watersheds are confined to a specific region, this region is likely to continue to see wildfire occurrence and thus examples from this region could be helpful in the future. Though all watersheds are located in the same geographic region, the watershed characteristics, downstream infrastructure, and circumstances of the wildfires are diverse enough to provide a basis for comparison. A brief discussion of each case study watershed follows:

**Ash Canyon** is located in the eastern Sierra Nevada Mountains and is a part of the greater Carson City Watershed. Both snowmelt and rainfall contribute to runoff and provide water supply for Carson City, NV, which is located immediately downstream. Approximately 67% of the watershed was burned in the 2004 Waterfall Fire, which initiated flooding and sediment flows in 2005 and 2006 that damaged Carson City infrastructure (Zonge, Lynn 2007).

**Duncan Canyon** is located on the western slope of the Sierra Nevada Mountains, and outflows empty into the middle fork of the American River, eventually flowing into the Folsom Lake Reservoir just above Sacramento, CA. The 2001 Star Fire was mostly concentrated at lower elevations along Duncan Creek and the middle fork of the American River, but part of the burn extended higher into the gaged portion of Duncan Canyon. This fire has been used to study forest management and fuel treatments (e.g., Tempel et al. 2015; Collins et al. 2011), but no studies were found concerning changes in runoff and erosion following this fire.

**Big Sulphur** is a watershed which empties into the Russian River just upstream of Cloverdale, California. The upper, gaged portion of the watershed was partially burned by the Geysers Fire in 1991, but this fire was relatively low-severity and only 26% of the watershed was burned. No studies were found concerning the runoff affects after the fire.

**Arroyo Seco** is a large, steep watershed draining eastward from the costal Santa Lucia range in California. The Arroyo Seco River eventually drains into the Salinas River near Greenfield, CA. This watershed was burned in the 1977 Marble-Cone Fire, and then again in the Basin Complex fire of 2008. Through burn properties were similar, less increases of runoff and erosion were observed following the 2008 Fire, likely due to lower precipitation in 2009 and 2010 (Warrick et al. 2012).
City Creek is located in the San Bernardino Mountains, and is controlled primarily by rain during the winter months. The river runs southward into the Santa Ana River, which drains into the Pacific Ocean near southern Los Angeles. The watershed was 85% percent burned by the 2003 Old Fire. Studies have shown significant increases in runoff during the rainy season for three years following the fire (Kinoshita and Hogue 2011), as well as sustained increases in low flows (Kinoshita and Hogue 2015).

Plunge Creek is located directly south of City Creek in the San Bernardino Mountains. It was also burned in the 2003 Old Fire, but with much less extent and severity. In this study, Plunge Creek serves as a direct comparison with City Creek, to estimate how burn severity and extent may affect flow response for two sister watersheds.

Some key characteristics of each are watershed are shown in Table 2.1. One of the most important characteristics for comparisons is the percent of precipitation as snow, as snow-dominated basins require additional model processes and the effects of the wildfire on snowpack must be considered. Ash Canyon and Duncan Creek are snow-dominated, while the southern California basins which receive most precipitation as rain during the winter months. Watershed area is also a major consideration. The Arroyo Seco watershed is an order of magnitude large than the other basins, which provides a comparison for response based on watershed size.

The distribution of the HRUs and the burn areas is also variable between watersheds, as shown in Table 2.1. Most notably, City Creek and Arroyo Seco have more burn area in the upper elevation portions of the basins, while the other fires are concentrated towards the middle and lower portions of the basins. Burn severity also varies greatly between basins, as shown by the total burn severities for each watershed in Table 2.2. The Arroyo Seco watershed also has the most HRUs, but is an order of magnitude larger than the other watersheds, so it’s average HRU area (20.4 mi$^2$) is twice as large as the average HRU area across all of the case study watersheds (10.2 mi$^2$).
Table 2.1 Characteristics of the Case Study Watersheds

<table>
<thead>
<tr>
<th>Basin</th>
<th>Area (mi²)</th>
<th>Dominant Vegetation</th>
<th>Mean Annual Precip. (in)</th>
<th>Precip. as Snow</th>
<th>Mean BFI</th>
<th>Maximum Elev. (ft)</th>
<th>Slope</th>
<th>Mean Runoff Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ash Canyon</td>
<td>5.2</td>
<td>Evergreen Forest</td>
<td>76</td>
<td>48%</td>
<td>70</td>
<td>9163</td>
<td>32%</td>
<td>0.54</td>
</tr>
<tr>
<td>Plunge Creek</td>
<td>17.1</td>
<td>Shrub/Scrub</td>
<td>72</td>
<td>3%</td>
<td>29</td>
<td>6512</td>
<td>31%</td>
<td>0.49</td>
</tr>
<tr>
<td>City Creek</td>
<td>19.5</td>
<td>Shrub/Scrub</td>
<td>78</td>
<td>7%</td>
<td>33</td>
<td>6437</td>
<td>34%</td>
<td>0.48</td>
</tr>
<tr>
<td>Arroyo Seco</td>
<td>241</td>
<td>Evergreen and Mixed Forest</td>
<td>81</td>
<td>3%</td>
<td>38</td>
<td>5856</td>
<td>35%</td>
<td>0.39</td>
</tr>
<tr>
<td>Duncan Canyon</td>
<td>10.5</td>
<td>Evergreen Forest</td>
<td>177</td>
<td>47%</td>
<td>62</td>
<td>7418</td>
<td>26%</td>
<td>0.53</td>
</tr>
<tr>
<td>Big Sulphur</td>
<td>13.1</td>
<td>Evergreen and Mixed Forest</td>
<td>149</td>
<td>1%</td>
<td>33</td>
<td>4475</td>
<td>29%</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Figure 2.2 HRU delineation and burn severities for the case study watershed
Table 2.2 Case study watershed burn severities

<table>
<thead>
<tr>
<th>Basin</th>
<th>Unburned to very low</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ash Canyon</td>
<td>7%</td>
<td>19%</td>
<td>25%</td>
<td>16%</td>
<td>67%</td>
</tr>
<tr>
<td>Plunge Creek</td>
<td>9%</td>
<td>18%</td>
<td>18%</td>
<td>5%</td>
<td>50%</td>
</tr>
<tr>
<td>City Creek</td>
<td>7%</td>
<td>18%</td>
<td>29%</td>
<td>30%</td>
<td>85%</td>
</tr>
<tr>
<td>Arroyo Seco</td>
<td>9%</td>
<td>11%</td>
<td>19%</td>
<td>13%</td>
<td>52%</td>
</tr>
<tr>
<td>Duncan Canyon</td>
<td>8%</td>
<td>15%</td>
<td>11%</td>
<td>10%</td>
<td>44%</td>
</tr>
<tr>
<td>Big Sulphur</td>
<td>6%</td>
<td>8%</td>
<td>10%</td>
<td>2%</td>
<td>26%</td>
</tr>
</tbody>
</table>

2.4. Identification of Burned National HRUs

The MTBS fires were overlaid with all HRUs from the NHM in order to identify burn percentages for each HRU on a national scale. For the final burned nation HRU dataset, only HRUs in the western United States were considered. Also, only fires that occurred after January 1, 2000 were used so that these HRUs could be examined using remote sensing ET products which are available after this date. The HRU identified are shown in Figure 2.3.

