

THESIS

EVALUATING THE INFLUENCE OF VEGETATION PARAMETERS IN A SNOW ENERGY
AND MASS BALANCE MODEL IN WILDFIRE IMPACTED LANDSCAPES

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ABSTRACT

EVALUATING THE INFLUENCE OF VEGETATION PARAMETERS IN A SNOW ENERGY AND MASS BALANCE MODEL IN WILDFIRE IMPACTED LANDSCAPES

High-elevation landscapes that accumulate deep, persistent snow have been increasingly impacted by larger and more intense wildfires in recent decades. Following wildfire, the snow mass and energy balance is altered, leading to changes in peak snow water equivalent (SWE), faster snow melt rates, and earlier snow disappearance dates. Despite the added complexity that post-fire areas present for water forecasting, few studies have assessed snow model performance in post-fire locations relative to in-situ observations. This study evaluates iSnobal, a widely-used physics-based model, over five winters following the 2020 Cameron Peak Fire burn scar (Colorado, USA) with a focus on vegetation parameters. I updated the LANDFIRE vegetation dataset used in the model setup to reflect post-fire conditions and tested the model sensitivity to each individual parameter. Snow disappearance dates improved by up to 45 days relative to the default run, bringing modeled dates within a median of -2 days (± 5 days) across stations and years. However, average daily net radiation differences of up to 47 W/m^2 (113% of observed value) were found between updated model runs and measured radiation at weather stations in burned areas. I also used published vegetation burn severity thematic classes to assign vegetation parameters, which led to improved agreement in High and Moderate burn severity forested areas later in the melt season. Finally, modeled a set of endmember 20-year post-fire vegetation recovery scenarios, which demonstrated limited SWE changes between excellent and poor recovery, highlighting the long-term, transformative impact of these disturbances on snow

processes. This work emphasizes the importance of vegetation parameters in iSnobal and the need for accurate parameterizations for post-fire snow water resource modeling.

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1. Introduction

1.1 Climatology of Seasonal Snow

Seasonal snow plays an important role in regulating global climate, and hydrological and ecological processes (Hammond et al., 2018; Slatyer et al., 2022; Vavrus, 2007; Wieder et al., 2022). In the Northern Hemisphere, snow covers around 60% of the land surface where it exerts strong influence over the land surface energy balance through its high reflectivity (albedo) (Figure 1a) and insulative nature (Hammond et al., 2018). The large snow-covered areas decrease the amount of radiation absorbed by the land surface, maintaining a more neutral energy balance specifically in the spring when radiation is increasing (Zhang, 2005). Additionally, the deep snowpacks that accumulate in the mountains act as crucial water sources, providing melt runoff for reservoirs that sustain municipal, recreational, and agricultural uses year-round.

The seasonal cycle in snow-dominated watersheds is characterized by winter snow accumulation and melting in the spring and summer, providing water to downstream environments and users (Butler et al., 2015; Kampf & Lefsky, 2016; Li et al., 2017; Sturm et al., 2017). The hydrograph in these systems is defined by a large peak in the late spring and early summer due to the influx of snowmelt with a return to baseflow in the late summer (Figure 1b), compared to rain dominated systems that have smaller peaks during individual precipitation events. Snowmelt accounts for over half of streamflow in the western U.S. making it an essential water resource across the region (Li et al., 2017). For example, the Colorado River Basin with over 40 million people receives up to 92% of its water as snowmelt from the Upper Colorado River Basin (Butler et al., 2015; Hammond et al., 2023). Over 22,000 km² of irrigated land relies

on water from the Colorado River that originates as snowmelt (Richter et al., 2024). Research suggests that the value of snow as a water resource is in the trillions of dollars (Sturm et al., 2017).

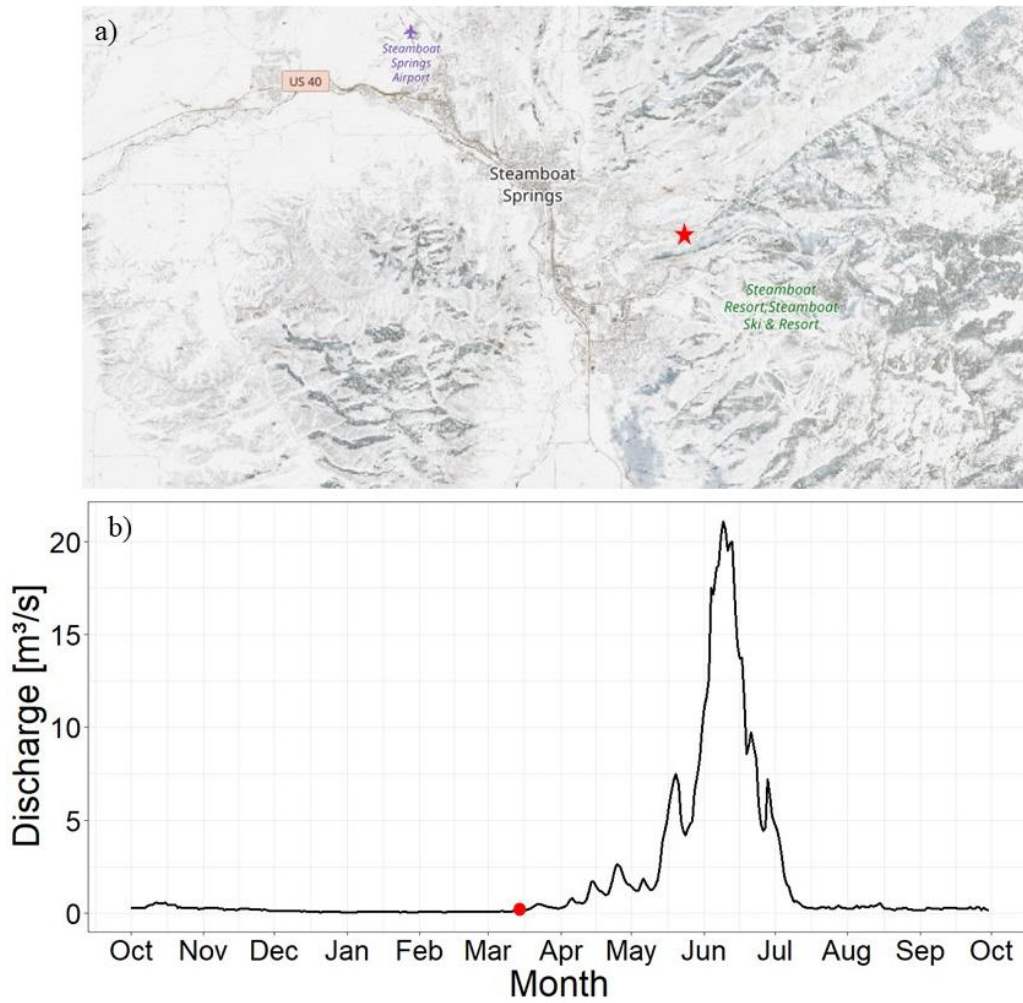


Figure 1. a) A true color satellite image from Sentinel-2 L2A from 11 March 2024. The red star denotes the location of USGS streamflow gauge Fish Creek at Upper Station near Steamboat Springs, CO (USGS-09238900). b) A characteristic hydrograph from WY 2024 at the USGS streamflow gauge. The red dot denotes the day of year that the Sentinel-2 image was taken.

1.2 Snow Measurements

Quantifying the amount of snow, and, more importantly, the amount of water contained in the snowpack, is a challenge that researchers and water managers are constantly trying to overcome

and has been identified as a “Most Important” priority for the U.S. National Academies of Sciences, Engineering, and Medicine (NASEM) Decadal Survey (NASEM, 2018). Seasonal snow varies significantly over space and time, especially in complex terrain like mountainous and forested regions (Rojas-Heredia et al., 2024; Varhola et al., 2010). In-situ observations can come in the form of automatic weather stations equipped with sonic snow depth sensors or snow pillows for measuring snow density, and the snow-water-equivalent (SWE) can be calculated if both are present. The Natural Resources Conservation Service has established and maintains a network of Snow Telemetry stations (SNOTEL) which take a variety of continuous measurements including SWE (Figure 2).

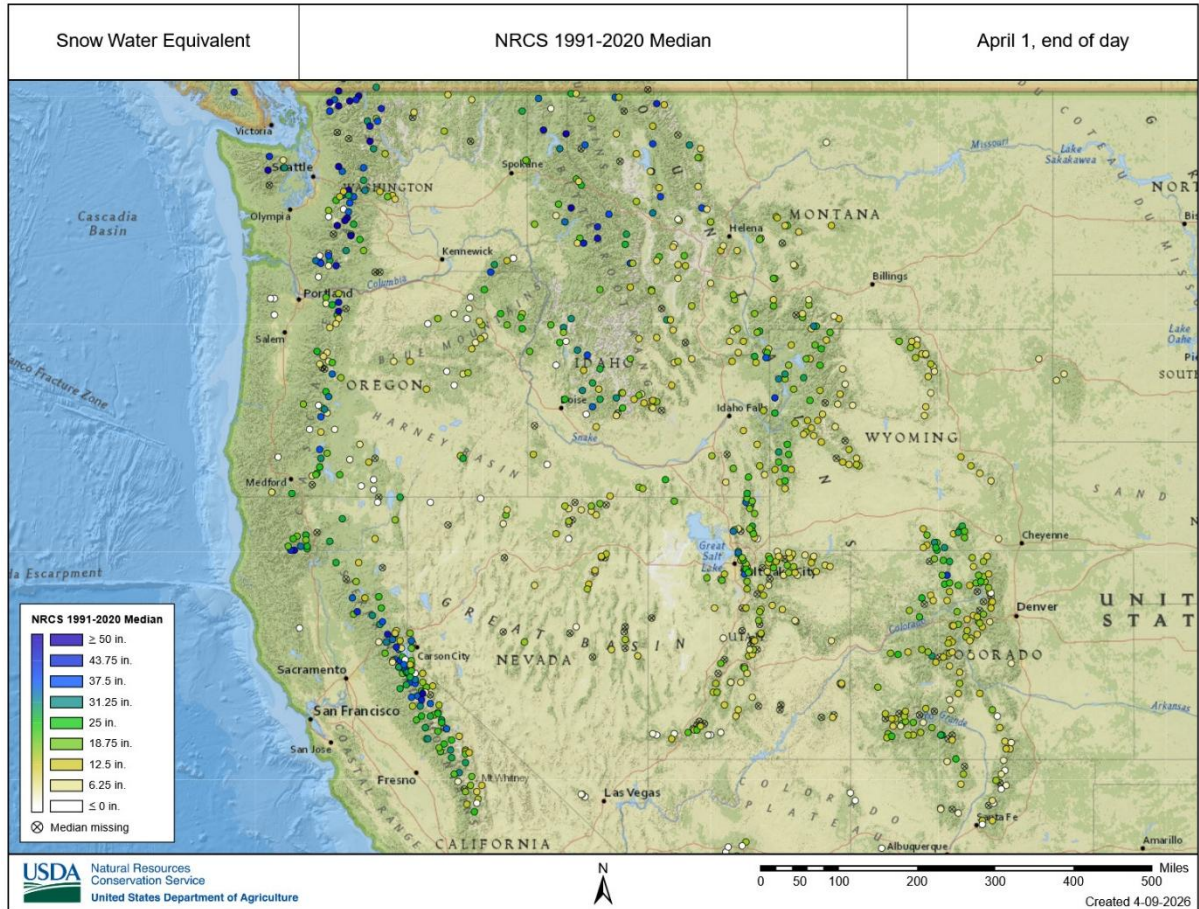


Figure 2. Median SWE on 1 April for the period 1991-2020 at the NRCS SNOTEL stations across the western U.S.

Efforts have been made to broaden the spatial scope of snow sampling from single point observations to kilometer-scale measurements using short-range remote sensing techniques like terrestrial laser scanners (TLS) and unoccupied aerial vehicles (UAV) (McGrath et al., 2022; Revuelto et al., 2017, 2021, 2025). Additionally, large-scale airborne remote sensing campaigns have been launched and are used at the watershed scale (Painter et al., 2016). However, each method is limited by spatial or temporal resolution usually caused by either financial or logistical constraints that come with measuring snow in remote and complex terrain.

Satellite-based snow measurements have largely been limited to measuring snow covered area using optical imagery (Nolin, 2010; Stillinger et al., 2023). However, again, SWE has been

challenging to capture accurately on the global scale (Lettenmaier et al., 2015). Synthetic Aperture Radar (SAR), an active remote sensing technique using microwave pulses, is a promising tool used on large scale and has been implemented in C-band wavelengths on the Sentinel-1 constellation to identify snowpack ripening and the onset of runoff, for example (Detre et al., 2025; Hale et al., 2025; Tarricone et al., 2025). The launch of the NASA-ISRO (NISAR) (Earth Science Data Systems, 2024) mission in July 2025 expands on the methodology from Bonnell et al., 2021 and 2024 which used C-band and L-band InSAR to measure SWE on a large scale. NISAR will provide a global 80-meter SWE product every 12 days (Detre et al., 2025; Earth Science Data Systems, 2024).

1.3 Recent Climate Impacts to Seasonal Snow

Recent observations indicate critical changes to snowpack dynamics including less accumulation, earlier peak SWE and earlier melt out (Hale et al., 2023; Ikeda et al., 2021; Mote et al., 2018; Musselman et al., 2021). For example, the timing of peak SWE was shown to shift eight days earlier for every degree of warming in the Sierra Nevada Mountains along the California/Nevada border (Kapnick & Hall, 2010). Another study found that 42% of 634 study sites across the western U.S. experienced more melt before 1 April than the historical average (Musselman et al., 2021). Earlier peak SWE timing and onset of melt both contribute to earlier runoff generation. Statistically significant declines in Snow Storage Index, a metric describing the seasonality of surface water inputs, were observed indicating earlier snowmelt (Hale et al., 2023).

Apart from observed changes in snow storage and melt timing, models are also demonstrating these changes. Modeling of future snowpack trends indicate that the western U.S. will continue to be vulnerable to water scarcity due to decreases in snow water resources (Allan

et al., 2020; Huning & AghaKouchak, 2020; Marshall et al., 2019; A. M. Rhoades et al., 2018; Siirila-Woodburn et al., 2021). For example, up to approximately $25 \pm 5\%$ SWE losses are expected by 2050 and $50 \pm 15\%$ by 2100 (Siirila-Woodburn et al., 2021).

Hydrologic processes that would be affected under these scenarios include surface water generation, groundwater storage, and evapotranspiration. Earlier snowmelt also alters ecosystem function via vegetation and microorganism response to changes in snow disappearance timing (Blankinship et al., 2018). Low snow years that deviated from the norm, like that experienced by the majority of the western U.S. in the 2025-2026 winter, will have direct and indirect impacts long into the future.

1.4 Changing Wildfire Patterns

Wildfire prevalence and intensity has increased in the western U.S. in recent years due to decades of fire suppression and aridification (Fornwalt et al., 2016; Harpold & Molotch, 2015; Higuera et al., 2021; North et al., 2024; Seidl et al., 2017; Westerling, 2016; Westerling et al., 2006). Between the years 1984 to 2011, the Rocky Mountains region of the U.S. experienced an average of one additional large fire per year (Dennison et al., 2014). These trends persisted into the 2000s with a three-fold increase in frequency and a four-fold increase in fire extent when compared to the 1980s and 1990s (Iglesias et al., 2022).

Vegetation regeneration is a commonly used metric to evaluate forest recovery. Large, unprecedented fires have strong implications for decreases in forest resilience and potential shifts from forest to non-forest landscapes (Coop et al., 2020; Stevens-Rumann et al., 2018). The historic 2020 fire season in the western U.S. constituted 44% of area burned in the Central Rocky Mountains since 1984 (Higuera et al., 2021). Regeneration failure is another aspect of changing

fire dynamics that could complicate natural resource management in the 21st century. In a comprehensive study, there was an 11% increase in sites with zero regeneration from the period before the year 2000 to the period after (Stevens-Rumann et al., 2018). Colorado has experienced the top 20 largest wildfires in state history since 2002 when the Hayman Fire occurred, which was the largest fire in state history at that time (557 km²). Regeneration after the Hayman fire was found to be low in areas that were further away from live trees such as large patches of high severity burn (Chambers et al., 2016). Another study conducted in Idaho also found that even species that are well-adapted to high severity fire like serotinous species fail to regenerate post-fire if the seed source is compromised or if the fire return interval is more frequent than what the species had adapted to (Agne et al., 2022). For example, lodgepole pine (*Pinus contorta*), a common serotinous species in the Southern Rocky Mountains, is generally resilient to wildfire. However, if wildfires occur more frequently and at higher severity than the historical norm, this species may not be able to reestablish to previous levels, changing forest composition (Agne et al., 2022; Turner et al., 2019). In the Southern Rockies, low seedling regeneration suggests potential landscape-level changes post-fire (Stevens-Rumann et al., 2018).

Wildfires have also shifted upwards in elevation into the persistent, or late, snow zone (Alizadeh et al., 2021; Kampf et al., 2022), indicating the possibility of long-term forest declines in a critical snow zone for water resources. In 2020, over half of the area burned in the Southern Rockies was in the late snow zone, and another 30% of area burned was in the middle snow zone (Kampf et al., 2022). More high-elevation forests are being exposed to wildfire because of changes in climatic norms. Between 1984 and 2017, fire risk in 11% of montane forests in the western U.S. increased due to changes in vapor-pressure-deficit (VPD) associated with increased air temperature due to climate change (Alizadeh et al., 2021). Increases in bark beetle-related

tree mortality in recent decades have also brought concern of increased fire risk. However, effects of bark beetle disturbance and wildfire have not been shown to compound in lowering forest resilience post-fire (Agne et al., 2016; Harvey et al., 2014; Stevens-Rumann et al., 2015). Another threat to forest resilience due to climate change is earlier spring snow melt out. Spring snow presence acts as a control on soil moisture and soil temperature, governing the onset of the growing season (Flynn et al., 2025; Williams et al., 2009) and providing an insulating layer that protects vegetation from potentially harsh conditions that can lead to poor recruitment (Slatyer et al., 2022). Climate change-related higher elevation fires, aridification, and earlier snowmelt all contribute to lower forest resilience in important snow-retaining forests.

1.5 Wildfire Impacts to Snow Dynamics

Wildfire has been found to impact snow dynamics in several key ways: decreasing snow albedo through deposition of ash/soot on the snow surface, increasing accumulation, increasing solar radiation reaching the snow surface, and decreasing snow sublimation from the canopy (Gallais et al., 2025; Gleason et al., 2019; Koshkin et al., 2022). These effects vary across burn severities because canopy structure is the main forest control on snow accumulation and solar radiation at the snow surface (Koshkin et al., 2022). Burn severity and, thus, canopy structure exist on a large gradient between nearly untouched forest to blackened landscapes with standing boles, creating varying intensities of impacts to snow dynamics. Several studies have been conducted in the Cameron Peak Fire burn scar investigating the impacts to snow dynamics in the first two years post-fire (Kampf et al., 2022; McGrath et al., 2023; Reis et al., 2024). Near Joe Wright Reservoir, both north and south aspects were found to have earlier snow disappearance dates and increased melt rates, both with greater magnitude on south-facing slopes, and peak snow water equivalent (SWE) occurred earlier on south-facing slopes compared to pre-fire

conditions (Reis et al., 2024). These changes and the continued evolution of these landscapes post-fire present a significant challenge to water managers, both here in Colorado and in numerous other basins across the western U.S.