Figure 2.3. Burned National HRUs
2.5. Model Calibration Methods

A generalized model calibration was first performed on all wildfire affected basins that were not significantly dammed, as identified in Figure 2.1b, in order to identify the final set of case study watersheds shown in Figure 2.1c. Those which performed well with a general calibration were selected as case study watersheds. Figure 2.4 shows the NSE values for all those watersheds for which an automated calibration was attempted. The few watersheds that were not in the California region in general did not perform well based on the NSE criteria.

![Figure 2.4 Nash-Sutcliff Efficiency for all NHM basins for which the general calibration scheme was applied](image)

2.5.1. General Calibration Scheme

Models were calibrated using a step-wise, multiple objective process that employed the Shuffled Complex Evolution (SCE) algorithm. SCE is a deterministic, global optimization algorithm that
distributes the random population of parameters into complexes in order to perform a local search on specific locations in the parameter space (Duan, Gupta, and Sorooshian 1993). Complexes are periodically shuffled in order to share information and refine the search around the most promising parameter ranges. With the onset of large-scale river forecasting models, SCE has proven to be an effective tool for automating calibration of watershed models in a manner similar to a manual calibration (Hogue et al. 2000; 2006).

The SCE algorithm has previously been applied to the PRMS model (Lauren E. Hay et al. 2006), where daily streamflow, mean monthly solar radiation, and potential evapotranspiration (PET) are used as target datasets. For the case study watersheds, a modified version of the calibration scheme used by Hay et al. (2006) is applied and adjusted to the specific modules used in the NHM parameterization. For the modified version, no solar radiation datasets are used as targets, because the NHM already incorporates solar radiation adjustments using a degree-day method. No PET datasets are used as targets because the NHM employs a temperature-based PET module using a modified Jensen-Haise formulation. Streamflows are separated into high flows and low flows on the basis on the environmental flow components as defined by Mathews and Richter (2007) and commonly employed by the nature conservancy to examine hydrologic alteration (The Nature Conservancy 2009). Those streamflow values classified as low flows and extreme low flows using The Nature Conservancy method are considered low flows for calibration. Those streamflow values classified as high flow pulses, small floods, and large floods using The Nature Conservancy method are considered high flows for calibration.

The calibration scheme used is shown in Table 2.3 with descriptions of each parameter. Not all parameters are calibrated for each watershed. A sensitivity analysis categorized sensitive parameters based on the top ten parameters that affect discharge for each HRU in the NHM. For each basin, parameters were calibrated only if they were sensitive for at least one HRU within that basin. Table 2.4 shows which parameters were sensitive for the six case study watersheds.
Table 2.3 Parameters and descriptions for each step in the general calibration scheme

<table>
<thead>
<tr>
<th>SCE Step</th>
<th>Objective Functions</th>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Monthly Mean NRMSE - All Flow</td>
<td>rain_cbh_adj</td>
<td>Monthly adjustment factor to measured rainfall</td>
</tr>
<tr>
<td></td>
<td></td>
<td>snow_cbh_adj</td>
<td>Monthly adjustment factor to measured snowfall</td>
</tr>
<tr>
<td>Step 2</td>
<td>NRMSE (w = 0.8) – High Flow NRMSE (w = 0.2) – All Flow</td>
<td>smidx_coef</td>
<td>Coefficient in non-linear contributing area algorithm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>smidx_exp</td>
<td>Exponent in non-linear contributing area algorithm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>strain_intcp</td>
<td>Summer rain interception storage capacity</td>
</tr>
<tr>
<td>Step 3</td>
<td>NRMSE (w = 0.8) – Low Flow NRMSE (w = 0.2) – All Flow</td>
<td>gwflow_coef</td>
<td>Linear coefficient to compute groundwater discharge</td>
</tr>
<tr>
<td></td>
<td></td>
<td>soil2gw_max</td>
<td>Max amount of the capillary reservoir excess that is routed directly to the GWR</td>
</tr>
<tr>
<td>Step 4</td>
<td>NRMSE (w = 0.8) – All Flow NRMSE (w = 0.1) – Low Flow NRMSE (w = 0.1) – High Flow</td>
<td>tmax_allrain</td>
<td>Monthly maximum air temperature when precipitation is assumed to be rain</td>
</tr>
<tr>
<td></td>
<td></td>
<td>tmax_allsnow</td>
<td>Monthly maximum air temperature when precipitation is assumed to be snow</td>
</tr>
<tr>
<td></td>
<td></td>
<td>potet_sublim</td>
<td>Fraction of potential ET that is sublimated from snow</td>
</tr>
<tr>
<td></td>
<td></td>
<td>rad_trncf</td>
<td>Transmission coefficient for short-wave radiation through the winter canopy</td>
</tr>
<tr>
<td></td>
<td></td>
<td>radmax</td>
<td>Maximum fraction of the potential solar radiation that may reach the ground</td>
</tr>
<tr>
<td></td>
<td></td>
<td>fastcoef_lin</td>
<td>Linear coefficient to route preferential-flow storage down slope</td>
</tr>
<tr>
<td></td>
<td></td>
<td>carea_max</td>
<td>Maximum possible portion of area contributing to surface runoff</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pref_flow_den</td>
<td>Fraction of the soil zone in which preferential flow occurs</td>
</tr>
<tr>
<td></td>
<td></td>
<td>slowcoef_sq</td>
<td>Non-linear coefficient to route gravity- reservoir storage down slope</td>
</tr>
<tr>
<td></td>
<td></td>
<td>soil_moist_max</td>
<td>Maximum available water holding capacity of capillary reservoir to rooting depth</td>
</tr>
<tr>
<td></td>
<td></td>
<td>soil_rechr_max</td>
<td>Maximum storage for soil recharge zone</td>
</tr>
<tr>
<td></td>
<td></td>
<td>transp_trmax</td>
<td>Temperature index to determine date of transpiration period start</td>
</tr>
<tr>
<td></td>
<td></td>
<td>tmax_cbh_adj</td>
<td>Adjustment to maximum air temperature</td>
</tr>
<tr>
<td></td>
<td></td>
<td>tmin_cbh_adj</td>
<td>Adjustment to minimum air temperature</td>
</tr>
</tbody>
</table>
Table 2.4 Sensitive parameters for each basin. The calibration only utilized those parameters which were sensitive or not included in the sensitivity analysis.

<table>
<thead>
<tr>
<th>SCE Step</th>
<th>Objective Functions</th>
<th>Parameter</th>
<th>Ash Canyon</th>
<th>Plunge Creek</th>
<th>City Creek</th>
<th>Arroyo Seco</th>
<th>Duncan Canyon</th>
<th>Big Sulphur</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Monthly Mean NRMSE - All Flow</td>
<td>rain_cbh_adj</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>snow_cbh_adj</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Step 2</td>
<td>NRMSE (w = 0.8) – High Flow NRMSE (w = 0.2) – All Flow</td>
<td>smidx_coef</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>smidx_exp</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>srain_intcp</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Step 3</td>
<td>NRMSE (w = 0.8) – Low Flow NRMSE (w = 0.2) – All Flow</td>
<td>gwflow_coef</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>soil2gw_max</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>tmax_allrain</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>tmax_allsnow</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>potet_sublim</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>rad_trncf</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>radmax</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>fastcoef_lin</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>carea_max</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pref_flow_den</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>slowcoef_sq</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>soil_moist_max</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>soil_rechr_max</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>transp_tmax</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>tmax_cbh_adj</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td></td>
<td>tmin_cbh_adj</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

- = Not included in sensitivity analysis; calibrated for all watersheds
x = Sensitive for watershed; used in calibration
2.5.2. Model Forcing

By default, the six case study watersheds models were forced with Daymet (Thornton et al. 2015) daily gridded precipitation, minimum temperature, and maximum temperature, at a 1km resolution. The \texttt{dd\_solrad} module was used to allow solar radiation to be calculated from temperature data, and the \texttt{potet\_jh} module was used to allow potential evapotranspiration to be calculated from temperature data. The following alternative precipitation and temperature forcing data were applied to the six case study watersheds in an attempt to improve calibration and model performance:

**PRISM** – Free access to this daily dataset at a 4km resolution for the CONUS is provided by the PRISM Climate Group, Oregon State University (2012). This dataset accounts for elevation changes, complex terrain, and climate normals to interpolate climate data (Daly 2006).

**Inverse Distance Weighting (IDE)** – Surrounding station data are used, and are the contribution of each station is weighted inversely with the distance from the center of each HRU.

**Multiple Linear Regression (XYZ)** – Surrounding station data are used to develop a multiple linear regression using the mean value of each month as the dependent variables, and the northing, easting, and elevation as independent variables. The regression equation is applied to each HRU for each day, using the center coordinates of the HRU. This method was originally developed to aid in climate down-scaling, but has been successful employed for station distribution (Hay et al. 2002).

Stations for the IDE and XYZ methods are selected from the National Weather Service (NWS) COOP network and the National Resources Conservation Service (NRCS) SNOTEL network. Some surrounding climate stations were not used because they had more than 20 percent of the data missing for the calibration period, or were visually identified as outliers based on the mean monthly values used in the linear regression.

2.6. Calibration Results

The evaluation statistics that resulted from applying the general calibration scheme to all forcing combinations are shown in Table 2.5. In general, the alternate forcing options yielded either marginal
improvements, or a decrease in the calibration success. Some alternate forcing methods improved the calibration for some basins, but not for others. There was no alternate forcing option that improved calibration across all study basins. Therefore, the original Daymet model forcing is used and the results of the general calibration scheme that were used for model selection will represent the final calibration used for the remainder of this study. Though the alternative forcing options did not result in better model calibration, the differences provide some insight into the use of gridded climate products, PRMS model setup, and the quality of surrounding climate station data.

Table 2.5 Statistics to compare calibration using each of the alternative forcing methods. The bold columns indicate the forcing option used as a final calibration

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NSE</td>
<td>Bias</td>
<td>NSE</td>
<td>Bias</td>
<td>NSE</td>
</tr>
<tr>
<td>Ash Canyon</td>
<td>0.64</td>
<td>-4%</td>
<td>0.61</td>
<td>-11%</td>
<td>0.45</td>
</tr>
<tr>
<td>Plunge Creek</td>
<td>0.58</td>
<td>-24%</td>
<td>0.66</td>
<td>-26%</td>
<td>0.67</td>
</tr>
<tr>
<td>Arroyo Seco</td>
<td>0.30</td>
<td>6%</td>
<td>0.60</td>
<td>-10%</td>
<td>0.08</td>
</tr>
<tr>
<td>Big Sulphur</td>
<td>0.57</td>
<td>12%</td>
<td>0.66</td>
<td>0%</td>
<td>0.62</td>
</tr>
<tr>
<td>City Creek</td>
<td>0.59</td>
<td>-23%</td>
<td>0.60</td>
<td>-32%</td>
<td>0.62</td>
</tr>
<tr>
<td>Duncan Canyon</td>
<td>0.52</td>
<td>47%</td>
<td>0.82</td>
<td>15%</td>
<td>0.82</td>
</tr>
</tbody>
</table>

2.6.1. Station Distribution Methods

Despite the use of HRU-specific distribution methods, the station-based forcing methods did not yield significantly better calibration statistics across all basins. Marginal improvements were achieved in the Ash Canyon, Plunge Creek, and City Creek basins using the XYZ method for precipitation while keeping Daymet temperature data. All of these basins are in mountainous regions where orographic effects are significant and the mountains immediately surrounding the watershed do not meander significantly, making it easier to correlate precipitation with latitude and longitude for surrounding gages.

The temperature data, especially minimum temperatures, were difficult to manually distribute using the XYZ or IDE methods. The temperatures were less variable across latitude and longitude, and were more correlated with the elevation. However, anomalies in this correlation due to geographic
location lowered regression performance. Additionally, temperature data at most stations seemed to be less reliable than precipitation data, and many of the stations had poor quality control for temperature data. This was especially true at the SNOTEL stations, where temperature data often displayed gaps in data and abrupt shifts from instrument maintenance.

Arroyo Seco was the only basin for which IDE was the best performing method. Perhaps this is due to the large area of this basin in comparison to the other basins. The distances between the centers of each HRU are more significant. Additionally, the difference in climate across HRUS may be more significant because Arroyo Seco is located in the coastal region where complexities in air movements may cause more climate variation across the basin.

2.6.2. PRISM Method

Because the PRISM method specifically accounts for terrain barriers, air temperature inversions, and coastal effects, it may be considered to be more suited than Daymet for coastal basins (Daly 2006), such as Arroyo Seco. Additionally, the large area (241 mi$^2$) of the Arroyo Seco watershed may be more suitable for the 4km PRISM resolution. Despite these expectations, Arroyo Seco performed more poorly with PRISM data than any of the other basins. The NSE was 0.30 using PRISM forcing, compared to an NSE of 0.60 for Daymet forcing.