1.6 Snow Modeling for Operational Water Forecasting

Water forecasting for operational purposes is challenging, especially in the western U.S. where the demand for snowmelt runoff exceeds availability, which is projected to further worsen this century (Li et al., 2017; Marshall et al., 2019). One operational snow model used widely by the NOAA River Forecast Centers, SNOW-17, predominantly relies on an average of historical snow measurements to calibrate future projections of snowmelt (Anderson, 1976; Franz et al., 2008; Meyer et al., 2023). Although improvements have been made to SNOW-17 through the use of Bayesian Model Averaging, the accuracy varies by location and snow condition (Franz et al., 2010) with greater error propagation in years that deviate from the historic norm (Meyer et al., 2023) which is common in post-fire areas. At the other end of model complexity are physics-based snow models that model snowpack energy and mass balance, including iSnobal (Marks et al., 1999; Marks & Dozier, 1992), SNOWPACK (Lehning et al., 2002), and SnowModel (Liston & Elder, 2006). Recently, there has been an increased focus on snow energy and mass balance models in operational settings such as the integration of iSnobal with other data products like Airborne Snow Observatories (ASO) LiDAR (Meyer et al., 2023; Painter et al., 2016) that provide snowpack information to water managers in the region (e.g. CASM, 2026).

1.7 iSnobal and LANDFIRE

This study investigates vegetation parameterizations for iSnobal, a physically based snow model that tracks the time evolution of the physical processes that comprise the snow energy and mass balances (Marks et al., 1999), and that has been evaluated to support operational water

supply forecasting (Hedrick et al., 2018; Meyer et al., 2023). iSnobal is forced by meteorological data from weather stations or gridded weather models such as the operational High Resolution Rapid Refresh (HRRR) numerical weather prediction model (Dowell et al., 2022). The use of HRRR in iSnobal has been shown to improve snow depth prior to peak accumulation (Meyer et al., 2023), and improved snowmelt rates and timing when integrated with remotely sensed albedo (Meyer et al., 2024).

Another major model input is the domain metadata that includes a digital elevation model, vegetation heights, and landcover classifications and their associated canopy radiation coefficient (k) and optical canopy transmissivity (τ) values (Marks et al., 1999). The k parameter dictates how much radiation is emitted by the vegetation to the snow surface, and the τ parameter informs the model on how much radiation passes through the canopy structure. These vegetation parameters strongly influence the net shortwave, net longwave, and turbulent flux components of the snowpack energy balance, but have not been a primary focus of previous studies. The vegetation information used in the model domain metadata file is generated using LANDFIRE (LF), a 30-meter resolution remotely sensed landcover classification dataset (LANDFIRE, 2026). LANDFIRE (LF) products were initially updated on an irregular, multi-year basin for the purpose of remapping (LANDFIRE, 2026). Since 2020, LF has been generating yearly updates that reflect disturbances, including wildfires, clearcuts, urban developments, and more (LANDFIRE, 2026).

In recent studies, iSnobal has been run with the 2016 LANDFIRE landcover classifications, which has proven sufficient in the absence of major land cover changes. However, as a growing proportion of the western U.S. is fire-impacted, the need to evaluate and improve land cover parameterizations is a critical knowledge gap. Current literature does not yet evaluate the impact

of using a more accurate representation of the forest structure and status post-wildfire rather than the “open meadow” scenario, including some of the other disturbance-based datasets like Monitoring Trends in Burn Severity (MTBS, 2025). Some key differences between meadow landscapes and burned forests that impact snow modeling are a lowered surface albedo and the influence of remaining boles (Surunis & Gleason, 2024). Other key characteristics that impact streamflow generation and ecological function are hydrophobic soils, and soil destabilization leading to erosion (Huffman et al., 2001; Woods et al., 2007). Additionally, high-severity and low-severity areas exhibit varying recovery responses and timescales, which also affect the snow energy balance but have not yet been quantified. Using different ecology- and observation-based forest parameters in iSnobal could potentially change the model output and more accurately depict the processes occurring in these post-wildfire landscapes. Such advances could improve snow water resource management by assessing the sensitivity of iSnobal to vegetation parameter adjustments and providing tools for improved model simulations.

1.8 Research Questions and Objectives

Snow dynamics are being altered on a larger scale due to increased wildfires in the mountains of the western U.S. iSnobal, while an effective tool for operational water forecasting purposes, does not account for these landscape-level changes. The vegetation parameters in iSnobal have not been evaluated in the context of wildfire or tested independently. To address the critical knowledge gaps presented here, I posed the following research questions: 1) How does iSnobal perform in post-fire areas, specifically the 2020 Cameron Peak Fire?; 2) How does adjusting vegetation parameters in the model affect snow metric outputs? Do these adjustments improve the model output? and 3) What are some clear, simple steps a water manager could use to improve model performance in burned areas of their watershed? To answer the questions, the

objectives of this study are defined as: : i) evaluate the performance of iSnobal in post-fire areas, ii) optimize post-fire vegetation parameterization in iSnobal using LANDFIRE, iii) assess differences in landcover classifications between LANDFIRE and Monitoring Trends in Burn Severity as methods of assigning vegetation parameters, iv) provide tools for water resource managers to update model setup, and v) model end-member recovery scenarios 20 years in the future.

2. Materials and Methods

2.1 Study Area

The study area is located near Cameron Pass in north-central Colorado, USA (Figure 3a). The mixed conifer forest in the study area is composed of subalpine fir (*Abies lasiocarpa*), Douglas fir (*Pseudotsuga menziesii*), Engelmann spruce (*Picea engelmannii*), and lodgepole pine (*Pinus contorta*). The Cameron Peak Fire burned around 845 km² from 13 August to 4 December 2020 becoming the largest wildfire in Colorado state history (MTBS, 2025). Five automatic weather stations (AWS) were installed in the years following the fire (Figure 3b). Named for their burn status and aspect, the stations are called Unburned Flat (UF), Unburned North (UN), Burned Flat (BF), Burned North (BN) and Burned South (BS) (Figure 3b). Monthly snow surveys involving snow depth transects and snow pits at each AWS were conducted during the months of November through June of each year following the methods described in Reis et al. (2024). In addition to the five weather stations, the Joe Wright (Site 551) Snow Telemetry (SNOTEL)

station is located approximately 3.5 km from the study site and was used as an additional unburned station for validation data.

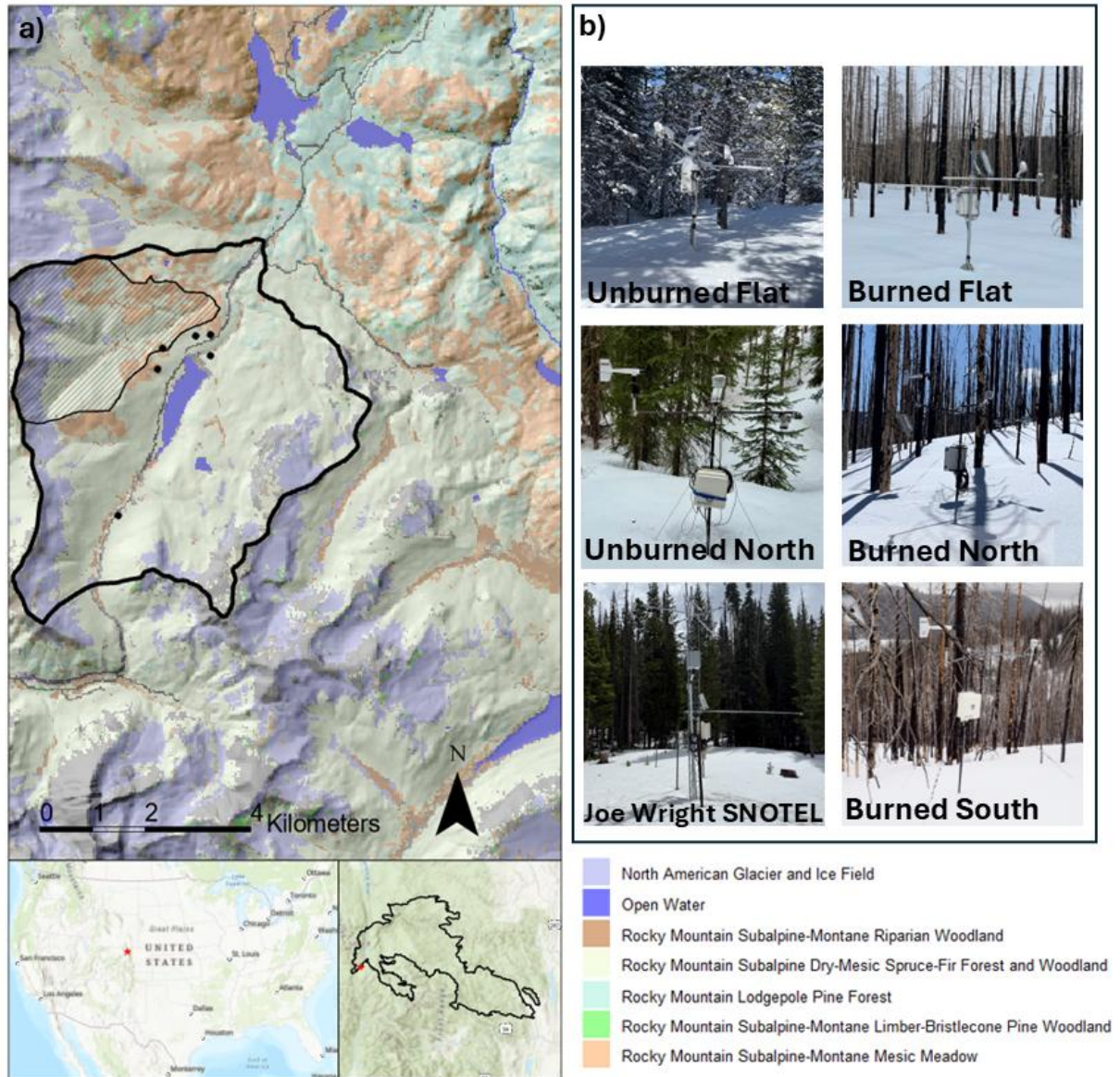


Figure 3. a) Map of the model domain and inset maps of its position in the Cameron Peak Fire burn scar and in the United States. In the lower right is an abbreviated legend of the LANDFIRE Existing Vegetation Type classes. The black dots are the automatic weather station locations, and the black star is the Joe Wright SNOTEL station. The solid black line outlines the Joe Wright Creek Headwaters. The crosshatched section is the sub-basin used for recovery scenarios; b) site photos of the automatic weather stations.

2.2 iSnobal Model Configuration and Base Run

The version of iSnobal used in this study is available through the iSnobal Community Github and is the result of efforts to update the model from multiple institutions (*iSnobal/AWSM: V20251208*, 2026). The climate forcing data for all model runs came from the High-Resolution Rapid Refresh (HRRR) numerical weather prediction model at 3 km resolution (Benjamin, et al., 2016; Dowell et al., 2022). The HRRR meteorological data are downscaled to the model domain through the Spatial Modeling for Resource Framework (SMRF) which is then iterated over hourly timesteps in conjunction with iSnobal via the Automated Water Supply Model (AWSM) (Havens et al., 2020)(Figure 4). I ran iSnobal on an hourly timestep at 30-meter resolution over a 172 km² area and saved 6-hour outputs for mass and energy balance components. The initial run with standard setup, referred to as the Base run, included a default albedo time-decay method starting on 15 March of each year. The model domain metadata file for the Base run was generated using the basin setup tool (*iSnobal/AWSM: V20251208*, 2026) in conjunction with the 2016 LF Existing Vegetation Type and Existing Vegetation Height and a digital elevation model for the area that was resampled from 1-meter to 30-meter resolution (U.S. Geological Survey, 2020). Using the vegetation parameters assignments designated by the iSnobal Community Github (*iSnobal/AWSM: V20251208*, 2026), the Existing Vegetation Type corresponds to and dictates the assignment of the k and τ parameters which are not supplied directly from LF.

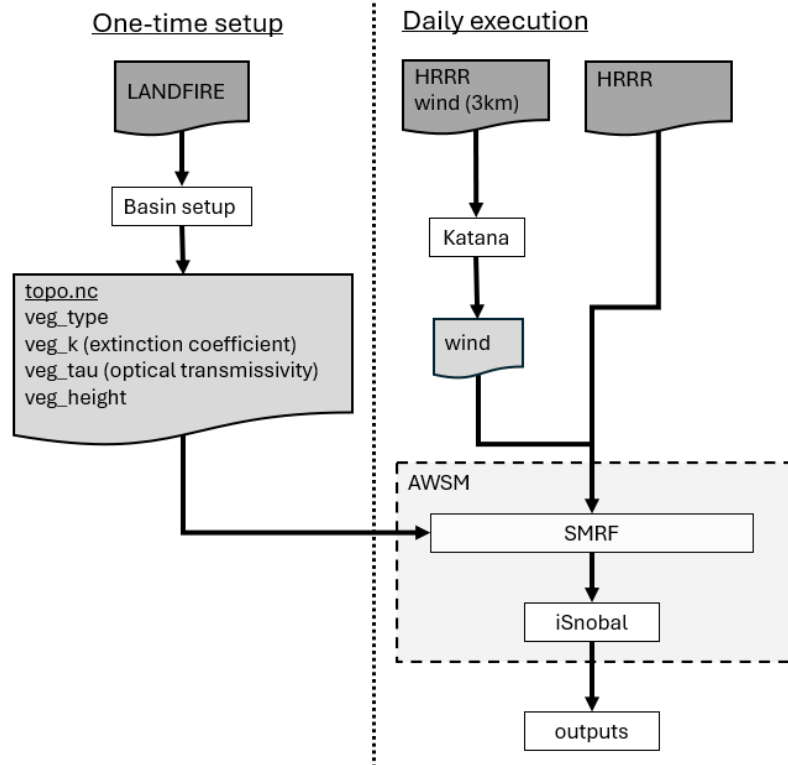


Figure 4. iSnobal model schematic adapted from Meyer, et al., 2023 indicating the implementation of vegetation parameters in the model setup.

2.3 LANDFIRE Updates

2.3.1 Implementation of Updated LANDFIRE

I used LF versions from 2022, 2023, and 2024 to make model domain metadata files for each year's corresponding water year. The model domain metadata file for WY 2021 was manually adjusted due to the lack of complete LF datasets immediately following the fire. At the time of the analysis, LF had not yet released version 2025, so the 2024 version was used for both WY 2024 and 2025. To edit the model domain metadata file, an update tool (iSnobal, 2025/2026) was created to read in the existing (pre-fire) file and edit the values using more current version of LF (Figure 5).

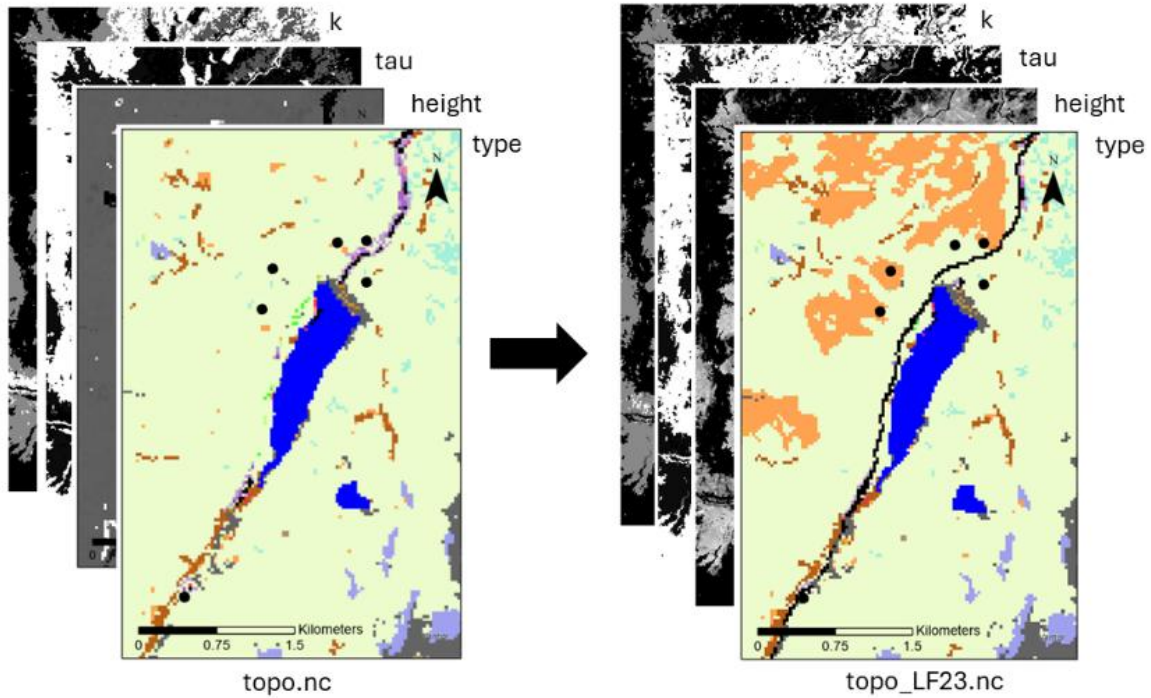


Figure 5. Schematic showing the difference between the Base run model domain metadata file with pre-fire (2016) version of LF and its associated vegetation parameters (left) and the updated basin setup file for the WY 2023 Post-Fire run.

A lookup table provided by the USDA-ARS NWRC is normally used in the basin setup tool to assign k and τ values (USDA ARS Northwest Watershed Research Center, 2017/2022). This is how the Base run model domain metadata file was created. However, the lookup table did not include the most up to date versions of LF and needed to be expanded to include landcover classes from the more recent versions. The k and τ values were assigned using the updated lookup table and vegetation height was assigned using the Expected Vegetation Height (EVH) layer from updated versions of LF. Using the domain metadata file update tool (Figure 5) (iSnoobal, 2025/2026), the Base run file could be overwritten to reflect any combination of post-fire vegetation parameters.

2.3.2 Model Scenarios

The Base run reflected pre-fire conditions across the vegetation parameters: vegetation types of lodgepole pine and spruce-fir forests, k of 0.074 and 0.04, τ of 0.16 and 0.2 and heights of 17.5 meters (Figure A1). Using this as a starting point, subsequent model runs used varying parameters from the updated LF datasets to revise pre-fire values to reflect post-fire conditions. The Post-Fire run was used to represent a complete post-fire scenario, meaning that k , τ and vegetation height were all assigned based on time-varying LF post-fire datasets. The only exception was that vegetation height was set to zero in the mesic meadow cells for WY 2021 immediately following the fire because there was no LF version available for the first year following the fire and very little recovery, if any had taken place in that time. The Post-Fire run vegetation parameters were: vegetation type of mesic meadow, k of 0, τ of 1 and heights between 0 to 0.6 meters depending on the WY (Figure A1).

To isolate the impact of each parameter individually, I also ran two more sets of model runs: Vegetation Type-Varying and Vegetation Height-Varying (Figure 6). The Type-Varying run held vegetation height at the 2016, pre-fire values while adjusting vegetation type (e.g., spruce-fir forest to mesic meadow) and, therefore, k and τ based on the corresponding LF dataset from the same WY. The Height-Varying run conversely held vegetation type, k and τ at the 2016, pre-fire values while using the post-fire, time varying LF datasets to assign vegetation height. Between the Post-Fire, Type- and Height-Varying runs, I created twelve distinct basin setup files, each with different combinations of vegetation parameters pulled from various LF datasets.