Ash Canyon was the only study watershed to display a better calibration with PRISM forcing than Daymet Forcing. The Ash Canyon basin is in close proximity to Lake Tahoe, so the combination of this water body and topographic effects from the surrounding Sierra Nevada Mountains could have accounted for the marginal improvement seen using PRISM for this specific watershed.

The study area watersheds were initially selected based on how well they calibrated using Daymet data, which may have pre-disposed these particular watersheds to a better calibration using Daymet. If PRISM data were used in the NHM and initial model selection, it is possible that different watersheds may have been selected. Additionally, the Daymet and PRISM products both utilize NWS CO-OP and SNOTEL stations. Those products are more likely to perform better in areas with high
density of gages with quality data, which may explain why the gage distribution methods did not significantly improve calibration.
CHAPTER 3
CHANGE DETECTION

The study watersheds were evaluated to determine if any changes could be detected following the wildfire given the current model setup and calibration. Because the watersheds used a somewhat low resolution HRU distribution from the NHM, some changes of the actual flow regime may not be detectable because they are within the model error. Additionally, some of those watersheds with detectable changes may have some of this signal attributed to model error. Complete attribution is not possible, but the current study seeks to ensure models examined for post-fire parameterization show changes that are statistically significant.

3.1. The Change Detection Method

To detect the magnitude of hydrologic alteration due to land-use or land-cover changes, many studies employ one of two approaches: (1) a time-series change detection approach or (2) a paired-watershed approach. In the time-series change detection approach, trend analyses and step-change analyses are applied to relevant time-series data (Kundzewicz and Robson 2004). Tests for distribution and autocorrelation of the time-series data are incorporated. For the paired watershed approach, a watershed with land-use or land-cover change is statistically compared to a nearby undisturbed watershed with similar properties (Hewlett 1971). The pre-disturbance period serves as the calibration period, and the flow regimes of the two watersheds are compared. After the disturbance, the flow regime relationship between the two watersheds is altered, and this change is statistically examined.

Given the current widespread use of hydrologic models, the change detection modeling approach has become more popular when the data for a paired watershed is not readily available. Seibert and McDonnell (2010) suggest this change detection approach be applied through two methods. First, optimal model parameter ranges are compared before and after the disturbance. Second, the runoff predicted using the pre-disturbance model is compared with the observed runoff. This approach was later demonstrated in a snow-dominated, wildfire-affected watershed to find that observed streamflow after the fire was 120\%
higher than the pre-fire model predicted in the post-fire period (Seibert, McDonnell, and Woodsmith 2010). Zégre et al. (2010) use this same approach, but apply a Generalized Likelihood Uncertainty (GLUE) framework and a statistical model in order to separate the effects of the disturbance from model uncertainty.

3.2. Study Methods

The current study uses a simplified change detection modeling approach in order to apply a deterministic model calibration. The pre-fire calibration for each of the case study watersheds resulted in a single set of parameters, and therefore does not allow a statistical approach based on different model realizations. Instead, we use the method to only to determine which of the case study watersheds display a statistically significant change in flow regime that can be detected within the error and uncertainty of the model. The parameterization is then examined in more detail for each of these watersheds in Chapter 4.

The general approach is the same as that used by Seibert and McDonnell (2010) and (Zégre et al. 2010). Using the pre-fire calibration parameters, PRMS is run for each case study watershed for ten complete water years after the fire, or through water year 2012, whichever comes first. Ideally, the model parameters represent pre-fire conditions. Thus, when this model is applied to the post-fire period, it represents how the watershed may have behaved if the wildfire had not occurred. A comparison between these modeled flows and the observed flows represents a combination of model error and the effect of the fire or other physical changes to the watershed at that time. The differences between modeled and observed flows are compared on a daily, monthly, and annual scale.

At the daily scale, a time-series of streamflow residuals was constructed. The streamflow residual for each day is the difference between the observed and simulated values. For the pre-fire period, the daily residuals indicate model error. For the post-fire period, the daily residuals indicate model error plus disturbance changes. A Wilcoxon Rank-sum test was used to determine if there was a statistically significant increase in the median daily streamflow residual between the pre-fire and post-fire period. The Wilcoxon rank sum test is non-parametric, so it is not contingent a specific distribution of the streamflow data. This test has been applied to streamflow data in former disturbance studies (e.g. Seibert, McDonnell,
and Woodsmith 2010), and is recommended for disturbance studies when the time of disturbance is known (Kundzewicz and Robson 2004). For the current study, the test is applied to each year after the fire, comparing the residuals from the pre-fire period with the residuals from the post fire period up until that year. This yearly approach helps to ensure changes remain statistically significant for the duration of the post-fire period used for each analysis.

At the monthly and yearly time scale, observed and modeled total streamflow volumes were compared. Annual streamflow comparisons help to determine how much the wildfire has affected the overall water budget, monthly distributions help to identify changes in timing. Monthly comparisons indicate whether the annual streamflow volume changes occurred in times of base flow, peak runoff, or the transition periods. Annual comparisons are done for each basin for ten complete water years after the fire, or water year 2012, whichever comes first. Monthly comparisons are done for four complete water years following the year of the fire.

3.3. Results

The Wilcoxon Rank-sum tests revealed a significant increase in streamflow residuals after wildfire for three of the watersheds: Ash Canyon, Plunge Creek, and City Creek. Because they displayed a response, these watersheds are used in the parametrization portion of this study, which will be discussed in Chapter 4 (Table 3.1). The other watersheds showed no significant increase in daily flow residuals, but may still provide valuable insight and are therefore discussed for the remainder of this chapter. Big Sulphur and Duncan Canyon had P-values of close to unity, indicating that there was actually a statistically significant decrease in daily streamflow residuals. The decrease in residuals was probably due to a poor model calibration, or other changes in the watershed that may not have been accounted for. Big Sulphur and Duncan Canyon also had lower burn area and severity as compared to other watersheds. It is possible that the low severity fires may have encouraged quicker vegetation re-growth in the following years and increased evapotranspiration.
Table 3.1. Wilcoxon Rank-sum text P-values for a statistically significant increase in daily residual streamflow for each cumulative time period following each wildfire