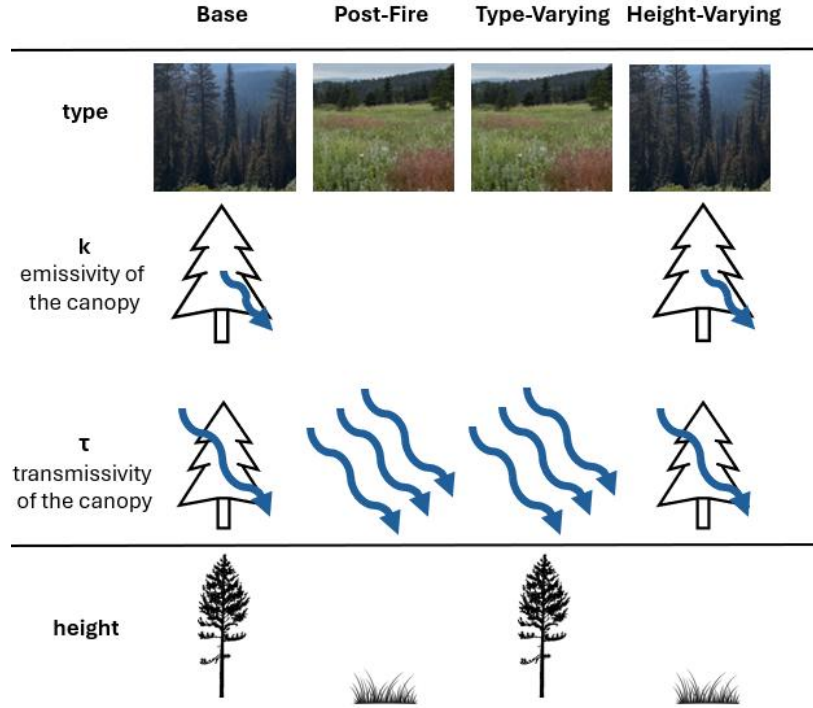


Figure 6. Schematic outlining the basic parametrizations of each model run with adjusted LF inputs. The size and number of blue arrows indicate the magnitude of radiation being emitted by or transmitted through the canopy. The Post-Fire and Type-Varying runs have k values of 0 indicating no radiation emission, and τ values of 1 indicating complete transmission of radiation, both due to the lack of canopy.

2.3.3 Model Evaluation

To evaluate model performance, I extracted key snow metrics including peak SWE timing and magnitude, melt rate, melt quantity, snow disappearance date (SDD) for both the AWS data and the model runs at station locations. The AWS were not equipped to record a daily SWE time-series, so I interpolated daily SWE using the daily mean snow depth from the AWS and a daily snow density estimate produced by adjusting the Joe Wright SNOTEL density time-series. I did this by first calculating the AWS site-specific density difference on each field survey date and then linearly interpolating between these differences. I then applied this linearly interpolated difference to the SNOTEL density time-series; the resulting time-series retains the day-to-day variability from the SNOTEL observations but aligns the magnitude to match the site-specific

snow pit density observations. I calculated the melt rate as the median daily difference in SWE between the date of 90% peak SWE after peak to SDD. The use of 90% peak SWE on the declining niveograph was implemented because of the tendency of SWE to modestly fluctuate during the ripening period around peak SWE prior to the period of sustained melt. Thus, I focus on the melt period between 90% peak SWE and SDD because this interval best characterizes the melt dynamics at these sites. I validated SDDs with in-situ timelapse imagery at each station for each WY. I subtracted observed values for each of the snow metrics from the modeled values to get the difference (i.e., difference = model-observed).

Two of the AWS (UF and BF) have continuous 4-component radiation observations from WY 2021–2025, allowing comparisons of observed and modeled radiation budget components. I calculated the full energy balance including net shortwave, net longwave, and net total radiation, and sensible heat, latent heat, and turbulent flux for the AWS with the available data using the methods described in Reis et al. (2024) with one modification to the turbulent flux estimation. The calculated snow surface temperature was adjusted to snow pit measurements using linear models applied at each station for each WY to make a continuous correction rather than the median error bias correction applied in Reis et al. (2024) which was applied seasonally (before and after 1 March). Energy balance components that were examined included net shortwave, net longwave and net total radiation, and the sensible heat, latent heat, and turbulent flux. For each station, run, and water year, I partitioned the AWS-model comparisons into the accumulation period prior to peak SWE and the melt period from peak SWE to SDD. Finally, I compared daily windspeeds between the AWS and modeled data by calculating averages for the accumulation and ablation periods for each station, run, and water year.

2.4 Implementing Monitoring Trends in Burn Severity (MTBS)

In order to compare LF classifications and MTBS burn severity classes, I identified a partially burned 30 km² sub-basin (Joe Wright Creek Headwaters, Figure 3). I conducted a pixel-by-pixel comparison between these products to assess similarities and identify any potential biases in LF relative to MTBS. For example, some pixels identified as spruce-fir forest were reclassified to mesic meadow between the pre- and post-fire versions of LF with these pixels spanning a couple different MTBS burn severity classes. Additionally, some low to moderate burn severity classified pixels retained the same LF spruce-fir class. Because of the differences between LF classes and MTBS burn severity classes, it was clear that LF did not represent burn severity.

To generate the MTBS-based burn severity run (referred to as MTBS run), I created a secondary model domain metadata file editor to assign k and τ based on the classes in the MTBS dataset. The original k and τ values used in the basin setup tool were assigned to burn classes on a gradient (i.e. the low burn severity class was assigned the lowest provided τ and highest provided k value, etc.). Vegetation heights were assigned in the burned cells (Low, Moderate, and High) based on the median vegetation height from LF in each MTBS burn class across the model domain. Unburned cells kept the pre-fire vegetation height.

I extracted iSnobal modeled SWE for dates in WY 2023-2025 when Airborne Snow Observatories Inc. (ASO) LiDAR surveys had been conducted in the model area (Figure 7).

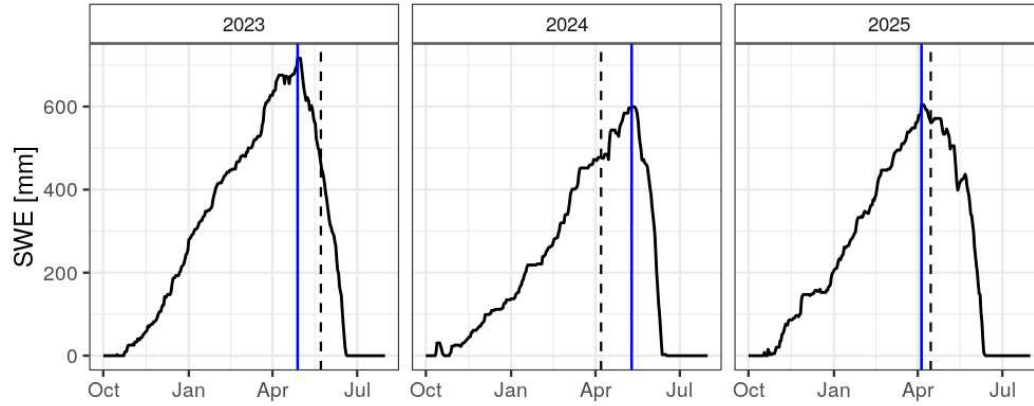


Figure 7. SWE at the Joe Wright SNOTEL station with solid, blue vertical lines denoting the date of peak SWE and black dashed vertical lines denoting the date of each ASO flight over the Poudre River basin.

I resampled the 30-meter iSnobal model outputs from the Base, Post-Fire and MTBS runs to match the ASO derived SWE at 50-meter resolution using bilinear interpolation and truncated the area to fit within the original basin extent. Then, I subtracted ASO-derived SWE from iSnobal modeled SWE. The distribution of SWE residuals was calculated for each LF vegetation class for each run and additionally sorted by MTBS burn severity class. Relevant vegetation classes were kept for analysis purposes.

2.5 Twenty-Year Post-Fire Recovery Scenarios

To demonstrate two endmember future scenarios for burned areas like Cameron Pass, I assigned vegetation parameters for “poor recovery” and “excellent recovery” scenarios (Table 1). The poor recovery scenario is meant to simulate the emerging trends that have been noted where forests are converting to meadows landscapes (Stevens-Rumann et al., 2018). Conversely, the excellent recovery scenario is meant to simulate the recovery potential of forest types that are more adapted to stand replacing fire like the lodgepole pine. I used the MTBS burn severity

dataset to assign values to specific cells for both scenarios and the HRRR forcing data from WY 2022 for these runs to simulate an average snow year.

Table 1. Values assigned to each vegetation parameter in the recovery scenario runs (PF = pre-fire values).

	Poor Recovery			Excellent Recovery		
MTBS burn severity class	k	τ	height [m]	k	τ	height [m]
Unburned to Low	PF	PF	PF	PF	PF	PF
Low	0	1	0.6	0.074	0.16	5
Moderate	0	1	0.6	0.074	0.16	5
High	0	1	0.6	0.074	0.16	5
Increased Greenness	PF	PF	PF	PF	PF	PF

I extracted model outputs for the 15th day of each month January through June, 1 May and 1 June for both the Poor and Excellent recovery scenarios. The sum, maximum, minimum, and mean SWE across the sub-basin were calculated for each extracted date.

3. Results

3.1 Evaluation of iSnobal in Post-Fire Areas

First, I addressed the differences between modeled and observed snow metrics like peak SWE, peak SWE DOY, melt rate and SDD. Then, using a subset of the energy balance data from WY 2022, I compared the modeled and observed or calculated energy balance components. Generally, radiation was higher at the burned station than the unburned station, and model runs varied between stations and runs (Base, Post-Fire, Height-Varying, Type-Varying).

3.1.1 Snow Metrics

We compared SWE time-series across the runs, stations, and WY (Figure 8) and then by specific metrics (Figure 9). The iSnobal output underestimated peak SWE in most of the runs, except for the BS stations in 2024 in the Base run and in 2025 for all runs. Including all WYs, the best agreement from modeled peak SWE came from the Base run at BF and BS with RMSE of 79 mm and 82 mm (14% and 15% of average peak SWE), and biases of -68 mm and -42 mm respectively. The worst agreement occurred at UN in the Height-Varying and Post-Fire runs with a RMSE of 250 mm (34% of average peak SWE) and bias of -249 mm for both runs, but as described in the Discussion, this offset is largely the result of the specific siting of this AWS station. The modeled peak SWE at the flat stations (UF and BF) generally showed better agreement to observations than at the BN and UN stations. The modeled SWE tended to peak later than the AWS, with offsets ranging from 24 days before (Post-Fire) to 61 days after (Base) (Figure 5) with the medians all falling after the observed AWS day of year (Base = 12, Post-Fire 4, Height-Varying = 6 and Type-Varying = 3).

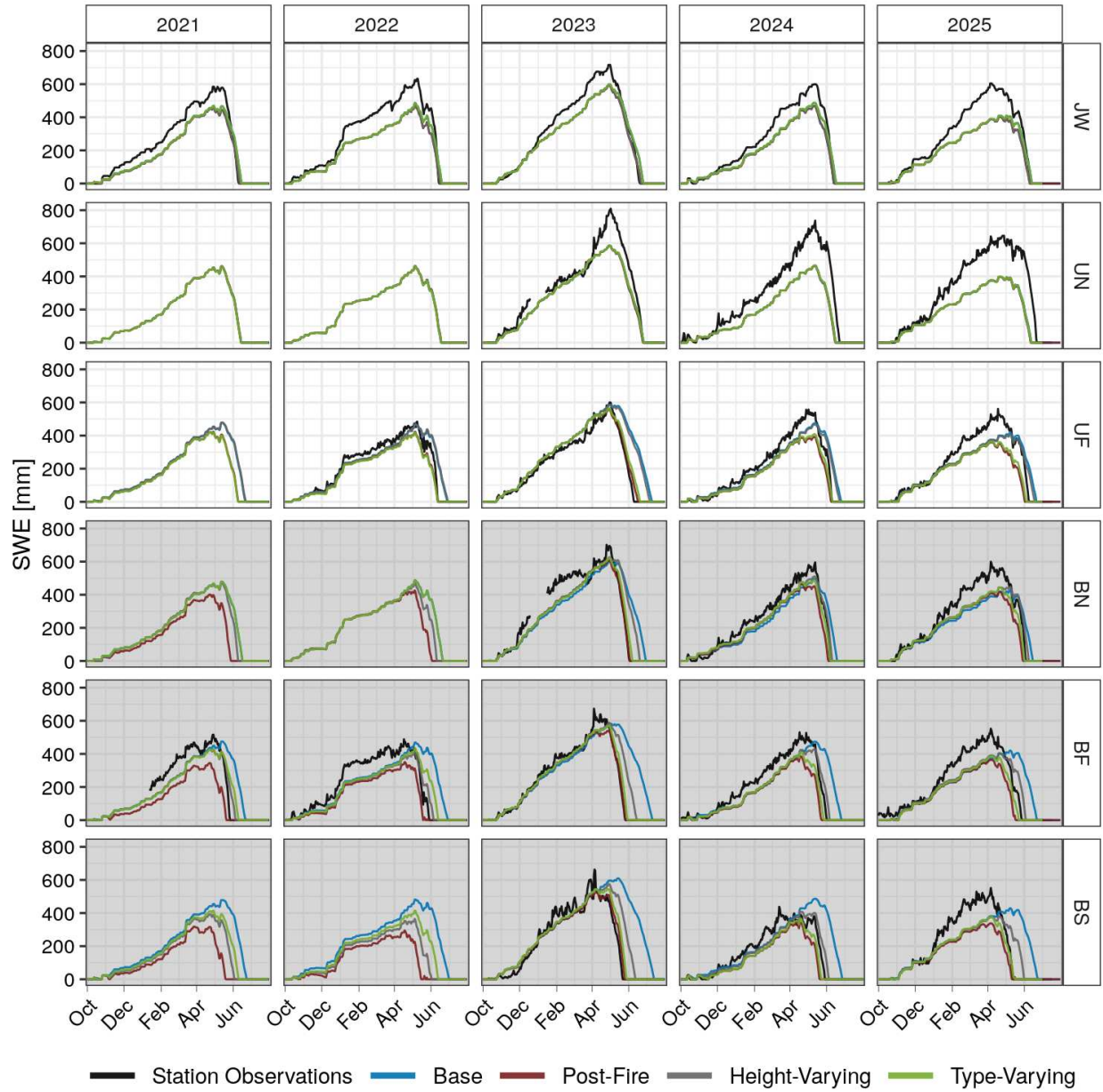


Figure 8. Modeled and observed snow-water equivalent timeseries WY 2021-2025 at each AWS point and the Joe Wright SNOTEL station. Each row represents a different site (JW: Joe Wright SNOTEL, UN: Unburned North, UF: Unburned Flat, BN: Burned North, BF: Burned Flat, BS: Burned South) and each column represents a single water year. The rows with grey backgrounds are burned sites.

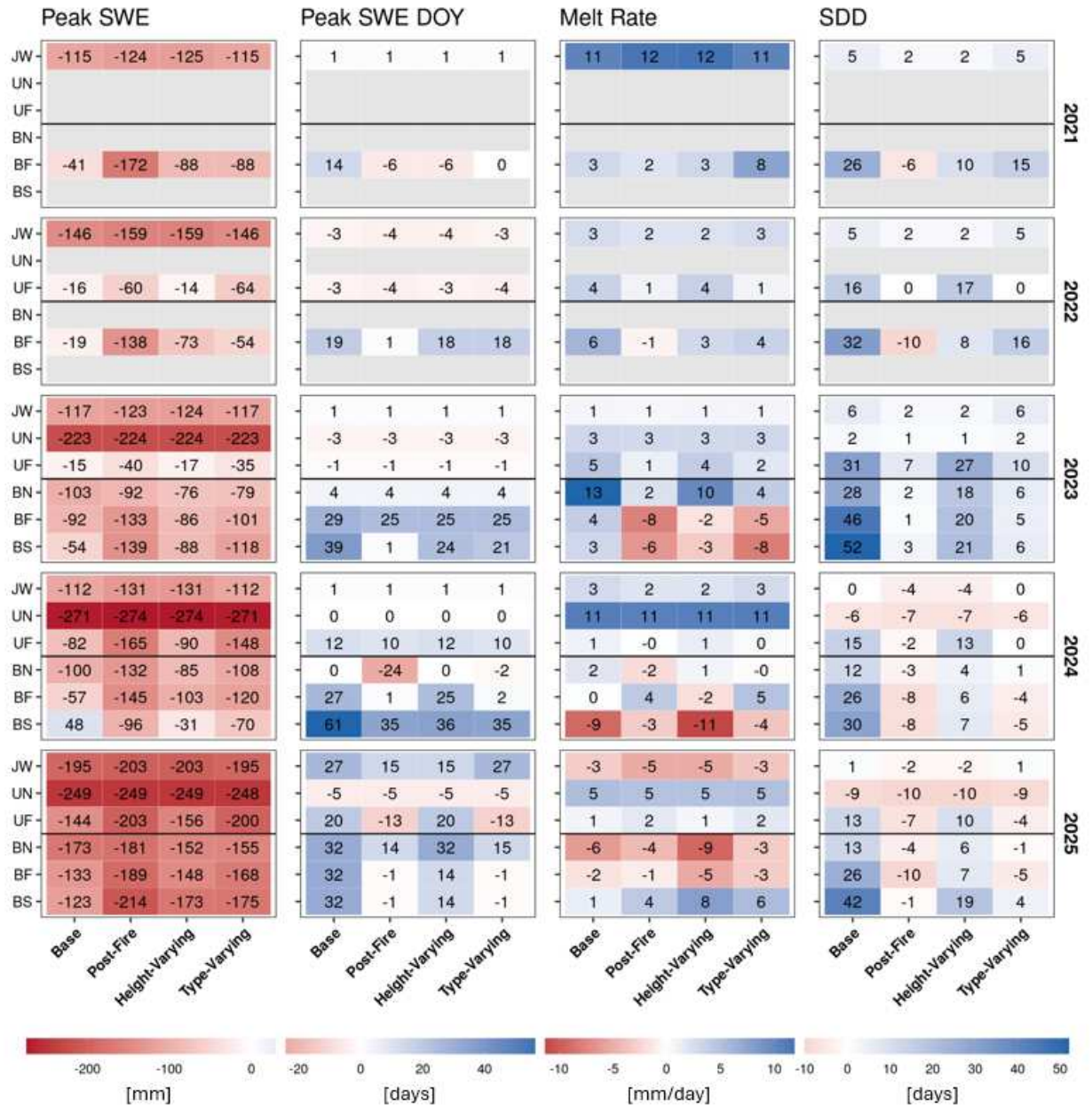


Figure 9. Summaries of the difference between modeled and observed peak SWE, peak SWE day of year, melt rate, and snow disappearance date. The black horizontal line in each grid separates unburned (above) and burned (below) stations.

Melt rates were similar between model runs and observed data with a median difference of 2 mm/day across stations. The maximum difference was 12 mm/day (Post-Fire and Height-Varying runs at JW in WY 2021; Figure 9) and the minimum difference was -11 mm/day (Base run at BS in WY 2024; Figure 9). The Base run at BN had the highest overall RMSE of 8.5 mm/day.

Finally, the SDD was often overestimated by the Base run, especially at the burned stations (median of 15 and range between -9 to 52 days). The Post-Fire run SDD was within 10 days or less of all of the stations every year. The Post-Fire and Type-Varying run were most accurate at modeling SDD across all stations and years with RMSE of 6 and 9 days and biases of -3 and -2 days. The Post-Fire run consistently shifted SDD earlier by a median of 35 ± 11 days at the burned sites relative to the Base run with the other two vegetation adjusted runs falling somewhere in between.

3.1.2 Energy Balance and Other Meteorological Variables

3.1.2.1 Observed Energy Balance Components

Considering only AWS data, BF received more net shortwave radiation each year with an average of 25 W/m² during accumulation compared to 12 W/m² at UF across years. During ablation, BF received an average of 101 W/m² while UF received 48 W/m². Similarly, BF had more negative net longwave values than UF each year with an average of -40 W/m² compared to -12 W/m² during accumulation and -44 W/m² compared to -12 W/m² during ablation, respectively. These two components factored into a greater overall net radiation at the BF station each year.

I estimated sensible heat, latent heat, and turbulent flux at the UF and BF stations for WY 2022–2025 (Figure 10). Estimated average sensible heat was higher at BF than UF with an

average of 21 W/m^2 and 2 W/m^2 during accumulation, and 17 W/m^2 and 0.2 W/m^2 during ablation. Latent heat was more negative at BF than UF with an average of -12 W/m^2 and -1 W/m^2 during accumulation, and -15 W/m^2 and -3 during ablation. The overall turbulent flux was slightly more positive at BF than UF with an average of 11 W/m^2 and -1 W/m^2 during accumulation, and 3 W/m^2 and -2 W/m^2 during ablation.

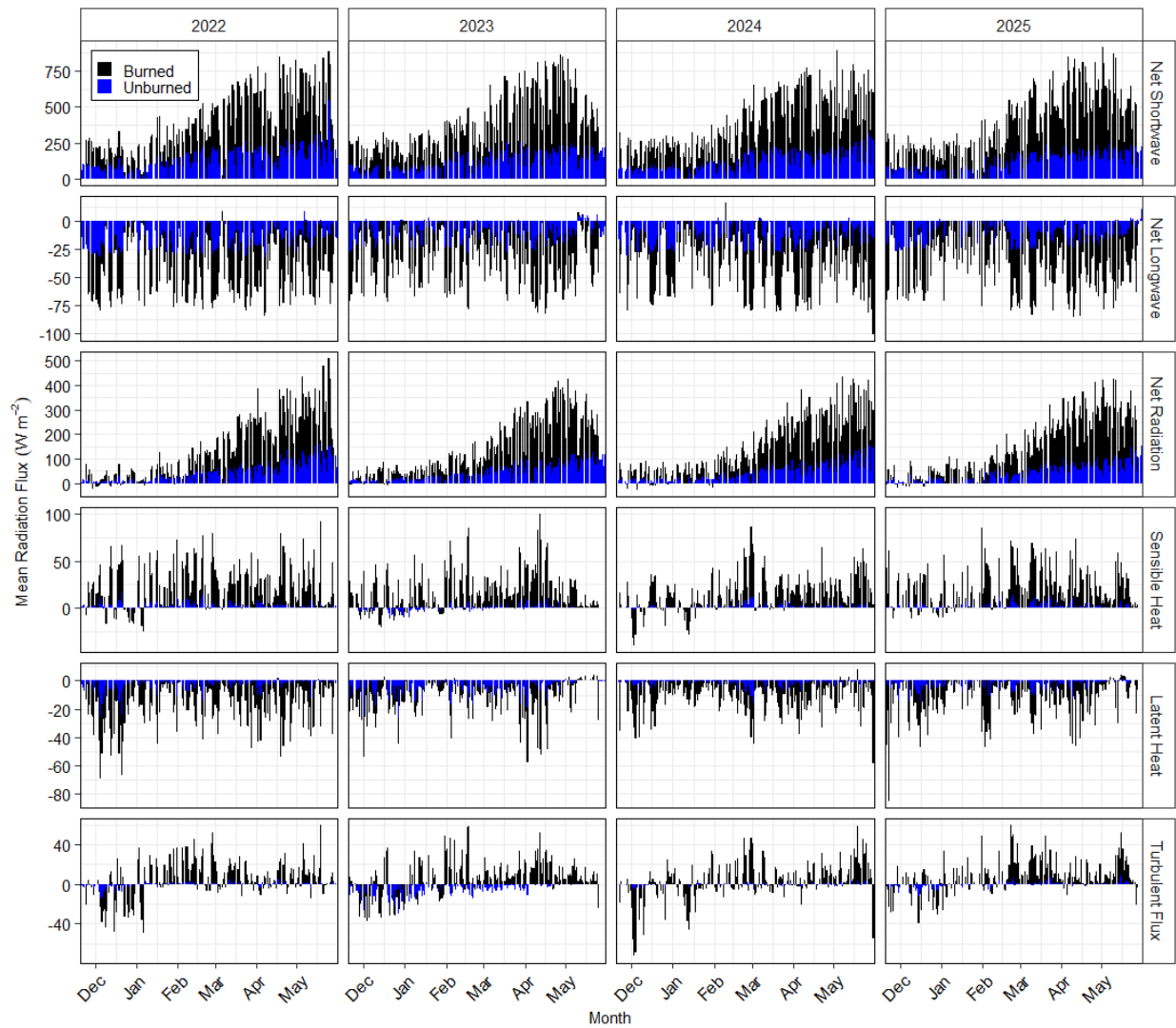


Figure 10. Observed mean daily energy balance components (net shortwave, net longwave, net radiation, sensible heat, latent heat, turbulent flux) from UF and BF WY 2022–2025.

3.1.2.2 Modeled and Observed Radiation Comparison

I used WY 2025 to illustrate how the modeled radiation components compare to the in-situ measurements at the UF and BF stations (Figure 11) but include the other WYs in the supplement (Figure A2-5). The unburned station, UF, showed better overall agreement in radiation components than the burned station with average differences in radiation ranging from -8 W/m² to 25 W/m². Conversely at BF, the Base run and vegetation updated runs showed worse agreement to observations and were notably distinct from each other in the net shortwave and net longwave (Figure 11). At BF, the Post-Fire, Height-Varying, and Type-Varying runs overestimated net shortwave by a maximum of 19 W/m², and the Base run underestimated by a maximum of -14 W/m² in the accumulation season (Figure 11). The overestimates in the vegetation adjusted runs were greatest in 2025 and ranged from 7 W/m² to 16 W/m² in 2023 and 2024 (Figure A6). The magnitude of differences in net shortwave at BF became more exaggerated in the ablation season with a maximum difference in vegetation adjusted runs of 34 W/m² (34% of average observed net shortwave) and Base run of -65 W/m² (66% of average observed net shortwave).

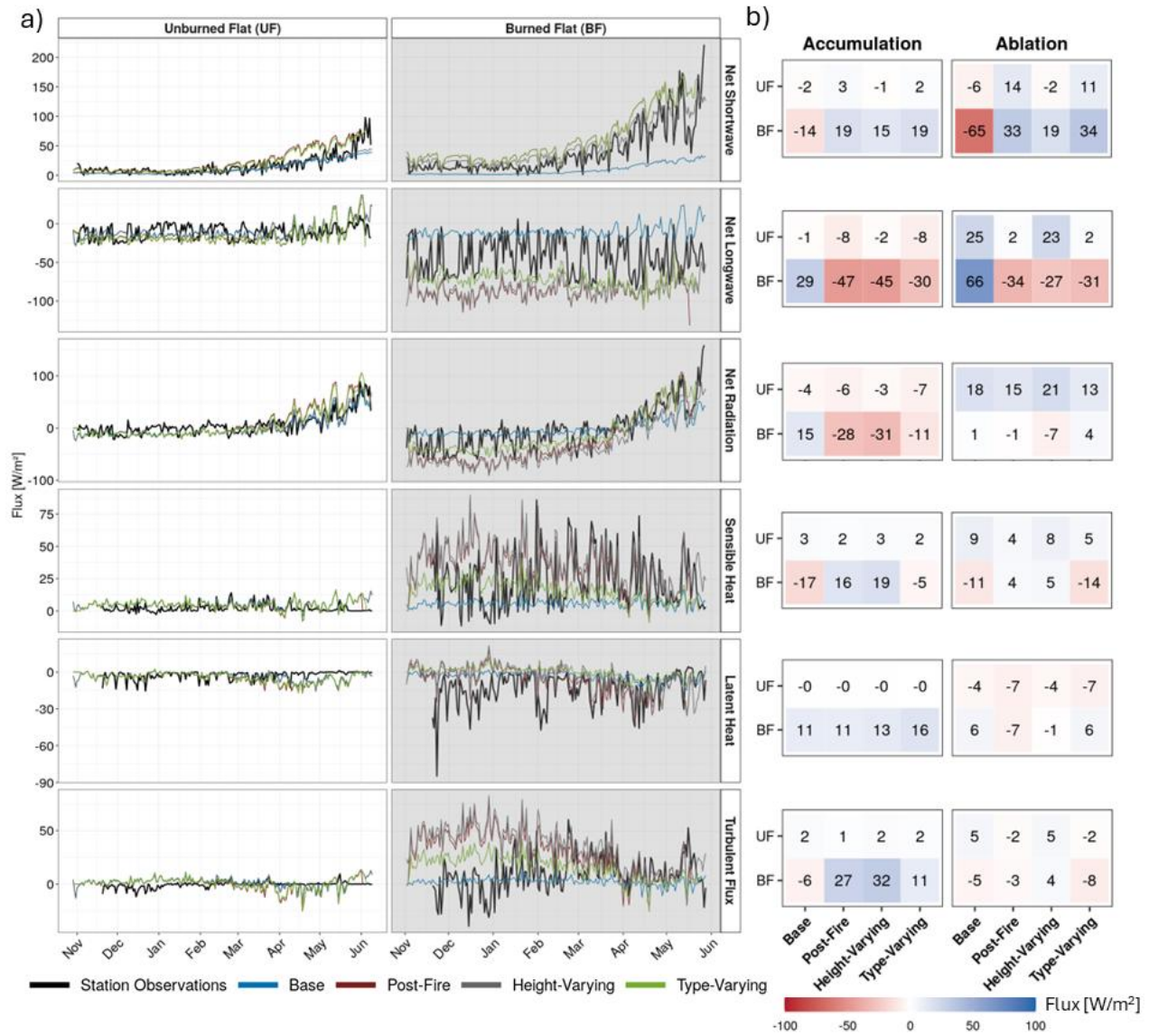


Figure 11. a) Observed and modeled net shortwave, net longwave, net total radiation, sensible heat, latent heat, and turbulent flux at the UF and BF stations for WY 2025. b) Difference between modeled and observed average energy balance components for WY 2025 at the UF and BF stations averaged by season.

For net longwave at BF, the Base run overestimated in the accumulation season by 29 W/m² (70% of average observed net longwave), and ablation season by 66 W/m² (138% of average observed net longwave). Conversely, the Post-Fire, Height-Varying and Type-Varying runs underestimated net longwave in both the accumulation season by a maximum difference of -47

W/m² (115% of average observed net longwave) and ablation by a maximum difference of -34 W/m² (71% of average observed net longwave).

In 2025 at BF, the underestimates of net shortwave and overestimates of net longwave by the Base run resulted in small overestimates of net radiation in the accumulation season (15 W/m²) and ablation season (1 W/m²) (Figure 11). The overestimates of net shortwave and underestimates of net longwave in the Post-Fire, Height-Varying, and Type-Varying runs resulted in underestimations of net radiation during accumulation (-31 W/m²) and values within 7 W/m² of observations during ablation (Figure 11). In 2023 and 2024, net radiation differences were between -41 W/m² and 10 W/m² (Figure A6).

3.1.2.3 Modeled and Observed Turbulent Flux Comparison

The turbulent flux components had lower magnitude differences overall, ranging from -17 W/m² to 32 W/m² in 2025 (-13 W/m² to 41 W/m² across WY 2023 and 2024) at BF, and -7 W/m² to 8 W/m² in 2025 (-7 W/m² to 9 W/m² across WY 2023 and 2024) at UF. The differences in sensible heat at BF showed the larger magnitude differences in the Post-Fire (16 W/m², 73% of observed average sensible heat) and Height-Varying (19 W/m², 86% of observed average sensible heat) runs during accumulation. The Base run underestimated sensible heat in the accumulation (-17 W/m²) and ablation (-11 W/m²) seasons. Latent heat showed the overall smallest magnitude of disagreement across runs and stations ranging from -7 W/m² to 16 W/m² (63% to 114% of observed average latent heat) (Figure 11).

Although the turbulent flux components (sensible heat and latent heat) showed greater overall agreement between the model runs and observations than the radiation components individually, the maximum difference of the turbulent flux values was 32 W/m² (400% of

observed average turbulent flux) (Height-Varying run at BF) compared to -31 W/m^2 in net radiation (155% of observed average net radiation) (Height-Varying run at BF) showing better agreement between observed and modeled net radiation than turbulent flux (Figure 11). As expected, I saw major differences between the Base run and the vegetation-adjusted runs. Again, UF showed better agreement than BF between observed and modeled components across runs for WY 2025 (differences at UF ranging from -9 W/m^2 to 14 W/m^2 vs -49 W/m^2 to 52 W/m^2 at BF) (Figure 11).

The Post-Fire and Height-Varying runs, which share the same vegetation height, tended to overestimate wind speeds at the burned stations while the Base and Type-Varying runs, also with the same vegetation heights, tended to underestimate wind speeds at the burned stations (Figure 12). The difference between modeled and observed wind speed only exceeded an average 3 m/s at BF during accumulation in 2021. Otherwise, the modeled wind speeds were within an average of 2 m/s of the observed wind speeds.

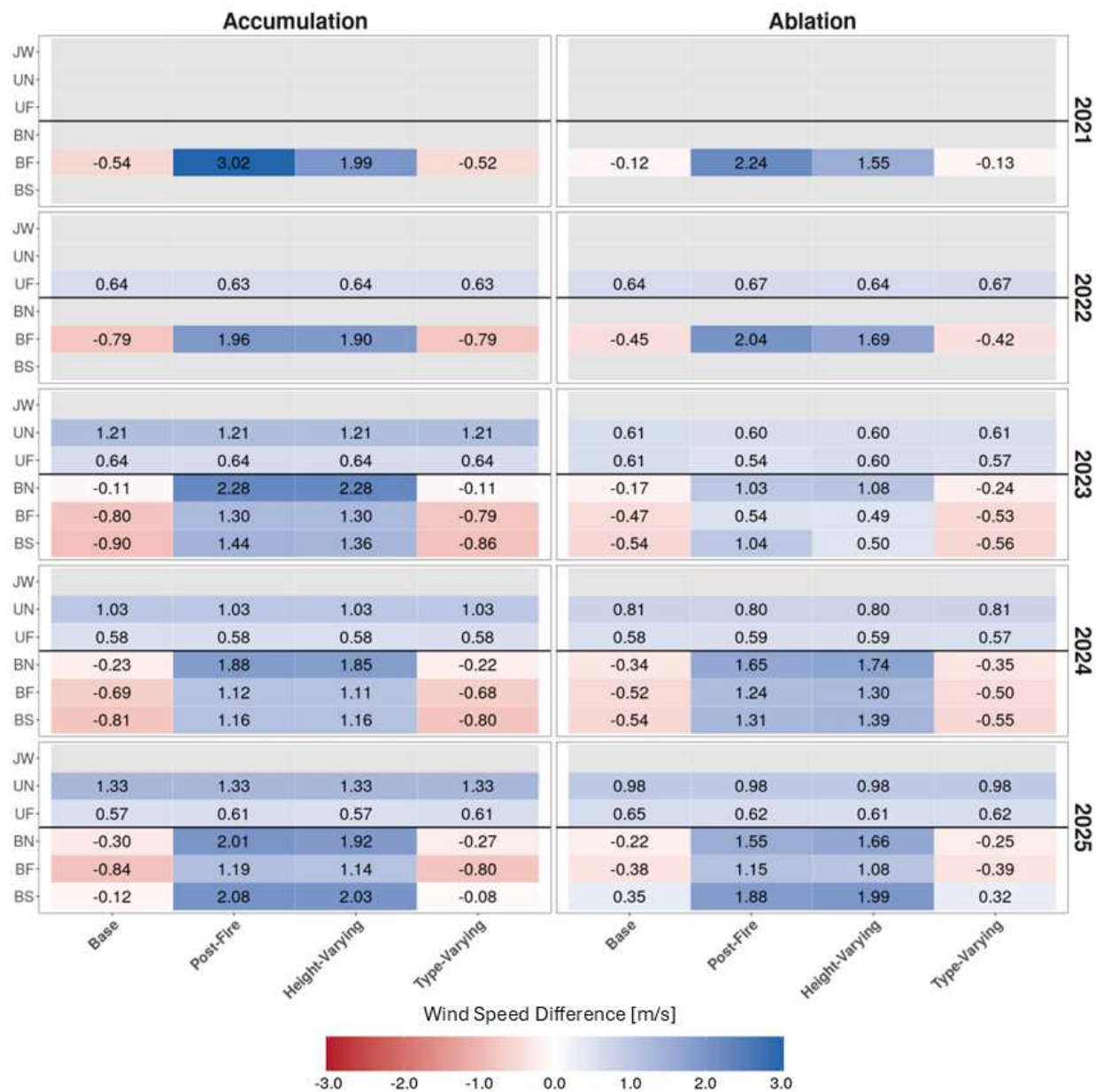


Figure 12. Average difference in modeled and observed wind speed. The black horizontal line in each grid separates unburned (above) and burned (below) stations.

3.2 Burn Severity Runs

Here I describe the results of the MTBS-based run in comparison to the Base and Post-Fire runs (Figure 13a). In the burned area of the Joe Wright Creek Headwaters basin, less than 1% of all pixels are classified as mesic meadow in the Base run compared to 34% in the Post-Fire run (Figure 13b). This would indicate that those cells were reclassified as the meadow type due to the fire. The LF 2023 dataset in the Joe Wright Creek Headwaters basin had 1% of Low burned pixels (25 pixels) classified as meadow, 11% (179 pixels) of Moderate, and 71% (2814 pixels) of High burn severity, indicating that the majority of the meadow pixels in the Post-Fire run were in High burned cells (Figure 13b). Of all the High severity pixels in the Post-Fire run, the spruce-fir type makes up 28% (Figure 13b).

After the cell-by-cell comparison between datasets, I compared the ASO SWE product (and snow depth; Figure A7) to iSnobal modeled SWE in the Base, Post-Fire and MTBS runs and found that there was less overall variability in the average difference between modeled and ASO SWE when comparing across landcover classes (mean standard deviation 87.4) than burn severity classes (mean standard deviation 98.5). The run, landcover class and burn severity combination that agreed most closely with the ASO SWE was the Post-Fire run in the Moderate, “Subalpine Dry-Mesic Spruce-Fir Forest and Woodland” classes on 22 May 2023 (-0.1 mm) (Figure 14).

Evaluating the results by burn severity, for the first ASO flight on 22 May 2023 (25 days after peak SWE at JW; Figure 6), the Base run was the only run that consistently overestimated snow depth across burn severity classes with an average difference of 58.3 mm in Unburned, 74.8 mm in Low, 124.1 in Moderate, and 210.6 in High. While both the Post-Fire and MTBS run

underestimated SWE on that date across burn severities by an average of -7 mm and -53 mm, respectively.