<table>
<thead>
<tr>
<th>Basin</th>
<th>1 yr</th>
<th>2 yr</th>
<th>3 yr</th>
<th>4 yr</th>
<th>5 yr</th>
<th>6 yr</th>
<th>7 yr</th>
<th>8 yr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ash Canyon</td>
<td>8.1E-45</td>
<td>1.1E-145</td>
<td>4.5E-74</td>
<td>9.9E-56</td>
<td>1.1E-60</td>
<td>8.4E-85</td>
<td>1.7E-121</td>
<td>1.5E-140</td>
</tr>
<tr>
<td>Plunge Creek</td>
<td>5.9E-65</td>
<td>1.2E-132</td>
<td>1.6E-176</td>
<td>2.7E-179</td>
<td>3.2E-229</td>
<td>6.5E-276</td>
<td></td>
<td></td>
</tr>
<tr>
<td>City Creek</td>
<td>9.1E-93</td>
<td>7.9E-187</td>
<td>2.2E-219</td>
<td>1.1E-170</td>
<td>6.7E-196</td>
<td>8.9E-212</td>
<td>1.2E-263</td>
<td>1.2E-284</td>
</tr>
<tr>
<td>Arroyo Seco</td>
<td>1.0E+00</td>
<td>1.8E-08</td>
<td>1.0E-15</td>
<td>9.0E-15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duncan Canyon</td>
<td>9.9E-01</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
</tr>
<tr>
<td>Big Sulphur</td>
<td>9.9E-01</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
<td>1.0E+00</td>
</tr>
</tbody>
</table>

For those watersheds with a statistically significant increase, the p values remained low for each time period after the fire. This consistency allows for the parameter comparisons used later in this study to be made for any range of years after the fire, not exceeding the years for which the rank-sum test was conducted. However, the p values for each time period after the fire do not imply there was an increase in residuals for that specific year because the time periods are assessed cumulatively. For example, if a watershed had a statistically significant increase in flows for five years following the fire, it is possible the fifth year could actually show a decrease in residuals, but the residuals for five years following the fire still be statistically significant.

In general, the comparison between simulated and observed annual streamflow is consistent with the results of Wilcoxon Rank-sum test (Figure 3.1). The difference between wet and dry years is an important result of the annual comparison. In general, the model seems to overestimate streamflow in dry years and underestimate streamflow in wet years. This result is consistent with previous studies using PRMS (Jeton and Maurer 2007). The model may underestimate in wet years because it is unable to sufficiently replicate infiltration-excess processes or storage fluctuations. In this case, the calibration may attempt to balance wet and dry year performance using other parameters, which would result in model overestimation for wet years.

To examine impacts of the fire, annual post-fire volumes must be compared to years during the pre-fire period with similar annual volumes. For example, Ash Canyon had an observed streamflow volume of 21 inches and a modeled streamflow volume of 11 inches in 2008. Water year 2000 had a
modeled streamflow of 10 inches and an observed streamflow of 9.6 inches. The model showed that these two years should be similar, but the observed streamflow volume was 10 inches higher in 2007. Thus, it is likely that much of this difference can be attributed to the effects of the fire. So, while 2007 this may have been considered a wet year even in the absence of a wildfire, the observed streamflow volume was still much higher than it may have been in the absence of the fire. Low flow years can be similarly examined, especially in the City Creek and Plunge Creek watersheds, which are controlled by winter rain and have largely varied annual runoff volumes. For extremely dry years such as 2007, City creek displayed 2.7 inches of observed runoff and Plunge Creek had 1.7 inches of observed runoff. These amounts are large in comparison to the modeled flows of 0.9 inches and 0.2 inches in City Creek and Plunge Creek, respectively. For both watersheds, the low flow years displayed much higher observed flows than for similar years before the fire. This result is consistent with significant low flow increases after fire found by Kinoshita and Hogue (2015).

On a monthly scale, volume increases were seen for both wet and dry months for the Ash Canyon, City Creek, and Plunge Creek watersheds, as shown in Figure 3.2. Ash Canyon showed increases in flows during the months of spring melt in the post-fire period, and the baseflow appears to remain elevated through the end of the water year for all four post-fire years shown. There was an increase in flow during January and February of 2008. Ash Canyon received an above-normal amount of rain that winter, but the observed flows are still higher than modeled flows, suggesting the fire may have played some role. It is possible that decreased interception allowed more rain to pass through the canopy, or that a greater amount short-wave radiation penetrating the canopy made the snowpack more susceptible to immediate rain-on-snow effects. City Creek and Plunge Creek displayed the most apparent increases in the spring months following the rainy winter season. This result is possibly related to increased slow interflow and baseflow.

There also may be some connection between change detection and burn percentages, though there are many other factors and no formal correlations can be made. All watersheds with detectable signals had greater the 50% total burn. However, Arroyo Seco showed no detectable response though it was also
over 50% burn, and had a greater percentage of high burn severity than Plunge Creek. City Creek showed the greatest changes and had the greatest overall burn percentage and percentage of high burn severity. The high burn severity was concentrated in the upper portion of the watershed, where the slope is steeper than the average slope of the watershed and there is likely higher precipitation. Thus, this area may be more likely to contribute to increased runoff. Duncan Canyon has areas of high burn concentrated near the basin outlet and did not show and detectable change.
Figure 3.1. Annual volume comparisons. Watersheds in the top row showed a statistically significant increase in daily flow residuals.
Figure 3.2. Monthly volume comparisons. Watersheds in the top row showed a statistically significant increase in daily flow residuals.
In order to examine the best ways to parameterize PRMS models after wildfires, model parameters that represent wildfire-affected physical processes must first be identified. These wildfire processes are divided into two general categories: (1) Vegetation-related processes and (2) soil related processes. The vegetation-related processes identified are canopy interception, evapotranspiration, and short-wave radiation, and are affected by tree mortality, density reduction, and understory removal. Soil related processes are infiltration and overland flow, which are altered by soil hydrophobicity, ash layer formation, soil sealing, and vegetation removal. The PRMS parameters associated with each of these categories are shown in Table 4.1. All parameters are also used for the general calibration scheme, so descriptions can be found in Table 2.3.

Table 4.1. Wildfire-related parameters and processes

<table>
<thead>
<tr>
<th>Fire Effects</th>
<th>Processes</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soils</td>
<td>Overland flow, Infiltration</td>
<td>carea_max</td>
</tr>
<tr>
<td></td>
<td></td>
<td>fastcoef_lin</td>
</tr>
<tr>
<td></td>
<td></td>
<td>fastcoef_exp</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pref_flow_den</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Canopy interception and evaporation</td>
<td>covden_win*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>covden_sum*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>srain_intcp</td>
</tr>
<tr>
<td></td>
<td>Evapotranspiration (availability - based)</td>
<td>transp_tmax</td>
</tr>
<tr>
<td></td>
<td></td>
<td>soil_moist_max</td>
</tr>
<tr>
<td></td>
<td></td>
<td>soil_rechr_max</td>
</tr>
<tr>
<td></td>
<td>Short-wave radiation</td>
<td>rad_trmcf</td>
</tr>
<tr>
<td></td>
<td></td>
<td>radmax</td>
</tr>
</tbody>
</table>
4.1. **Case study watershed parameterization**

For the study watersheds, parameterizations for the pre-fire and the post-fire periods were compared. In this case, the model calibration used in the change detection portion of the study was not used because it provides only a single set of parameters for each watershed. Instead, a range of parameters is desirable to represent multiple model realizations and account for parameter interactions. So, Monte-Carlo simulations were used for each basin to determine the best range of parameters for the pre-fire and post-fire period. This approach is similar to that used by Seibert, McDonnell, and Woodsmith (2010), where the authors applied the HBV model to a wildfire-affected, snow-dominated basin. While the HBV model (Bergström 1992) is conceptual, PRMS is physically based, and thus the parameterization may provide more in-depth insight into the how the different hydrologic processes are affected.