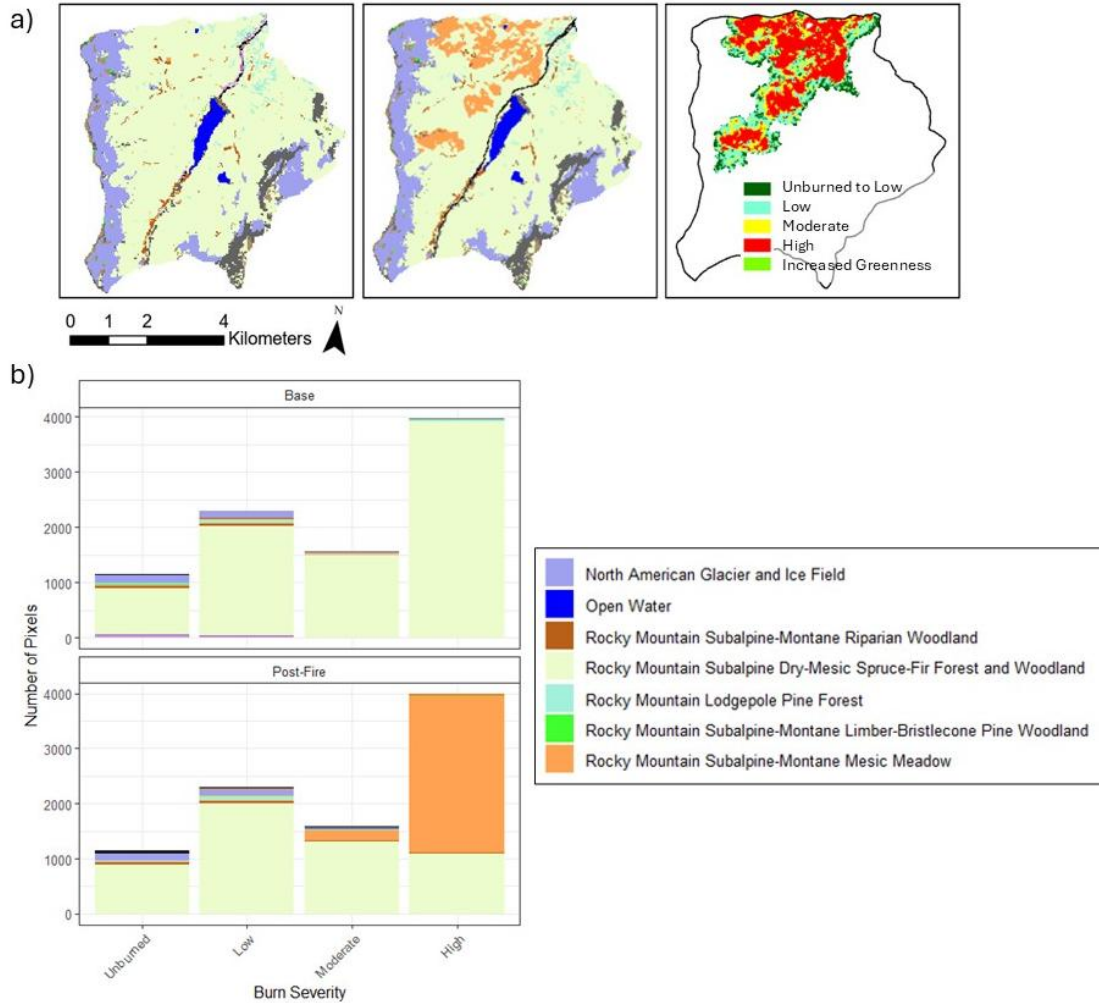


Figure 13. a) The Joe Wright Creek Headwaters located within the model domain with maps showing (left to right) the 2016 LF Expected Vegetation Type, 2023 LF Expected Vegetation Type and Cameron Peak Fire MTBS burn severity classes. b) Summary bar chart showing pixels in each LF Expected Vegetation Type separated by MTBS burn severity thematic class and iSnoal run (Base above, Post-Fire below).

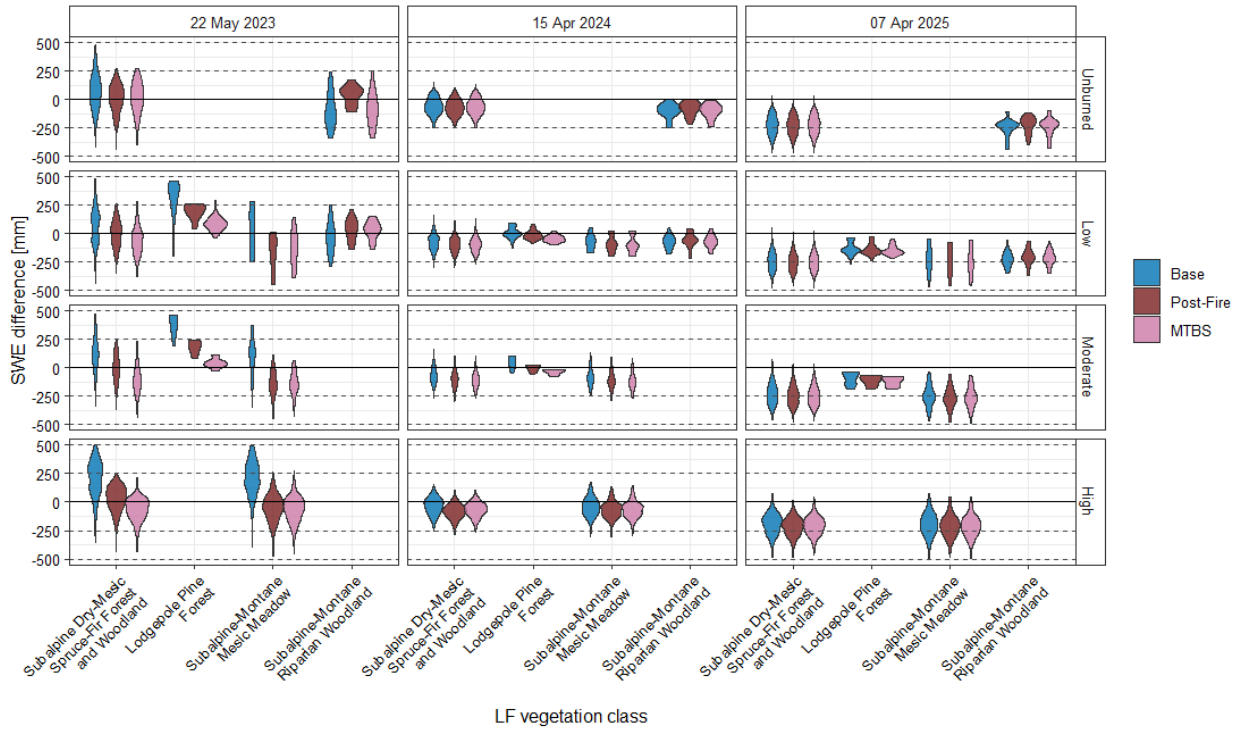


Figure 14. Violin plots showing the distribution of difference between iSnobal modeled SWE and ASO LiDAR-derived SWE separated by LF vegetation class and MTBS burn severity for each ASO flight date.

On 15 April 2024 (25 days before peak SWE at JW; Figure 6), all the runs underestimated SWE by at least 41.1 mm across burn severities with the Base being the closest to zero in each burn class on average. The MTBS run again underestimated to a greater degree than the Post-Fire run. The same general patterns continued for the final ASO flight in this study on 7 April 2025 (2 days after peak SWE at JW; Figure 6). All runs underestimated SWE by at least 195.5 mm across burn severities (Figure 14). Again, the Base run was the closest to zero with the Post-Fire and MTBS runs subsequently underestimated to a greater degree.

When assessed by LF landcover class, the results showed more nuanced patterns. On 22 May 2023, the Post-Fire run performed the best with an average of 7.1 mm difference in the “Subalpine Dry-Mesic Spruce-Fir Forest and Woodland” class across burn severities. The MTBS run followed with -60.0 mm difference, and finally, the Base run with 111.1 mm. The

“Lodgepole Pine Forest” class was best represented by the MTBS run with an average difference of 78.6 mm, then the Post-Fire run (187.7 mm) and the Base run (319.0 mm). The “Subalpine-Montane Mesic Meadow” class was best represented by the Post-Fire run with an average difference of -59.8 mm closely followed by the MTBS run (-68.1) and the Base run (204.2 mm). The “Subalpine-Montane Riparian Woodland” was best represented by the Post-Fire run with an average difference of 35.3 mm, then the MTBS run (-18.5 mm) and the Base run (-56.4 mm).

On 15 April 2024 the Base run generally showed the best agreement across landcover classes with the Post-Fire and MTBS runs nearly equal, with the exception of the “Subalpine-Montane Riparian Woodland” class where the Post-Fire run showed the best agreement with the ASO SWE (-68.0 mm) and the MTBS (-82.1 mm) and Base (-83.9 mm) run followed. On that date, nearly every run underestimated SWE across landcover classes with the exception of the Base run in “Lodgepole Pine Forest” (13.0 mm). The same was true on 7 April 2025, where all runs largely underestimated SWE by at least 126.3 mm across landcover classes. Again, the Base run performed the best in each landcover class except for the “Subalpine-Montane Riparian Woodland” class where the Post-Fire run showed the closest agreement with the ASO SWE (-212.0 mm) and the MTBS (-224.4 mm) and Base (-235.6 mm) run followed..

3.3 Recovery Scenarios

The recovery scenarios were compared across the partially burn sub-basin to show how modeled SWE can vary spatially and how recovery can influence snowpack evolution across space. The average SWE in the burned pixels of the sub-basin was greatest on 15 April with 390 mm in the poor recovery, and 332 mm in the excellent recovery. The average difference between the two scenarios was 38 mm in January which gradually increased to 59 mm on 15 April and then declined to 0 mm by 15 June (Figure 15). The max SWE of the dates selected was 506 mm

on 15 May in the poor scenario. The average difference between the two scenarios became less substantial after 1 May. The largest average difference between scenarios was greater in the burned cells (59 mm) than when evaluating the entire sub-basin (29 mm). A brief comparison of the energy balance components indicated higher net shortwave radiation and more negative net longwave radiation in the Poor scenario (Figure A8). This resulted in less net radiation during accumulation and similar, but still less, net radiation during April and May (Figure A8).

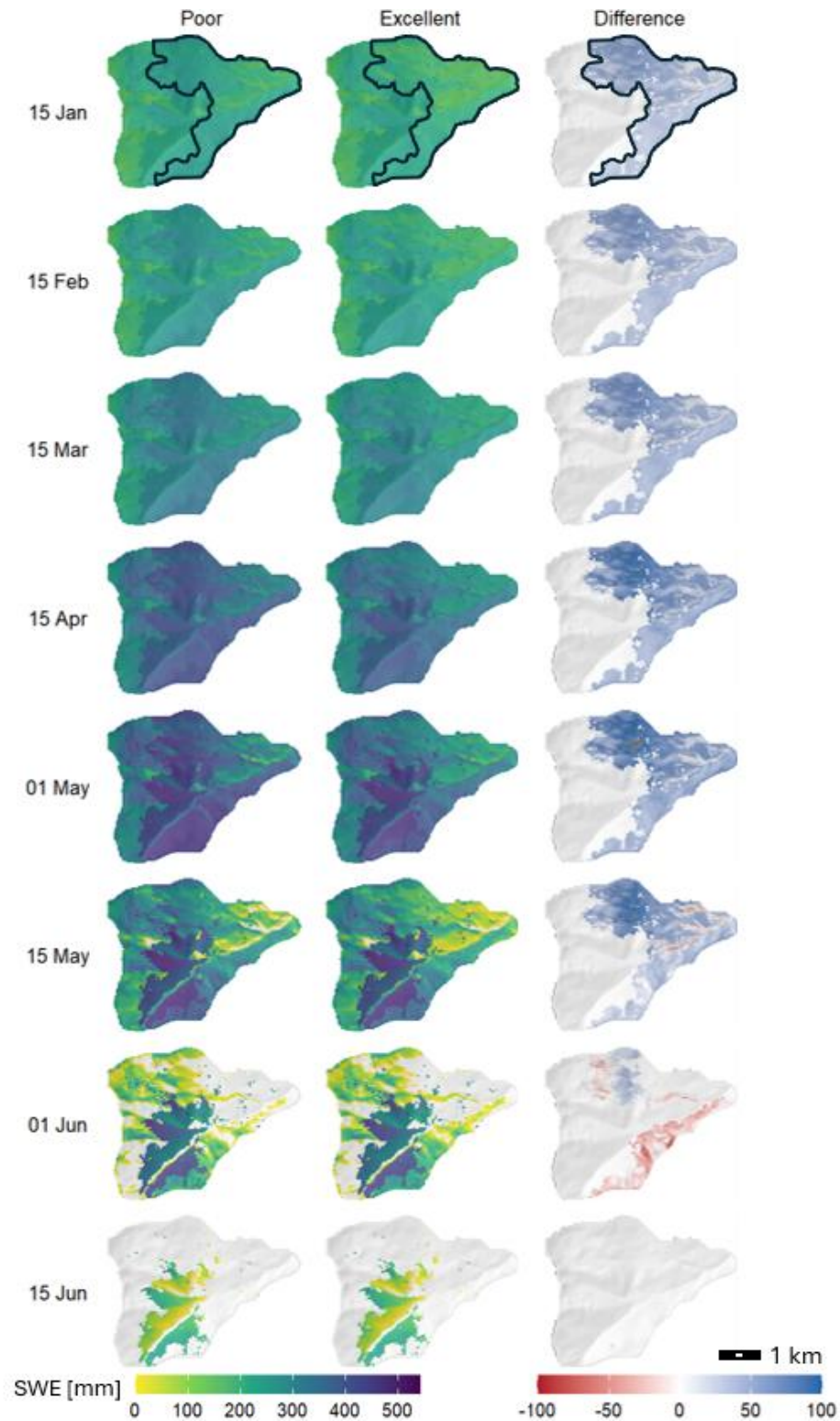


Figure 15. SWE across the sub-basin on selected dates from January to June of the post-fire poor and excellent recovery scenarios. The difference between the two runs is shown in the far-right column. The burn area of the sub-basin is outlined in black in the top panel.

4. Discussion

4.1 Evaluation of iSnobal in Post-Fire Areas with Updated LF Landcover Classes

Updating the vegetation parameters in iSnobal had variable effects on snow metrics depending on the parameters adjusted, station, time of year, and WY. I found several consistent patterns amongst unburned and burned stations and used the energy balance components, wind speed, and other limiting factors like precipitation forcings to reveal what caused the differences in snow metric outputs.

4.1.1 Key Limitations

There are a number of limitations regarding forcing data and snow and environmental processes that are either simplified or not included in iSnobal that could impact the results presented in this study. SWE was underestimated in all but one station-run-water year combination (BS, Base, WY 2024; Figure 8) suggesting a fairly consistent negative bias in the precipitation forcing. This is a common issue facing snow models and previous studies have addressed this in different ways deriving corrections from remotely sensed, modeled and in-situ data. For example, one study applied a spatially varying Landsat-based correction using snow persistence to improve precipitation forcing in SnowModel (Sexstone et al., 2025). Another study used a model to generate a snow metric and climatology dataset, SnowClim v1.0, and used modeled precipitation forcing data from the Weather Research and Forecasting model (WRF) that was bias corrected using PRISM (Group at Oregon State University, 2026), another coarse resolution meteorological dataset (Lute et al., 2022). In previous versions of iSnobal that use WRF forcings, efforts to bias correct the temperature and precipitation with the nearest available

in-situ measurements were applied successfully (Havens et al., 2019). Subsequent work on iSnobal implemented the HRRR datasets to eliminate the need for precipitation corrections and facilitate operational usage of the model (Meyer et al., 2023). Based on previous studies using the HRRR precipitation data, I predicted that the Base run would have performed well in the unburned areas. However, it consistently underestimated peak SWE in the unburned (median = -130 mm, 20% of average peak SWE) and burned (-92 mm, 16% of average peak SWE) areas (Figure 8). To investigate this further, I compared modeled precipitation data (derived from HRRR and distributed through AWSM) to observed precipitation data at JW which showed that the precipitation inputs to iSnobal used in this study underestimated actual precipitation (Figure 16). Precipitation observed at JW was consistently higher than the modeled precipitation with end-of-season differences ranging between 162 mm to 408 mm in WY 2021 through 2025, respectively (Figure 16). These differences were between 22% (WY 2023) and 64% (WY 2022) of observed peak SWE at JW.

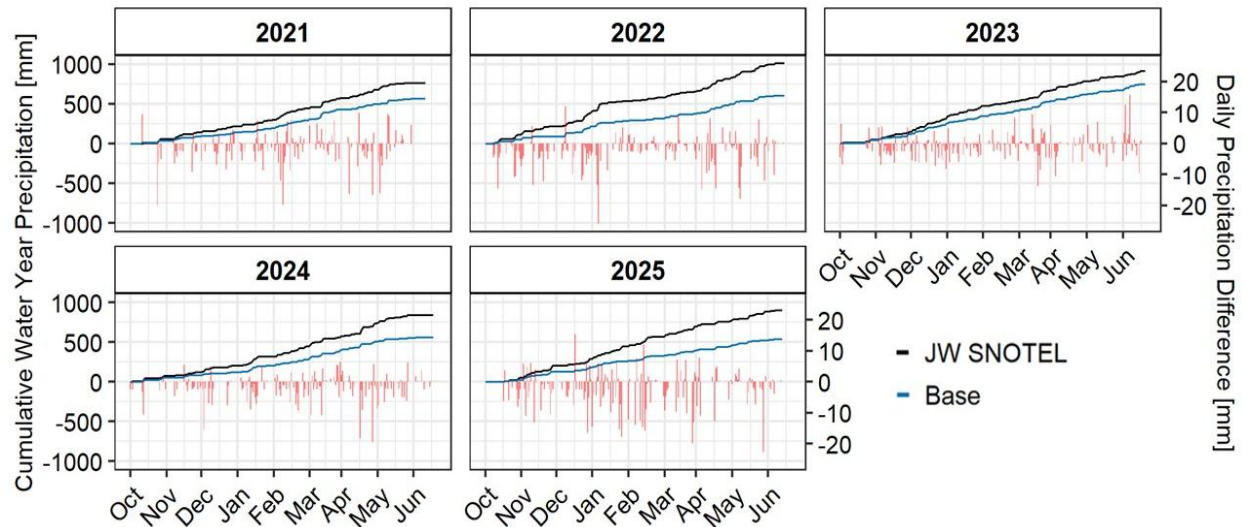


Figure 16. Observed (black line) and modeled (blue line) cumulative precipitation at the Joe Wright SNOTEL station with daily differences on the right y-axis (red bars).

The greatest negative bias in modeled peak SWE was at the UN station across years (difference of -200 mm or less in WY 2023 through 2025) (Figure 8). That weather station is located on the leeward side of a small, forested, north-facing hill in a drainage gulley (Figure 17). The area accumulates more snow and retains it for much longer than nearby locations, such as a time-lapse camera (UN Camera) located ~30 m away. For example, SDDs were DOY 173 to 176 at UN station vs 160 to 164 at the UN Camera (Figure S13). Thus, the model-observation difference at this site is strongly attributed to the specific siting of the station rather than model/forcing errors. The burned stations also showed large disagreement between observed and modeled peak SWE (ranging from -214 to 48 mm) that can be at least partially attributed to precipitation forcings. Future studies modeling across resolutions much smaller than the 3 km HRRR forcings, like this study, should evaluate the need for and consider the use of a precipitation correction.

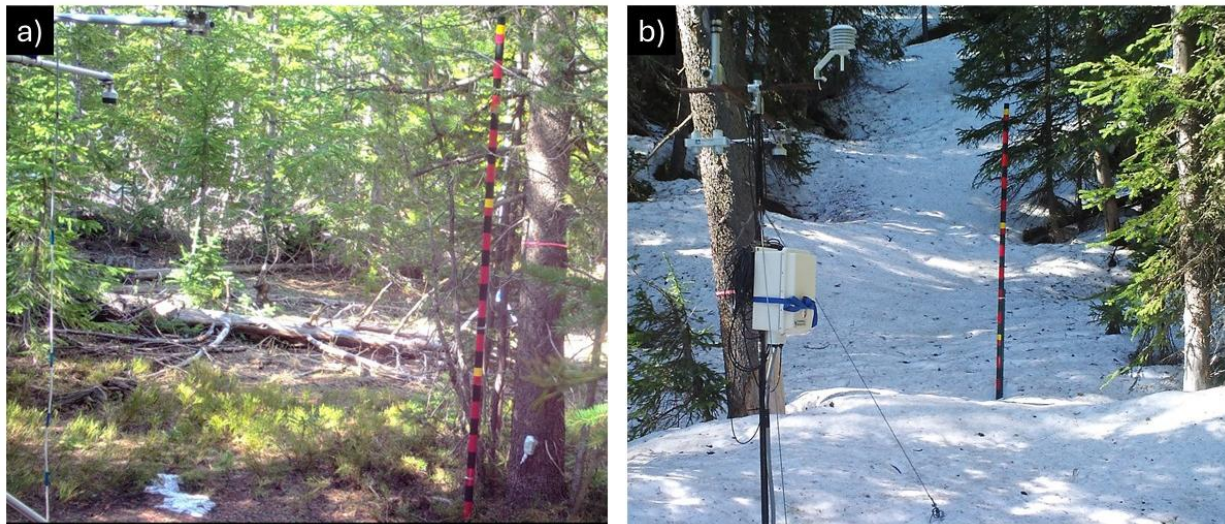


Figure 17. UF (a) and UN (b) on 9 June 2025 (SDD for UF) demonstrating spatial variability in the unburned areas.