4.1.1. **Methods**

The Monte-Carlo simulation was performed for each watershed over the pre-fire period, and several post-fire periods. The pre-fire period consisted of ten complete water years before the fire, which is the same time period used for the deterministic calibration from Chapter 2. For each year following the fire, the Monte-Carlo simulation was run cumulatively. That is, it was run from the first year following the fire through that year.

For each time period and each watershed, 10,000 model runs were performed. Only those parameters listed in Table 4.1 were randomized, and the rest were held constant at the values determined from the deterministic pre-fire calibration. The randomization used a Latin Hypercube distribution in order to evenly sample the parameter space in all dimensions. This distribution has been successfully employed in watershed models to reduce computation power needed (Muleta and Nicklow 2005).

A Generalized Likelihood Uncertainty Estimation (GLUE) analysis was used to determine the best parameter sets. The GLUE analysis was initially proposed by (Beven and Binley 1992), and is based on the assumption that there is not a single set of parameter to describe hydrologic conditions, but rather there are a number of equally likely solutions. The GLUE analysis employs modeler judgement to select objective function criteria that define the most likely parameter sets. While this approach has sometimes
been criticized for not being formally Bayesian, the GLUE method can still predict reasonable uncertainty bounds and its straightforward approach is advantageous (Vrugt et al. 2008). For the current study, the best 50 model runs are chosen based on a weighted objective function using the Euclidean distance method (Madsen 2000), with weights chosen based on modeler judgement. NSE, Percent Bias, and root mean squared error (RMSE) are used as objective functions, and the values of these objective functions for the least likely behavioral model are shown in Table 4.2, Table 4.3, and Table 4.4, respectively. For each model and time period, the range of parameters for the behavioral sets were examined.

Table 4.2. NSE values for the least likely GLUE model

<table>
<thead>
<tr>
<th></th>
<th>Ash Canyon</th>
<th>Plunge Creek</th>
<th>City Creek</th>
</tr>
</thead>
<tbody>
<tr>
<td>pre-fire</td>
<td>0.56</td>
<td>0.59</td>
<td>0.53</td>
</tr>
<tr>
<td>1 yr post-fire</td>
<td>0.52</td>
<td>0.70</td>
<td>0.68</td>
</tr>
<tr>
<td>2 yr post-fire</td>
<td>0.38</td>
<td>0.66</td>
<td>0.67</td>
</tr>
<tr>
<td>3 yr post-fire</td>
<td>0.33</td>
<td>0.70</td>
<td>0.64</td>
</tr>
<tr>
<td>4 yr post-fire</td>
<td>0.32</td>
<td>0.67</td>
<td>0.66</td>
</tr>
<tr>
<td>5yr post-fire</td>
<td>0.37</td>
<td>0.66</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Table 4.3. Percent bias values for the least likely GLUE model

<table>
<thead>
<tr>
<th></th>
<th>Ash Canyon</th>
<th>Plunge Creek</th>
<th>City Creek</th>
</tr>
</thead>
<tbody>
<tr>
<td>pre-fire</td>
<td>15.6 %</td>
<td>-0.8 %</td>
<td>1.0 %</td>
</tr>
<tr>
<td>1 yr post-fire</td>
<td>2.8 %</td>
<td>-0.9 %</td>
<td>-4.0 %</td>
</tr>
<tr>
<td>2 yr post-fire</td>
<td>-11.7 %</td>
<td>-0.7 %</td>
<td>-1.8 %</td>
</tr>
<tr>
<td>3 yr post-fire</td>
<td>-4.6 %</td>
<td>-3.6 %</td>
<td>-0.2 %</td>
</tr>
<tr>
<td>4 yr post-fire</td>
<td>0.7 %</td>
<td>-3.6 %</td>
<td>0.8 %</td>
</tr>
<tr>
<td>5yr post-fire</td>
<td>0.4 %</td>
<td>3.3 %</td>
<td>1.8 %</td>
</tr>
</tbody>
</table>

Table 4.4. RMSE (cfs) for the least likely GLUE model

<table>
<thead>
<tr>
<th></th>
<th>Ash Canyon</th>
<th>Plunge Creek</th>
<th>City Creek</th>
</tr>
</thead>
<tbody>
<tr>
<td>pre-fire</td>
<td>1.9</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>1 yr post-fire</td>
<td>1.7</td>
<td>37</td>
<td>94</td>
</tr>
<tr>
<td>2 yr post-fire</td>
<td>3.9</td>
<td>29</td>
<td>70</td>
</tr>
<tr>
<td>3 yr post-fire</td>
<td>3.4</td>
<td>23</td>
<td>59</td>
</tr>
<tr>
<td>4 yr post-fire</td>
<td>3.2</td>
<td>21</td>
<td>50</td>
</tr>
<tr>
<td>5yr post-fire</td>
<td>2.8</td>
<td>20</td>
<td>44</td>
</tr>
</tbody>
</table>
4.1.2. Results

For surface runoff, \textit{pref\_flow\_den} was the most significant parameter. Some changes were apparent in \textit{carea\_max} while \textit{fastcoef\_lin} showed no significant changes (Figure 4.1). In many watershed models, the parameter for impervious area is increased after fire to represent hydrophobicity and other soil changes that reduce infiltration. For example, Cydzik and Hogue (2009) found that percent impervious should be increased to model post-fire runoff using the HEC-HMS model. However, City Creek is the only watershed which showed an increase in the impervious parameter, \textit{carea\_max}, and the preferential flow density still showed a greater change. In both the Ash Canyon and City Creek watersheds, \textit{pref\_flow\_den} was elevated after the fire. This result may be explained physically. Stoof et al. (2014) proposed preferential flow as a primary mechanism for increased streamflow after fire. They found that variability in soil moisture and infiltration capacity following a wildfire created more opportunities for preferential flow paths to form. It is also possible that \textit{pref\_flow\_density} was more sensitive than \textit{carea\_max} in the situation, or that parameter interaction with other processes constrained changes in \textit{carea\_max} and allowed \textit{pref\_flow\_density} to compensate. For future parameterization of post-fire watersheds, both parameters should be increased to model an increase in surface runoff.