I did not evaluate the capability of iSnobal to model sublimation or evaporative losses in this study. Studies have found that snow sublimates at a higher rate from the canopy than it does from the snow surface (Moeser et al., 2020; Montesi et al., 2004; Sexstone et al., 2018) and sublimation losses from the canopy decrease following wildfires (Gallais et al., 2025). Conversely, sublimation from the snow surface has been shown to increase relative to pre-fire conditions (Harpold et al., 2014; Lundquist et al., 2024; Reis et al., 2024). Clearly, where this sublimation is taking place in the canopy structure is a key detail. At the Cameron Pass study site, higher wind speeds were consistently observed in the burned areas relative to unburned sites, indicating a high likelihood of increased sublimation at the snow surface post-fire. This is not to say that these potential increases in sublimation at the snow surface outweigh the decrease caused by the loss of the canopy but rather that there are additional complexities in the post-fire landscape that should be evaluated in physical snow models. Because the energy balance observations presented here are relative to the snow surface and are below the canopy in the unburned sites, they are not well suited for quantifying the total contribution of sublimation (Gallais et al., 2025). SWE losses to sublimation should be quantified and compared to modeled estimates in post-fire areas in the future.

Post-fire impacts on the snow energy and mass balance depend heavily on the amount of canopy remaining in an area. Previous studies have used burn severity to make this distinction, finding that high severity burned areas experience greater solar radiation, lower canopy interception and lower snow albedo than low and moderately burned areas (Koshkin et al., 2022; Smoot & Gleason, 2021). It is estimated that 39% of the area in the Cameron Peak Fire boundary burned at High severity (Carter & Hart, 2026). However, all of the weather stations in the burned area in this study were established in High burn severity pixels as designated by MTBS (Figure

7a) (MTBS, 2025). Although higher burn severities have greater impacts on snow dynamics, not having in-situ data from Low and Moderate burned areas limits our ability to understand how these processes are modified at lower burn severities.

Other key post-fire canopy processes like shadowing from boles, snag fall through time, and elevated temperatures and hence longwave fluxes from bole surfaces are not captured by the model. I parameterized the Post-Fire run using low vegetation heights (< 1 meter) and k and τ values on the edge of the range, as assigned by the mesic meadow class (Figure A1), which does not account for the large number of standing boles. However, standing boles are still present in the Cameron Pass study area and do provide scattered shading throughout the day (Figure 18). While minimal at the individual bole-scale, the cumulative impact of this shading has not been quantified, and it is clear that representing this area as an empty meadow is not completely accurate.

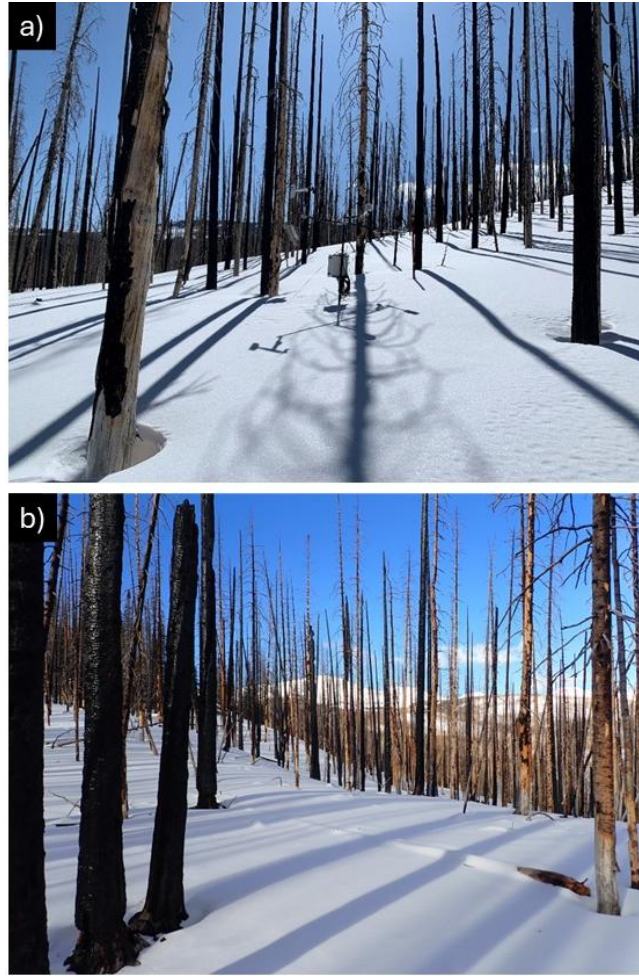


Figure 18. Examples of midday shadows cast on the snow surface in March 2025 (a) and December 2025 (b).

Beyond the shadowing effect, standing boles are very dark and directly exposed to incoming shortwave radiation due to the lack of canopy. The dark surface absorbs this radiation, resulting in surface temperatures that are up to 7 °C higher than unburned trees (Lee, 2025). The longwave radiation emitted from these boles appears to cause increased melt in the immediate vicinity of the tree, forming larger tree wells and up to 13-day earlier melt out in the radius surrounding the boles than in the surrounding open areas (Lee, 2025). Bole/tree well driven melt out (likely further enhanced due to the low albedo of the exposed ground surface) is the dominant pattern of snow disappearance in the burned areas and results in significant patchiness (Figure 19). This

effect could be amplified across the burned landscape depending on the density of the stand, and future studies could quantify total SWE losses due to standing boles, particularly given the vast number remaining in the study area. Similarly, if an area undergoes low-severity fire, the presence of dispersed live trees may extend the duration of the snowpack depending on the size and distribution of the remaining trees (Teich et al., 2022).

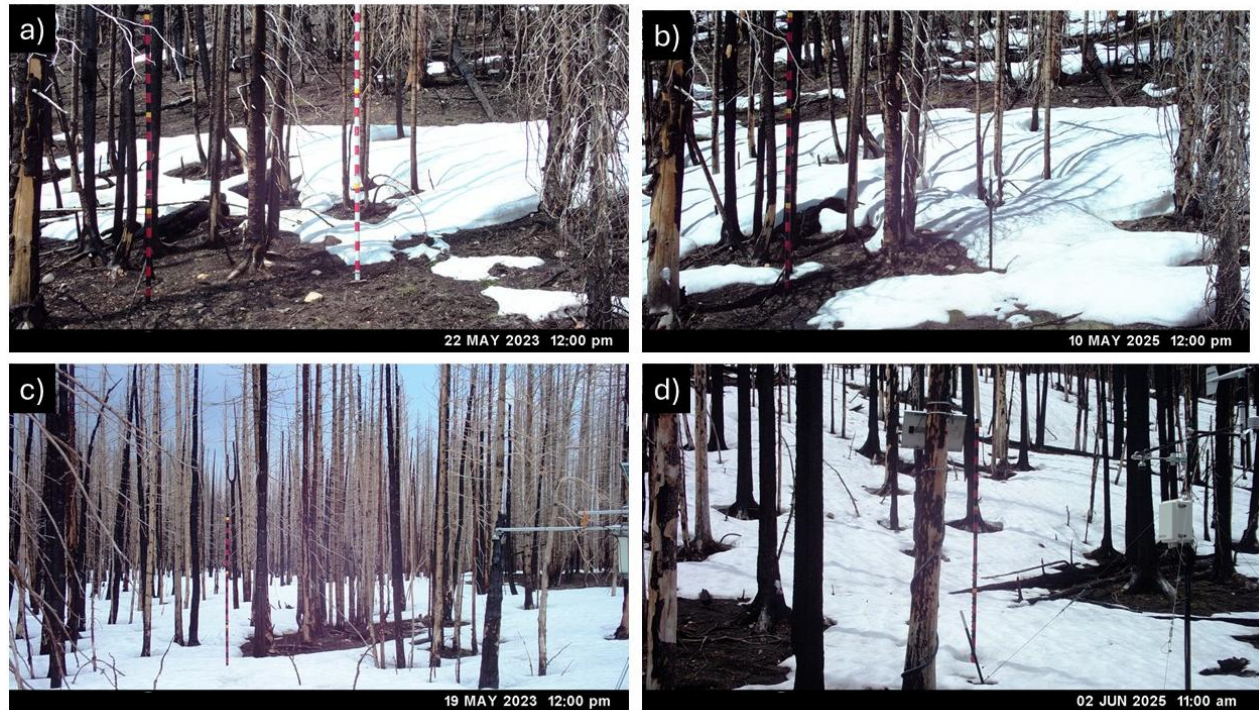


Figure 19. Patchy melt patterns at BS in 2023 (a), BS in 2025 (b), BF in 2023 (c), and BN in 2025 (d) with exact dates and times listed in the lower right corner of each image.

The rate of standing bole loss or snag fall rates, post-fire has been the focus of previous studies (Bohlin et al., 2017; Kiel et al., 2023; Nelson et al., 2016; Oberle et al., 2018) and would decrease the impact of shadowing and heat transfer overtime as boles fall. The fall rates were influenced by burn severity, species, live status at the time of the fire, tree height and density, elevation and slope angle. Boles with larger trunks that were dead at the time of the fire stayed standing the longest (Bohlin et al., 2017; Kiel et al., 2023). In a study using SnowModel, forest

structure was modeled to represent the loss of standing boles and transition from burned forest to open meadow landscape over a 15-year post-fire period (Surunis & Gleason, 2024). The model results showed immediate and longer-term decreases in SWE and earlier SDD highlighting the critical role that post-fire forest structure has on the snow energy and mass balance (Surunis & Gleason, 2024).

Like most snow modeling studies, there are significant differences in the spatial resolution of the forcing data, the model, and the in-situ validation observations, which likely impact my results given that snow can vary significantly over short spatial scales. For example, the model downscales the 3 km precipitation forcing data to 30-meter pixels, which in complex, high-relief terrain, likely introduces some error. Future work could focus on further evaluating the HRRR forcing data with in-situ precipitation measurements and implementing a bias correction based on that comparison. Further, the comparison of point observations of snow depth and SWE, specifically, to model results at 30-meter spatial resolution also introduces error given the variability of snow across complex mountainous regions (Elder et al., 1991; Fassnacht et al., 2017; Kraft et al., 2022). However, despite this stated limitation, few, if any, previous studies have evaluated iSnobal with the breadth of in-situ post-fire meteorological and snow data in post-fire landscapes as presented in this study.

4.1.2 Accumulation and Peak SWE

In post-fire areas, certain processes are enhanced relative to unburned areas that can lead to increased snow variability (Kampf et al., 2022; Koshkin et al., 2022; McGrath et al., 2023; Reis et al., 2024). For example, in burned areas, faster wind speeds can lead to more transportation and increased turbulent fluxes relative to the snow surface, while the lack of canopy limits interception but increases the potential for midwinter melt due to increased availability of

shortwave radiation (Gleason et al., 2019; Harpold et al., 2014; Hatchett & McEvoy, 2018; Koshkin et al., 2022; Smoot & Gleason, 2021).

As noted above, I expect that the larger driver of the disagreement in peak SWE is the precipitation forcing data. However, another source of disagreement between modeled and observed peak SWE in this study were differences in radiation components, specifically in the burned areas. Alternating periods of melt (from increased net shortwave radiation) and SWE additions (from spring storms) lead to SWE stabilization around peak SWE (Figure 8). Inaccurate modeling of the radiation components could reduce this phenomenon in the model. Although overall radiation is lower in the accumulation period, the larger magnitude differences could still have an impact on the mass balance at the burned sites.

Modeled SWE during accumulation and peak SWE in WY 2025 stood out relative to the other water years given the poor agreement with the observations. There were no run-station combinations that resulted in peak SWE within 120 mm of the observed peak SWE (Figure 8). The discrepancies in peak SWE in WY 2025 may be related to the slow start to the accumulation season during that winter and the increasing divergence between the observed and modeled precipitation data that occurred in January 2025 (Figure 16).

Excluding WY 2025, all the runs showed strong agreement with the observed peak SWE DOY at the unburned stations (ranging between -4 to 12 days) indicating that despite the precipitation-related peak SWE biases, the timing of peak SWE in unburned areas reasonably matched in situ observations (Figure 8). However, in the burned areas, the agreement was variable. Peak SWE DOY was similar between the Base and Height-Varying runs, and the Post-Fire and Type-Varying runs, indicating that peak SWE DOY is more often controlled by vegetation type, k and τ than by vegetation-height.

4.1.3 Melt Rate

The differences in the melt rate between the model runs and the observations were all within the range of -11 to 13 mm/day (Figure 8). In some cases, the model underestimated melt rates which, combined with an underestimation in peak SWE magnitude, contributed to a more accurate SDD (see 4.1.5 below).

Given that the model and in situ stations experienced sustained melt at different intervals, melt rate comparisons do not account for seasonally varying radiation magnitudes. For example, the burned sites melted out up to a month before the unburned sites (SDD on 26 May at BF and 23 May at BS vs 10 June at UF and 25 June at UN in WY 2023) (Figure 9) meaning that they melted out during a period with significantly less incoming/net shortwave radiation than the period when the unburned sites melted out. Overall, iSnobal captured daily melt rates with variable accuracy (median difference = -1.15 mm/day) which likely contributed to SDD accuracy. Melt rates at the burned stations were more often underestimated than at the unburned stations, especially in the vegetation-adjusted runs (Figure 8). WY 2025 had the most station-run-water year combinations with underestimated melt rates further demonstrating modeling difficulties for that WY (Figure 8).

4.1.4 Snow Disappearance Date

SDD is a simple metric that integrates peak SWE magnitude, peak SWE date, and melt rates, and thus provides useful comparison across different locations. Burned stations in study area melted out up to a month earlier than the unburned stations (Figure 9) consistent with other studies (Koshkin et al., 2022; McGrath et al., 2023; Reis et al., 2024). The Post-Fire run consistently modeled SDD within 10 days of the observed SDD at burned sites (Figure 8), which

is an encouraging finding, but the modeled processes driving this improvement were more nuanced.

As noted above, peak SWE magnitudes were consistently underestimated, and although more variable on the whole, median melt rates were slightly negatively biased in the model. As a result, over the course of the ablation season at the burned stations (median = 45 days), the reduced melt rate adds up to 52 mm of SWE, accounting for ~44% of the median difference in peak SWE magnitude (median difference = -118 mm). While this was not necessarily the case in every station-run-water year combination, it illustrates how overall model agreement in one metric (SDD) may be the result of lower agreement in other metrics (peak SWE and melt rates), highlighting the need to evaluate each individually.

I have already identified the precipitation forcing data as a potential source of error in this study which may be further complicated by spring snowstorms, which may be more isolated in nature than major disturbances early in the season and thus are more difficult to accurately model. Cameron Pass is in a continental snow regime region that experiences spring snow refreshes that add small but not insignificant amounts of SWE. In maritime climates, rain on snow events are more common and do not prolong the accumulation season like spring snow events (Trujillo & Molotch, 2014). The frequent spring snowstorms in the continental climate of Colorado allow for additional instances of inputs to SWE that may be forced inaccurately.

Another potential source of disagreement between modeled and observed SDDs could stem from single-point validation data. Using time lapse imagery, I observed melt out patterns where patchy snow can exist for 5 or more days within a single 30 m pixel (Figure 19), illustrating the limitation of using point observations to evaluate distributed model output.

4.1.5 Energy Balance and Meteorological Variables

I observed clear differences between the Base run and the vegetation-adjusted runs for the various radiation components. However, I found inconsistent patterns between the vegetation-adjusted runs across the different stations and WYs, precluding clear recommendations for future improvement. As would be expected given previous model development and testing, I found better overall agreement at Unburned Flat compared to Burned Flat across runs. Importantly, the strong shift in radiation values between the Base run and vegetation-adjusted runs illustrate the notable influence of the vegetation parameters on all aspects of the snowpack energy balance. At BF during ablation, the Post-Fire, Height-Varying, and Type-Varying runs had similar magnitudes in the net shortwave (30 W/m^2 to 52 W/m^2) and net longwave (-31 W/m^2 to -35 W/m^2) radiation while the Base run had nearly the opposite magnitude in net shortwave (-45 W/m^2) and net longwave (51 W/m^2) (Figure 11). While the Base run and vegetation-adjusted runs had distinct biases relative to the station observations, both compensated in ways that resulted in net radiation being reasonably close to observed values, again highlighting the importance of evaluating individual energy balance components rather than the combination of all together.

Although the Post-Fire run tracks SDD well, I noted that the net shortwave is overestimated (46 W/m^2) and the net longwave is underestimated (-35 W/m^2) during ablation in 2025 at BF which equilibrated in net radiation (11 W/m^2) (Figure 11), but still likely interfered with ablation processes in non-realistic physical ways. These agreements between modeled and observed data that occurred due to compensation in other areas of the model emphasize the importance of examining each component to understand how improvements were generated rather than accepting them as accurate representations of physical processes.

On the basis of magnitude, the agreement between observed and modeled turbulent flux components showed better agreement than radiation components in WY 2025. I found sensible and latent heat RMSEs of 8 W/m^2 and 11 W/m^2 , respectively, while net shortwave and net longwave RMSEs were 24 W/m^2 and 28 W/m^2 (Figure 11). At the burned sites, I found that the turbulent flux model-observation comparison exhibited an opposite seasonal bias to net radiation. In other words, the modeled turbulent flux was positively biased during the accumulation season and slightly negatively biased during the ablation period, which was consistent across nearly all vegetation-adjusted runs.

Wind speed is an important component of the turbulent flux calculations and is a difficult parameter to model accurately at high spatial resolution, particularly in complex terrain. In general, the model-observed wind speed exhibited solid agreement, but the different burn conditions and model runs yielded interesting patterns. The model consistently overestimated wind speeds at the unburned sites in all years and all sites, but at a relatively low magnitude ($1 \pm 0.4 \text{ m/s}$). In contrast, the differences at the burned sites were larger in magnitude and varied with model run – for example, the Base run and Type-Varying run were primarily negatively biased, while the Post-Fire and Height-Varying runs were positively biased. This difference, as would be expected, highlights the role of vegetation height in modeling windspeeds. Given this observation, future work could compare the LF vegetation height product with either UAV or airborne-lidar derived canopy heights.

4.2 Assigning Vegetation Parameters via Burn Severity

Our analysis revealed important differences between the LF vegetation classes and MTBS burn severity classes, highlighting the importance of assessing the product being used to assign vegetation parameters post-fire. The LF 2023 version reclassified many cells in the High and

Moderate severity burn as mesic meadow, but still 30% of High and 89% of Moderate burned cells were vegetation classes other than mesic meadow (Figure 13b). Of the remaining 30% of High burned cells in the Post-Fire run, 28% were spruce-fir forest meaning that those cells were parameterized as untouched, living forests despite being burned at high severity. This could lead to an overestimation of SDD in burned areas which have been shown to melt out up to a month earlier in this study and others (Koshkin et al., 2022; Reis et al., 2024) due to an unrepresentative classification by LF. These differences will have fire-specific implications, as fires that are dominated by low to moderate burn severity may not generate significant change in remotely sensed LF products, ultimately underestimating the fire influence on snow processes.

This work highlights a limitation of solely relying on the LANDFIRE products to parameterize burned landscapes. I illustrate an approach for using MTBS burn severity class to assign k and τ values within the iSnobal workflow. The streamlined implementation of the MTBS product demonstrated that another burn-severity product like MODIS (Alonso-González & Fernández-García, 2021) or another layer from MTBS such as Differenced Normalized Burn Ratio (dNBR) could be viable substitutes for LF.

I found the largest differences in SWE (and snow depth; Figure A7) between model runs on 22 May 2023 which is the only ASO flight date that occurred well into the melt period when the Base run tended to demonstrate the worst agreement with observations compared to the other runs. The Base run was overestimating SWE consistently, as is shown in the other model runs at the AWS points from the first part of this study (Figure 8). The other two ASO flights were conducted before peak SWE (15 April 2024; Figure 6) or within a week after peak SWE during the ripening phase (7 April 2025; Figure 6) which led to disagreement with the Post-Fire and MTBS runs. It has been shown in this study that the Post-Fire run consistently performs better

(within 10 days of SDD) during the ablation period while the Base run tends to overestimate SDD (max of 52 days) (Figure 8). The MTBS run performed well in certain landcover classes such as lodgepole pine, but the relatively few number of cells of that class in the basin led to overall worse agreement than the Post-Fire run (Figure 14).

4.3 Vegetation Recovery Scenarios

The influence of vegetation height was particularly notable in the vegetation recovery scenarios. The Poor run, with shorter vegetation heights than the Excellent run, accumulated more SWE (Figure 15). This contrasts with some of the results from Section 3.1.1 where the Base run accumulated more SWE than the Post-Fire run which had shorter vegetation heights (Figure 8). However, this was explained when examining the radiation components. The Excellent scenario had less shortwave radiation and less negative longwave radiation resulting in higher net radiation throughout the season (Figure A8). The Poor scenario had a more negative net radiation balance in accumulation but nearly matched the Excellent scenario from mid-April to the end of ablation due to increases in net shortwave (Figure A8). This likely caused the Excellent scenario to have less cold content and more rapid ripening and melt during the melt period than the Poor scenario, which remained in a more negative energy balance for longer. This differed from the Base run which had taller vegetation heights (17.5 m vs 5 m in Excellent) that led to longer snow persistence which did not occur in the Excellent run. These dynamics demonstrated the importance of examining energy balance components when making changes to physical snow models like iSnobal. Further validation data is needed to confirm the results of the vegetation recovery scenarios across landscapes with variable vegetation height.

Although the results of the different vegetation recovery pathways primarily demonstrated nuances within the model physics, they also illustrate the long-term impact of fire

disturbances. While annual fire extent exhibits year to year variability, the cumulative land area impacted by wildfires is growing year over year (Higuera et al., 2021). As a result, the post-fire impacts to the snowpack energy balance have a lasting impact, especially given the slow nature of vegetation recovery. In California, the Pacific Northwest and the Lower Colorado Basin multiple watersheds have experienced 80% or greater area burned with strong impacts to streamflow for decades to come (Hallema et al., 2018). Understanding future snow dynamics in relation to the mid- to long-term recovery in these areas is important as well as the immediate impacts especially in the context of water forecasting for basins like the Upper Colorado River Basin that have millions of water users and increasing burned area (Hammond et al., 2023; Higuera et al., 2021).

The modeled endmember recovery scenarios were designed to capture the range of variability expected in the dry, high elevation coniferous forests of the Southern Rocky Mountains post-fire. Previous studies have shown that cool, wet forests show greater regeneration post-fire (C. S. Stevens-Rumann & Morgan, 2019), and that lower severity fires allow species to be more resilient because of adaptations to lower severity disturbances (Rhoades et al., 2025; Schapira et al., 2021) or shorter distance to surviving seed source (Harvey et al., 2014). However, regeneration is very site and condition dependent. In the Northern Rockies of Idaho and Montana, the climatic conditions post-fire were strongly related to regeneration with drier and warmer climatic norms due to climate change suggesting potential changes in species composition and threatening regeneration overall (Hankin et al., 2019). In the Cascades Mountains region, regeneration has been found to be similarly tied to seed source distance and post-fire climatic conditions (Boag et al., 2020; Crotteau et al., 2013). Certain species of deciduous trees, like quaking aspen (*Populus tremuloides*), have higher regeneration potential

post- high-severity wildfire (Carter & Hart, 2026; Kreider & Yocom, 2021), but do not play an integral role in the snow energy and mass balance because of their canopy structure (Pomeroy & Dion, 1996).

Five years post-fire, the levels of recovery in the Cameron Pass study area exist on a gradient from very limited to substantial (Figure 20). This recovery gradient can be driven by forest type (Harvey et al., 2014; C. S. Stevens-Rumann et al., 2022; C. S. Stevens-Rumann & Morgan, 2019), burn severity (C. S. Stevens-Rumann & Morgan, 2019), pre-fire soil conditions, and compounding disturbance effects like bark beetle epidemics or previous fires (Rhoades et al., 2022; Schapira et al., 2021; Stevens-Rumann & Morgan, 2016). However, the recovery that has been experienced at the Cameron Pass study area five years post-fire is still not enough to dramatically shift the snowpack energy balance back towards that of a fully forested area (Figure S16) (Carter & Hart, 2026). Research shows that some of these landscapes will not recover in a way that impacts snowpack evolution because many areas are experiencing low overstory regeneration or converting to non-forested landscapes due to post-fire climatic stress (Davis et al., 2023; Hessburg et al., 2019; C. S. Stevens-Rumann et al., 2018, 2022; C. S. Stevens-Rumann & Morgan, 2019). Even if this area were to recover to the excellent recovery scenario over the next 14 years, the model physics suggest that the snowpack does not vary substantially from what can be expected under poor recovery conditions. Future studies should focus on the long-lasting impacts that large-scale historic wildfires have on snow, including detailed field observations to evaluate model performance.



Figure 20. Varying amounts of post-fire forest regeneration at the Cameron Pass study area (a and b) and lower elevation sites (2740 m) (c and b). Pictured species include Douglas-fir (a), lodgepole pine (b and d) and quaking aspen (c).

4.4 Vegetation Parameters

This study demonstrated the strong influence of vegetation parameters on the snowpack energy balance and therefore the ability of iSnobal to capture post-wildfire snow dynamics. However, a limitation of this study and of the current iSnobal model setup is the categorical nature of the vegetation parameters. Forest types with functionally similar structure in the

context of snow dynamics like lodgepole pine and spruce-fir forests should not have large differences between values (e.g. k of 0.074 vs 0.04 and τ of 0.16 vs 0.2) which are scaling factors for the energy balance components in iSnobal.

Both k and τ , and vegetation height were adjusted significantly (k from 1 to 0, τ from 0 to 1, height from 17.5 m to $\sim < 1$ m), so the radiation components for the Post-Fire, Height-Varying, and Type-Varying runs showed large differences from the Base run, while having similar ranges to each other. It is certainly true that the magnitude of the adjustment in all the vegetation parameters plays a significant role in this pattern and smaller adjustments would have less impact. For example, had I adjusted height from 17.5 m to 16 m, the Height-Varying run would not look distinctly different from the Base run. To that end, I can see the result of changing the landcover classifications, and thus k and τ , slightly when looking at UF in WY 2022. In the Base run (LF 2016), UF was classified as lodgepole pine ($k = 0.074$, $\tau = 0.16$), but this classification was updated to spruce-fir ($k = 0.04$, $\tau = 0.2$) in the 2023 version of LF (Figure A1). This caused modest differences between the Base and Type-Varying runs at UF in 2022 (Figure 8). However, if an iSnobal user is adjusting the vegetation parameters from a forested landscape to a post-fire landscape, they will likely be adjusting the parameters in a similar fashion to the Post-Fire run ($k = 0$, $\tau = 1$, height $\sim < 1$ m) to drive significant changes in the snowpack energy balance that more closely replicate post-fire conditions.

In this study, updates to LF and the use of MTBS burn severity classes were done on a categorical basis for simplicity. However, alternative approaches exist; for example, an empirical relationship can be established between leaf area index (LAI), vegetation height, the transmissivity of the canopy (τ) and the extinction coefficient (k) (Lang et al., 2025; Link & Marks, 1999; Pomeroy et al., 2002; Pomeroy & Dion, 1996; Sicart et al., 2004). Remote sensing

products like Sentinel-2 which can provide LAI or airborne/UAV LiDAR which can provide canopy height could then be used to calculate the k and τ parameters across the landscape along a continuous spectrum rather than as discrete bins. More research and consideration of these values is essential for ongoing work in post-fire areas and areas that experience large-scale landscape change.

5. Future Work

As wildfires continue to increase in size and frequency, especially in high-elevation persistent snow zones, understanding how landscape changes influence the evolution of the snowpack will continue to be important. The historically dry 2025–2026 winter in Colorado also demonstrates the need for accurate snow modeling to aid management decisions in these altered landscapes. Adjusting vegetation parameters and taking canopy structure into account, regardless of the specific physical model, should become common practice in watersheds with large, burned areas. Through the sensitivity testing conducted in this work, vegetation height was identified as having a strong influence over the energy balance components in iSnobal. The changes in the k and τ parameters were also notable as identified by the reclassification of the UF station between LF versions. Additionally, a viable way to implement burn severity rather than LF landcover classification was presented with the caveat that categorical parameter assignment could be improved using a continuous scale. This study provides the basis and justification for future work to focus on refining vegetation parameter values and finding more accurate ways to represent each.

The influence of the vegetation parameters and the capability to improve model agreement to observations during the ablation period and SDD has been clearly shown in this study. However, a limitation of this study and of the current default iSnobal model setup in general is the categorical nature of the vegetation parameters. In future work, this approach should be reevaluated. An empirical relationship can be established between leaf area index (LAI), vegetation height, the transmissivity of the canopy (τ) and the extinction coefficient (k) (Lang et al., 2025; Link & Marks, 1999; Pomeroy et al., 2002; Pomeroy & Dion, 1996; Sicart et al., 2004). Remote sensing products like Sentinel-2 which can provide LAI or ASO LiDAR which can provide canopy height could then be used to calculate the k and τ parameters across the landscape continuously. More research and consideration of these values is essential for ongoing work in post-fire areas and areas that experience large-scale landscape change.

An essential component of this study that sets it apart from other similar modeling efforts is the vast collection of in-situ data. The installation of weather stations and consistent monitoring of the Cameron Pass study area provided ample data that allowed me to disentangle the relationship between the vegetation parameters and components of iSnobal that have not yet been evaluated in post-fire areas. Also, the contribution of the ASO SWE product allowed for a more robust spatial comparison of SWE than the point-by-point extrapolated SWE comparison at the stations. The launch of NISAR and efforts to develop an accurate global SWE product will hopefully supplement the spatial and temporal extent of validation data used to fine tune modeling efforts. Ongoing work should continue the use of in-situ and remotely sensed data in tandem to evaluate spatial accuracy and reveal lapses in specific components of snow energy and mass balance models.

6. Conclusions

In this study, I adjusted vegetation parameters in iSnobal using updated versions of LF and burn severity from MTBS, testing the sensitivity of the model to each parameter individually. I developed two tools (iSnobal, 2025/2026) that other iSnobal users working in burned areas can easily implement into their workflow to update the vegetation parameters. Additionally, I modeled two end-member recovery scenarios to demonstrate the gradient of possible snow accumulation throughout the season.

Through the updating of vegetation parameters using post-fire versions of LF, modeled SDD in the Post-Fire run was within 10 days of observed SDD across weather stations and water years. Although this was a large improvement from the Base run, key differences persisted in peak SWE (differences ranging between -274 to 48 mm) and energy balance components (average seasonal difference ranging between -49 to 52 W/m²) indicating that there is still work to be done. The use of LAI and empirical relationships between the k and τ parameters should be further investigated to improve these parametrizations.

The use of burn severity to assign vegetation parameters showed different results from the LF updates, and the largest differences between runs were demonstrated during the ASO flight that occurred the latest in the melting season (25 days after peak SWE). The Base run overestimated SWE by an average of 117 mm while the Post-Fire run underestimated by -7 mm and the MTBS run underestimated by -53 mm on average across burn severity classes. This is consistent with results from the Objective 1 analysis that show the runs with updated vegetation parameters outperforming the Base run in the ablation season. The vegetation parameters were assigned on a

categorical scale for the MTBS run which should also be reevaluated to assign values on a gradient of burn severity, potentially using dNBR.

The recovery scenarios demonstrated the differences in SWE under poor and excellent forest recovery 20-years post-fire. The poor recovery scenario, which was parameterized to have no regeneration, had a greater average SWE throughout the season with this difference peaking at 58.5 mm (14% of peak SWE) in April. Future work could evaluate the consequences of these differences on larger scales and identify implications for water management under the increased wildfire activity of the 21st century.

The implementation of iSnobal for operational water management could be improved in post-fire areas through the use of this research and the tools that it provides. As the western U.S. continues to be exposed to larger and more intense wildfire in critical snow zones, it is important to consider the consequences these fires will have on snow modeling now and in the years following the fires. Through the analysis of impacts to the energy and mass balance that adjusting vegetation parameters caused, this study better informs the water resource management community on potential ways to improve the use of iSnobal.

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Appendix

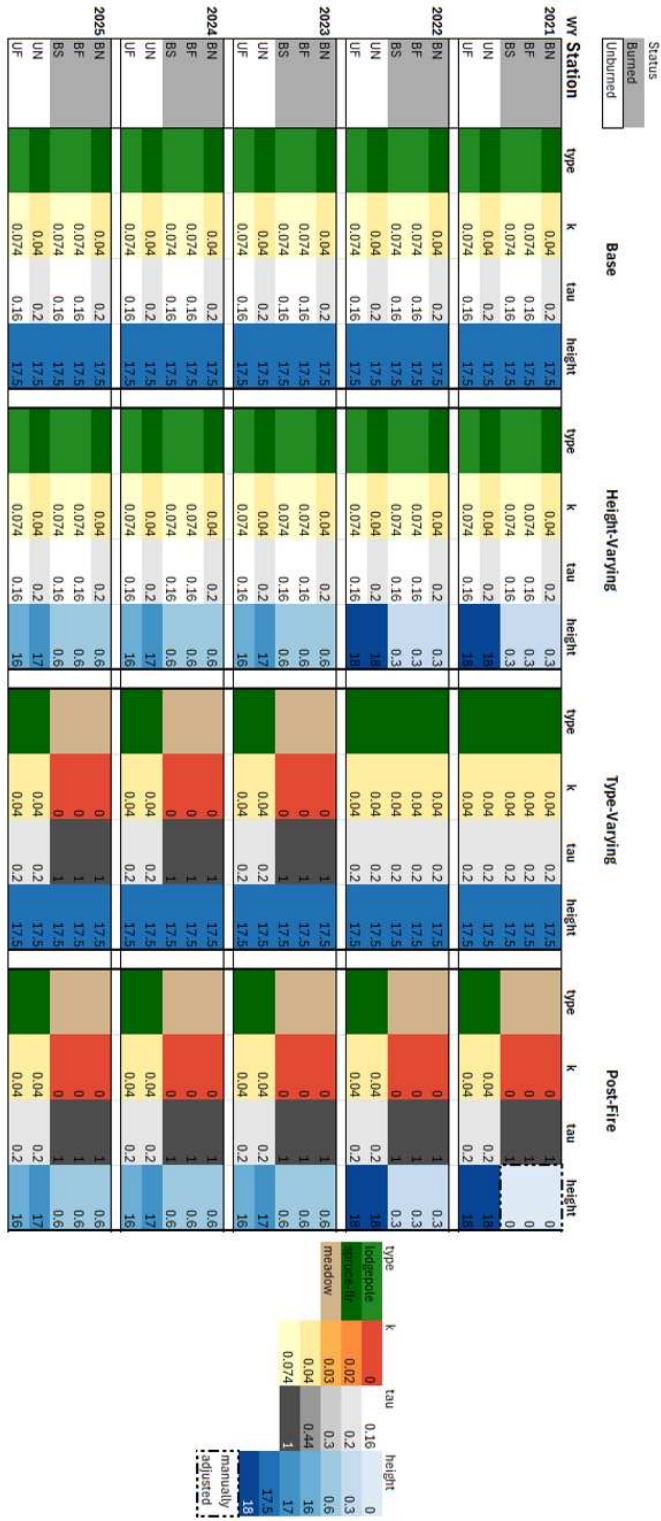


Figure A1. A summary table of the vegetation parameter values used at each station for each water year and run.

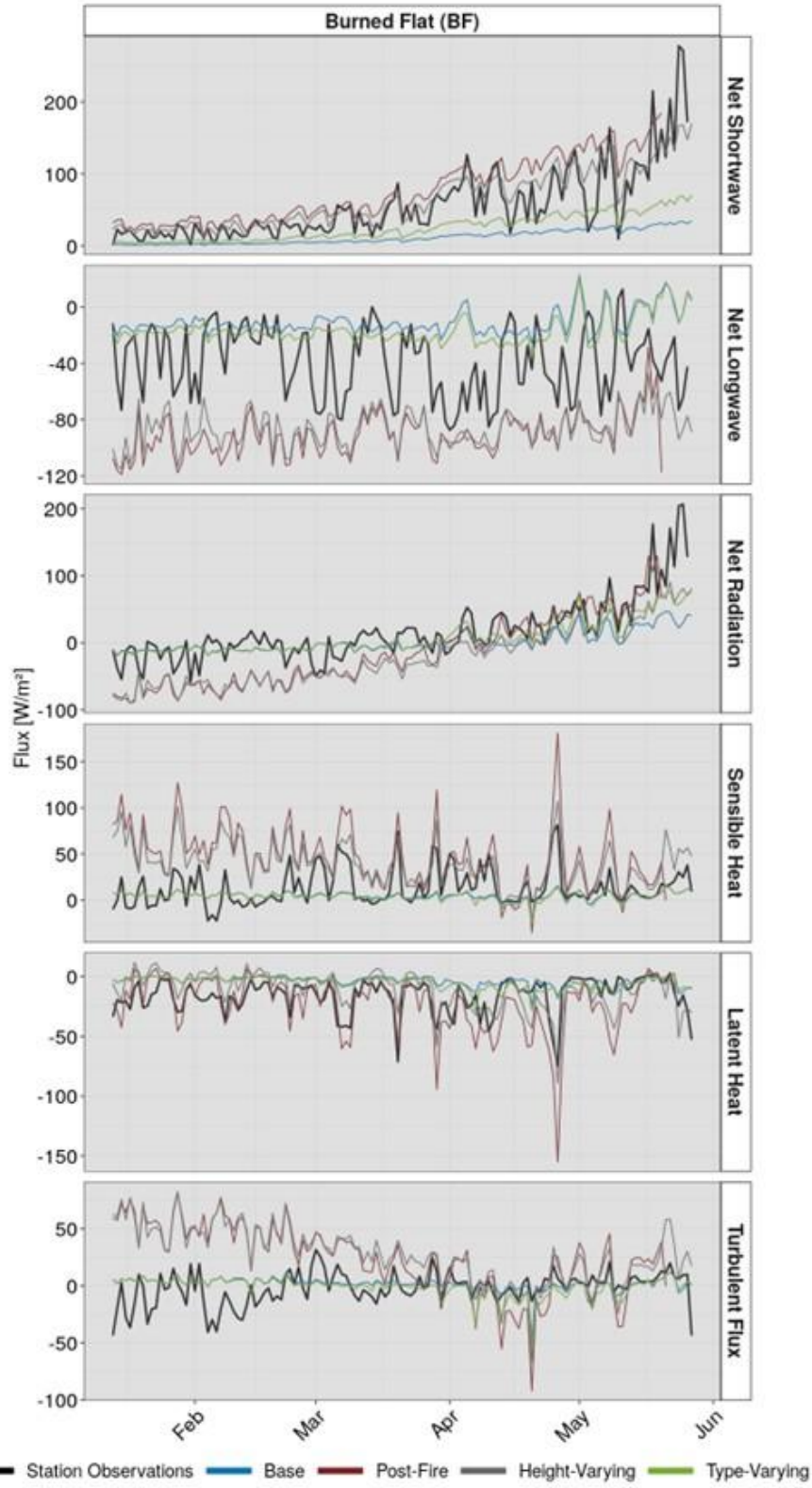


Figure A2. Modeled and observed mean daily energy balance components (net shortwave, net longwave, net radiation, sensible heat, latent heat, turbulent flux) from BF WY 2021.