In contrast to Ash Canyon and City Creek, Plunge Creek showed a decrease in both the \textit{carea\_max} and \textit{pref\_flow\_density} parameters. Because this basin displayed a lower burn severity, it is likely that surface runoff was not as significant of a driver for an increase in flows. The increase in daily residual, monthly, and annual streamflow could be accounted for through reduced interception and evapotranspiration in the model, rather than effects at the soil surface.

The only interception parameter to display changes between pre-fire and post-fire time periods was \textit{srain\_intcp} (Figure 4.2). This parameter showed a decrease for the first year in City Creek and Plunge Creek, as would be expected. Wildfires reduce the interception storage available through vegetation thinning or mortality. The effect was not apparent in Ash Canyon, most likely because this watershed is primarily snow-dominated. For City Creek, the parameter range returned to normal after the first year, but the parameter reduction remained for several years after the wildfire in Plunge Creek. This
may represent a recovery in the watershed. Because City Creek has dominantly shrub/scrub vegetation, it is possible that recovery in the vegetation may happen more quickly in the second year following the wildfire. However, Plunge Creek has similar watershed characteristics with a lower burn severity and did not show any apparent recovery with the $srain\_intcp$ parameter. Additionally, the elevated water yield of the City Creek watershed from two to five years after the fire does not suggest such recovery in the vegetation. So, it is more likely that the return of the $srain\_intcp$ parameter to pre-fire conditions is a result of parameter interactions.

Figure 4.1. Surface runoff parameter ranges of the top 50 behavior models in the GLUE analysis for each watershed for each time period.
Neither of the cover density parameters showed changes between the pre- and post-fire periods. The primary function of the cover density parameters in PRMS is to control the amount of precipitation that reaches the ground to become available to infiltration, storage, runoff, or evaporation. The cover density parameters do not affect the amount of transpiration from the vegetation or the amount of solar radiation that reaches the ground. Thus, these parameters are not very sensitive to water budget changes, and are especially prone to effects of parameter interactions. These parameters should be approached with caution when used to represent post-fire conditions.

The evapotranspiration parameters were perhaps the most informative from this analysis. As shown in Figure 4.3, the range of \textit{soil\_moist\_max} decreased for all years following the wildfire for all watersheds. The change was most apparent in the City Creek watershed, where the median parameter value dropped from about five inches to less than one inch. The decrease of the \textit{soil\_moist\_max} parameter represents less water being made available for evapotranspiration. This water must instead become runoff or recharge. The \textit{soil\_rechr\_max} parameter show no changes in the ranges between periods. However, this parameter is constrained by the model to be less than \textit{soil\_moist\_max}, so the value of \textit{soil\_rechr\_max} was set equal to \textit{soil\_moist\_max} for any model runs for which \textit{soil\_rechr\_max} has a higher randomized value. Future post-wildfire PRMS parameterization may require a decrease in both \textit{soil\_moist\_max} and \textit{soil\_rechr\_max} to represent a decrease in evapotranspiration. While these parameters are most effective and the most physical way to represent a change in evapotranspiration following wildfire, the relationship between \textit{soil\_moist\_max} and evapotranspiration is complex, and is thus explored more in depth later in this chapter.

The parameter, \textit{rad\_trncf} is one of the most sensitive parameters for snowmelt process. The snowmelt controlled basin from this study, Ash Canyon, displayed an increase in this parameter after the fire (Figure 4.4). Increasing \textit{rad\_trncf} is suggested for future post-fire model to represent an increase in short wave radiation through the canopy and to the snowpack. The behavior displayed for the \textit{radmax} parameter in all basins is not as conceptually defensible. A decrease in \textit{radmax} would lead to a decrease in the overall amount of radiation reaching the ground surface, which does not align with a post-fire
conceptual model. For Plunge Creek, the effects of \textit{rad_trncf} could be counteracting the effects of \textit{radmax}, since one parameter increases while the other decreases. However, City Creek showed a decrease in both radiation parameters.

Figure 4.2. Interception parameter ranges of the top 50 behavior models in the GLUE analysis for each watershed for each time period.
Figure 4.3. Evapotranspiration parameter ranges of the top 50 behavior models in the GLUE analysis for each watershed for each time period.

Figure 4.4. Solar radiation parameter ranges of the top 50 behavior models in the GLUE analysis for each watershed for each time period.
4.2. **Evapotranspiration**

Further investigation was conducted related to evapotranspiration and model parameterization. Based on the examination of evapotranspiration parameters from the previous analysis, it is clear that proper estimation of soil moisture parameters is critical to post-wildfire modeling in PRMS. Furthermore, the interaction between soil zone processes and evapotranspiration in PRMS is complex, and in some ways, counterintuitive. ET is perhaps the most difficult to predict and the most critical for accurately modeling post-fire conditions. Thus, evapotranspiration parameterization is critical to future post-wildfire studies, and may ultimately help to improve model structure. For a more in-depth look at this component of the model, we move beyond the limited data from the study area watershed, and use all NHM burned HRUs that were identified in Chapter 2.

4.2.1. **National Model Vegetation and Evapotranspiration Response**

From a conceptual standpoint, ET should decrease following a wildfire. Vegetation that is lost reduces overall transpiration rates and plant-available water and drives down ET. However, the response of ET to wildfires has not been comprehensively studied across the United States. In order to generalize post-wildfire evapotranspiration response in PRMS, it is necessary to evaluate how vegetation and evapotranspiration are changing across the entire western United States. To do this, remote sensing data from MOD16 (Mu, Zhao, and Running 2011) and SSEBop (Savoca et al. 2013) products were examined for the NHM burned HRUs. These evapotranspiration products are also compared with the Normalized Difference Vegetation Index (NDVI). NDVI represents the normalized difference between the red and near-infrared bands, and is one of the most popular indications of vegetation health. NDVI has been shown to directly affect the relationship between PET and actual ET (Li et al. 2013). Each NDVI timeseries was created from LANDSAT data using the Google Earth Engine platform (Google Earth Engine Team 2015), which allowed the use of massive parallelization in order to compute the average monthly NDVI for 15 years over 900 different HRUs. The final time series used in the comparison was the actual ET calculated by PRMS using default NHM parameterization. Because parameterization is not dynamic in this version of the NHM, this time series shows the ET from pre-fire conditions.
As a first examination, the ensemble mean of all HRUs with greater than 10% high burn severity were examined. Each time series was shifted to be relative to the date of the fire (Figure 4.5). SSEBOP, and MOD16, and NDVI all showed a sharp decrease following each wildfire, but the PRMS actual ET does not because the wildfire events have not been incorporated into the model. The SSEBOP ET time series produced much higher estimates of ET during the peak season, compared to MOD16. This is result consistent with the comparison of the two products done by Velpuri et al. (2013), who found that SSEBOP often predicted annual ET of 100 to 300 mm higher per year in mountainous areas in the western United States. The time series of SSEBOP ET also appears more similar than the MOD16 ET to the time series of NDVI, even though MOD16 incorporates remote sensing measures of vegetation cover and SSEBOP does not. Additionally, seasonal variations in both the MOD16 and SSEBOP products were smoother and more distinct than those seen in the PRMS model ET and NDVI.

4.2.2. National Model Vegetation and Evapotranspiration Sensitivity

The soil\_moist\_max parameter showed greatest magnitude of any of the wildfire-related parameters examined. However, the relationship between the soil\_moist\_max parameter and ET is complex. Thus, a national-scale sensitivity analysis was performed to examine how soil\_moist\_max affects ET.

Evapotranspiration from the soil zone in PRMS is based on the conceptualization presented by Zahner and Stage (1966), and is focused on the availability and accessibility of soil moisture. As soil moisture decreases from the field capacity to the wilting point, the pore water tension increases, the soil water becomes more difficult for plants to access, and root uptake decreases. In the model this is represented mathematically through the relationships shown in Figure 4.6. However, this conceptualization assumes full vegetated stand health, and does not provide a method to account for decreased root uptake demand from the vegetation due to reduced density or mortality. Thus, for vegetation disturbances such as wildfires, a method is needed to represent decreased root uptake within this framework. The simplest and most conceptually meaningful approach is to use soil\_moist\_max to represent changes in root water demand. Because soil\_moist\_max essentially represents the amount of
water available to the dominant vegetation between the surface and rooting depth, a change in soil\textsubscript{moist\_max} could represent a change in root water demand as well as a change in root water availability.

![Graphs showing ensemble mean time series for remote sensing products, NDVI, and PRMS actual evapotranspiration for all burned national HRUs.](image)

**Figure 4.5.** Comparison of ensemble mean time series for remote sensing products, NDVI and PRMS actual evapotranspiration for all burned national HRUs

The results of the Monte-Carlo analysis showed a decrease in soil\textsubscript{moist\_max} needed to model a decrease in evapotranspiration due to the wildfire, which is consistent with the conceptualization of soil moisture availability and evapotranspiration. To test this on a national scale, soil\textsubscript{moist\_max} was varied across the range of parameters, and the fraction of actual ET available ET in the soil zone was examined. This was done for all burned HRUs.
Figure 4.6. Method used by PRMS to calculate evapotranspiration based on soil zone saturation for each soil type.

A visualization of this sensitivity analysis for the first 100 HRUs in Figure 4.7 showed divergent sensitivity. Some HRUs showed a higher fraction of actual ET corresponding to a higher soil_moist_max value throughout the entire range of parameter values. However, some HRUs reached a peak fraction of actual ET, after which the actual ET fraction began to decrease as soil_moist_max was increased. This difference in sensitivity is best explained by the consistency of soil moisture in each HRU, which can be approximated based on the aridity index (AI) of each HRU. The ensemble mean of soil_moist_max sensitivities for arid and semi-arid regions (AI < 0.50); and humid regions (AID > 0.65) are compared, showing that the maximum fraction of actual ET will often occur at the maximum value of soil_moist_max for humid regions. As the capacity of the capillary reservoir is made to be very large for arid and semi-arid regions, the soil zone is more likely to consistently operate a low soil moisture fraction, which can drastically reduce the fraction of actual ET. When this low soil moisture effect is more significant than the increased water available for ET, the actual ET fraction will display the behavior shown in Figure 4.7 for arid and semi-arid climates.
Figure 4.7. Sensitivity of actual evapotranspiration to $soil_{moist\_max}$. (Left) the first 100 HRUs are shown for simplicity. (Right) HRUs are categorized by aridity index and the ensemble mean for each range is shown.
CHAPTER 5

CONCLUSIONS

A deterministic, distributed-parameter, physical-process hydrologic model (PRMS) was applied to wildfire-impacted watersheds in the western United States in order to characterize changes in flow regimes and evaluate model parameterizations. The model was first used for detection of post-fire changes, and then model parameters were examined in order to inform post-fire predictions and examine the recovery of each watershed.

Out of all watersheds available in the NHM, only six were identified for having more than 25% area burned, a sufficient period of available streamflow data, no significant dams, and a reasonable calibration with a generalized automated SCE calibration. These watersheds were located in either the San Bernardino Mountains, the Sierra Nevada Mountains, or California coastal ranges, all of which areas have had several post-wildfire runoff studies previously published. This narrow range of study areas may explain the low number of national scale post-wildfire studies, and highlights the critical role of remote sensing data to help inform runoff modeling and disturbance studies.

Parameterization from the NHM was used to model these six study area watersheds. While the NHM is a useful tool to identify wildfire-affected watersheds and initiate modeling, studies to inform water resources decisions in specific basins should refine the spatial discretization and use more stringent calibration criteria than were used in the current study. Statistically significant changes in daily streamflow residuals following the wildfire were detected in three of the six study area watersheds. The other watersheds may have shown a decrease in flows following the wildfire, or did not have a sufficient calibration in order to discern the effects of the wildfire from the model error.

Based on the results of the GLUE analysis for all post-fire processes, some general recommendations can be made regarding post-fire parameterization for future studies. There is not enough information to specify how much parameters should be changed based on characteristics of the fire or the watershed. Instead, these recommendations can serve as guidelines and provide insight into
wildfire processes in PRMS. Modeler judgement will be required to construct scenarios based on the specific watershed and wildfire in the future.

Increases in surface runoff may be modeled by increasing the $carea_{\text{max}}$ parameter and the $pref\_flow\_den$ parameter. The $pref\_flow\_den$ parameter may be more significant for representing these changes, though preferential flow may not necessarily be the most significant mechanism for direct runoff generation. The $srain\_intcp$ parameter can be used to increase precipitation that penetrates the canopy, especially in areas like the San Bernardino Mountains, which are controlled by winter rain storms.

However, cover density parameters should be approached with caution. Decreases in evapotranspiration may generally be modeled by reducing the capacity of the capillary reservoir using the $soil\_moist\_\text{max}$ parameter, though the opposite affect may occur for arid and semi-arid watersheds if the initial value of $soil\_moist\_\text{max}$ is high. The examination of solar radiation parameters was inconclusive.

The national-scale investigation into post-fire ET parameterization provided valuable insight into the relationship between post-fire vegetation changes and ET, both in the model and in the real world. There is opportunity for future analysis to more specifically relate post-fire vegetation changes to ET. Future work will examine the time series of ET products and NDVI based on burn severity of each HRU in order to form a generalized relationship. Combined with the results of the ET sensitivity analysis, this information can inform how to best incorporate post-fire vegetation changes into the model in a way that accurately accounts for changes in ET, and thus help improve the model’s applicability to disturbance and land-cover change studies.
REFERENCES