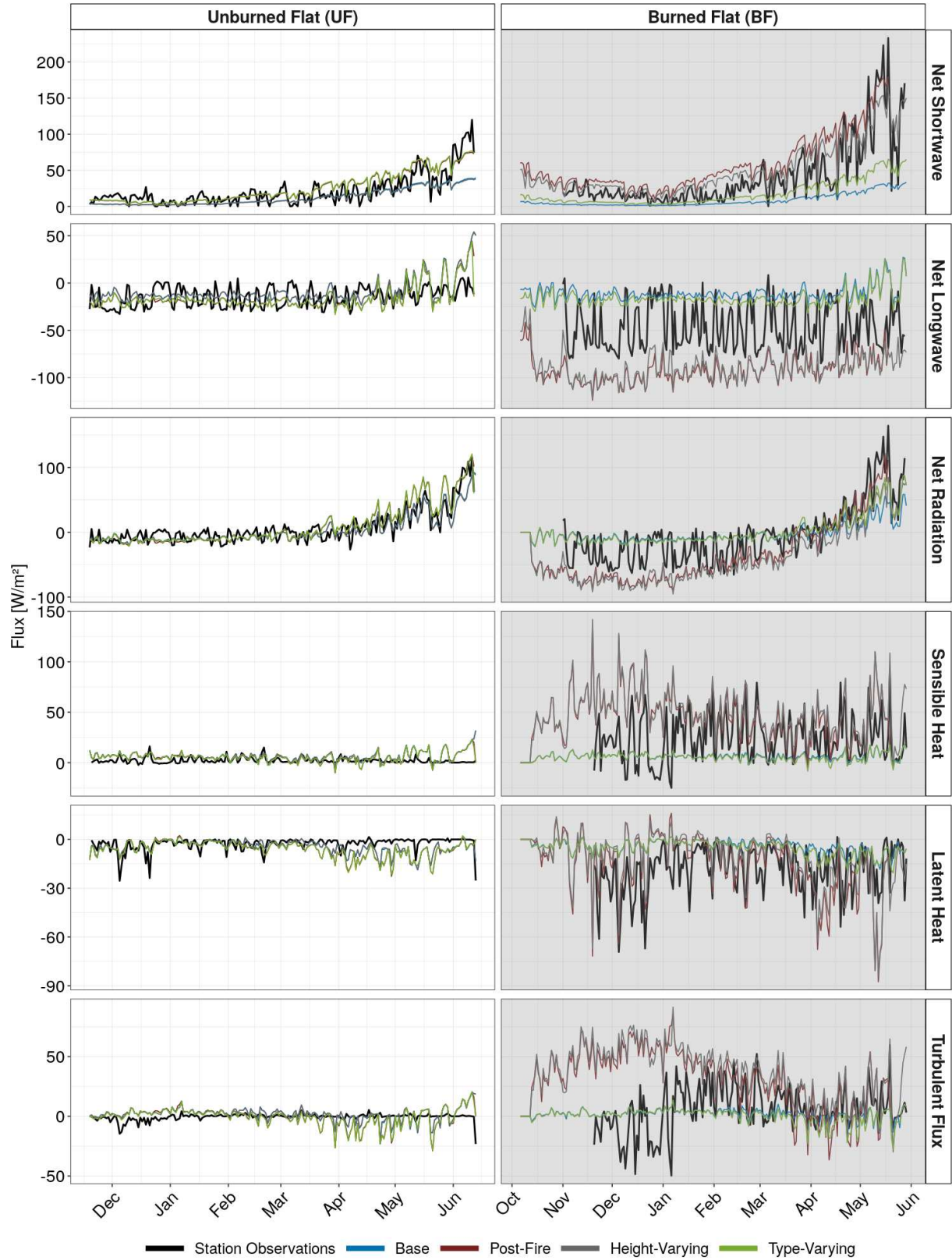


Figure A3. Modeled and observed mean daily energy balance components (net shortwave, net longwave, net radiation, sensible heat, latent heat, turbulent flux) from UF and BF WY 2022.

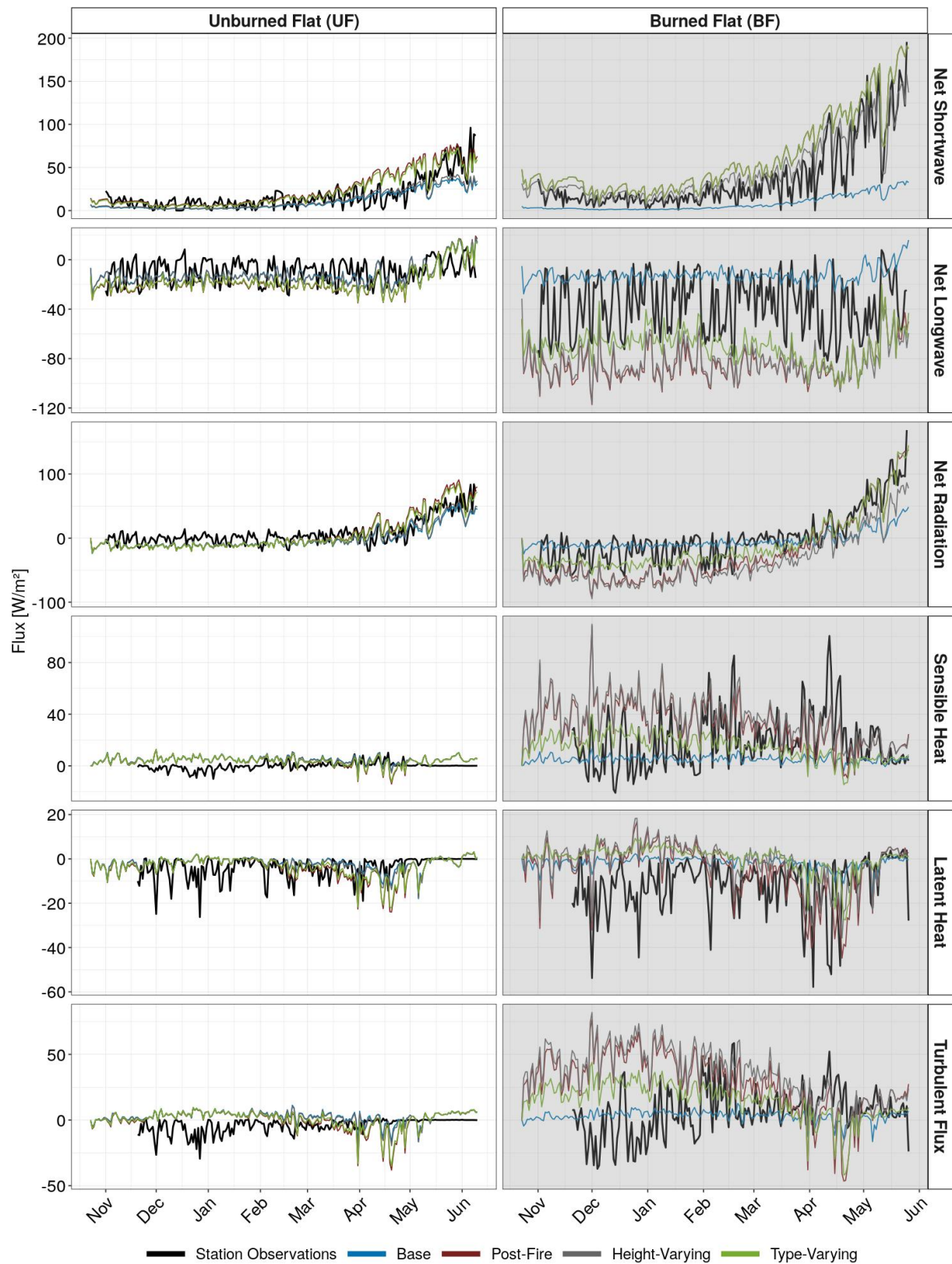


Figure A4. Modeled and observed mean daily energy balance components (net shortwave, net longwave, net radiation, sensible heat, latent heat, turbulent flux) from UF and BF WY 2023.

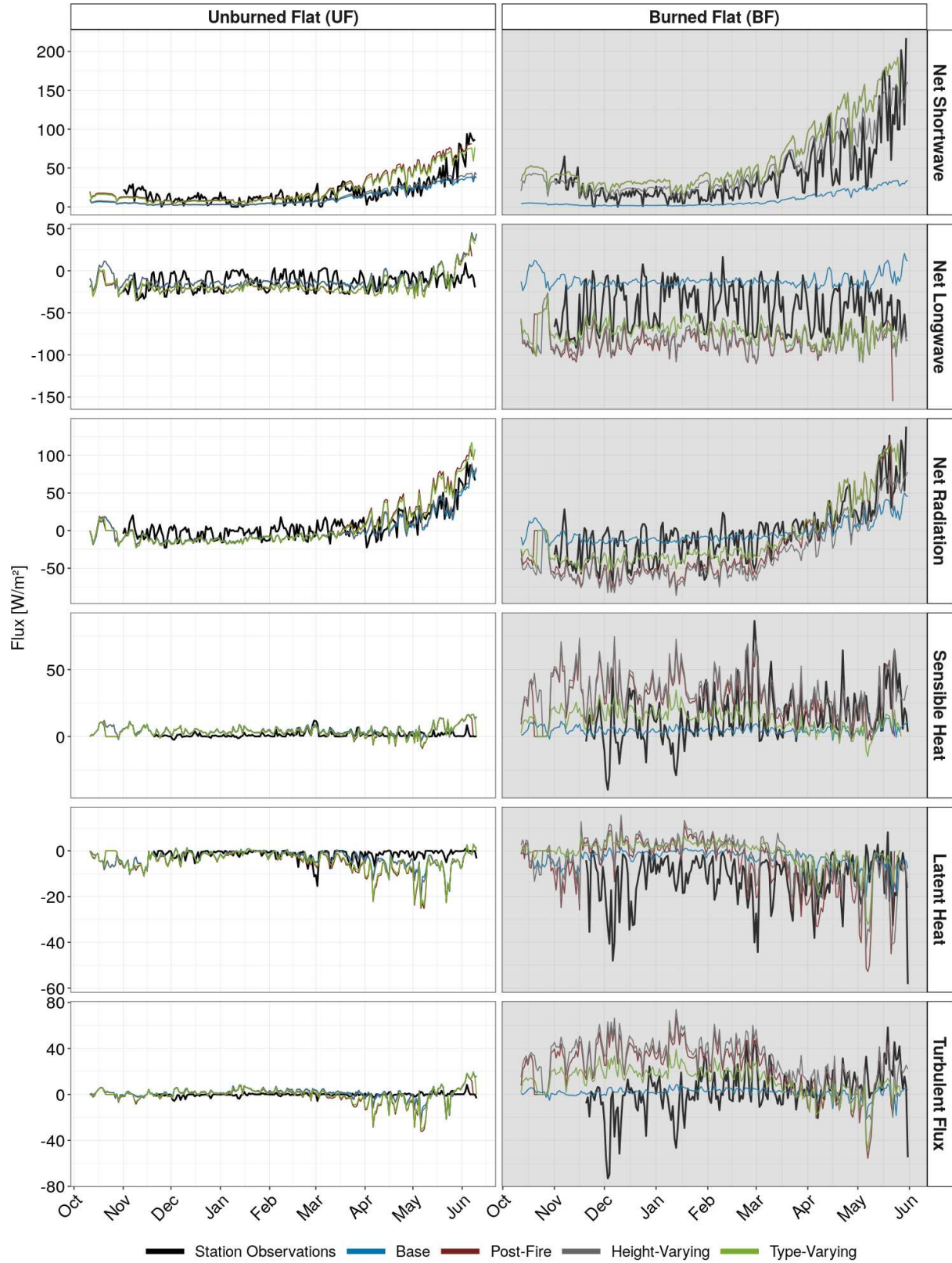


Figure A5. Modeled and observed mean daily energy balance components (net shortwave, net longwave, net radiation, sensible heat, latent heat, turbulent flux) from UF and BF WY 2024.

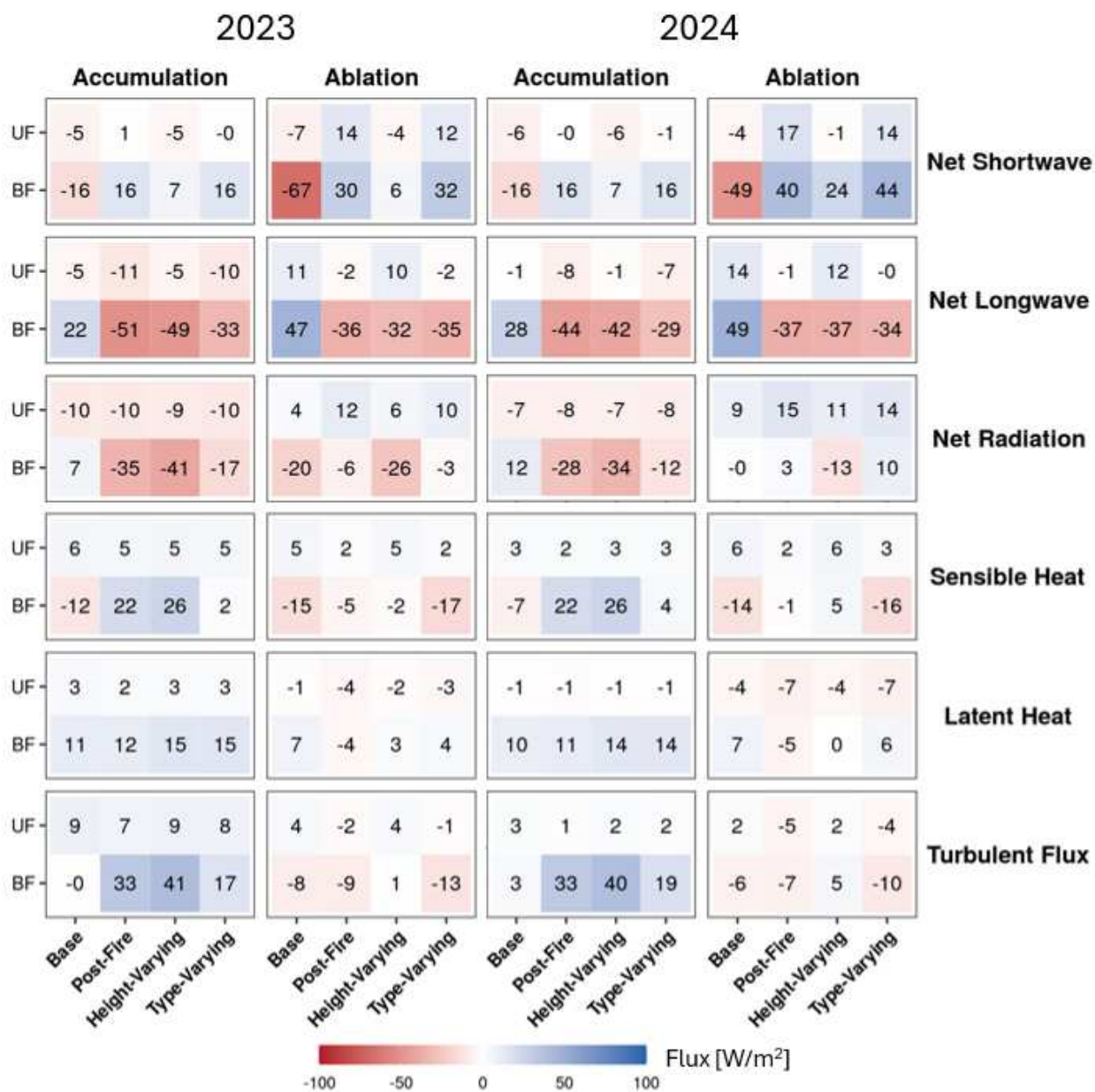


Figure A6. Difference between modeled and observed average energy balance components for WY 2023 and 2024 at the UF and BF stations.

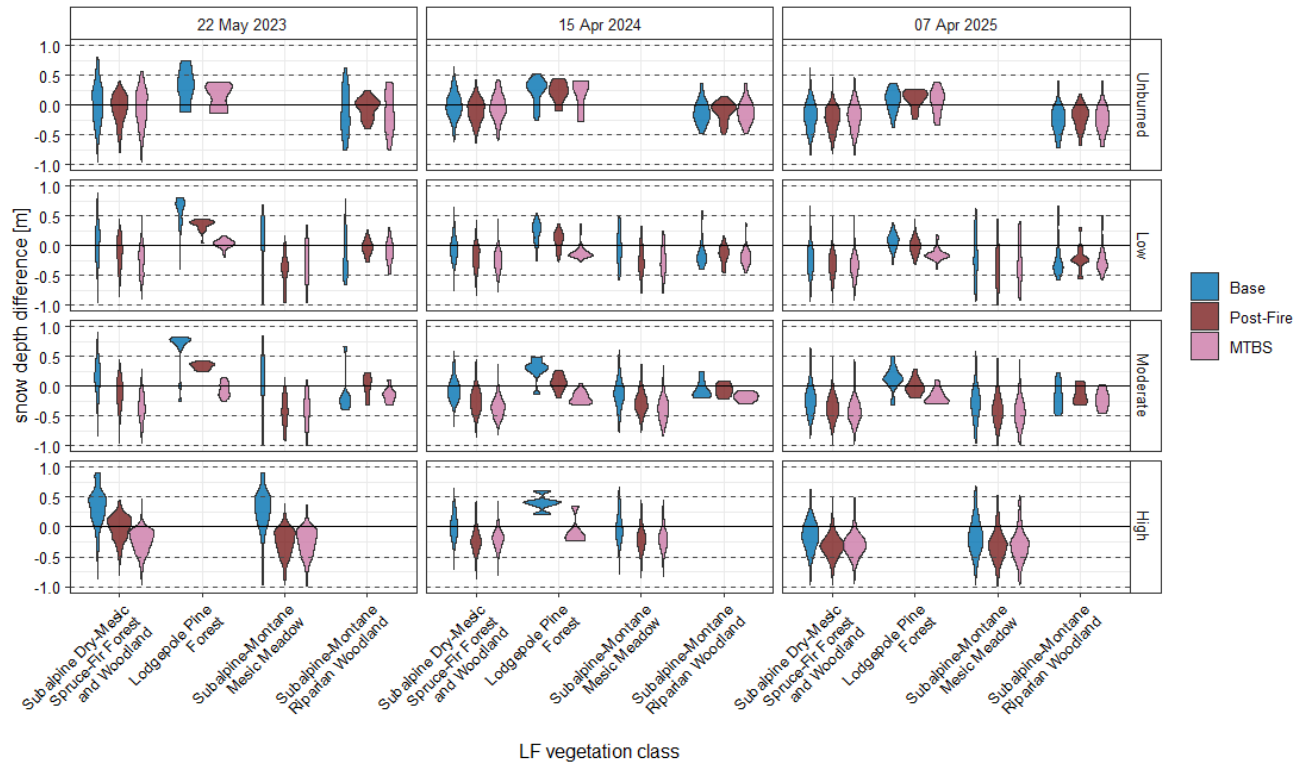


Figure A7. Violins plots showing the distribution of snow depth difference between iSnobal modeled and ASO LiDAR separated by LF vegetation class and MTBS burn severity for each ASO flight date.

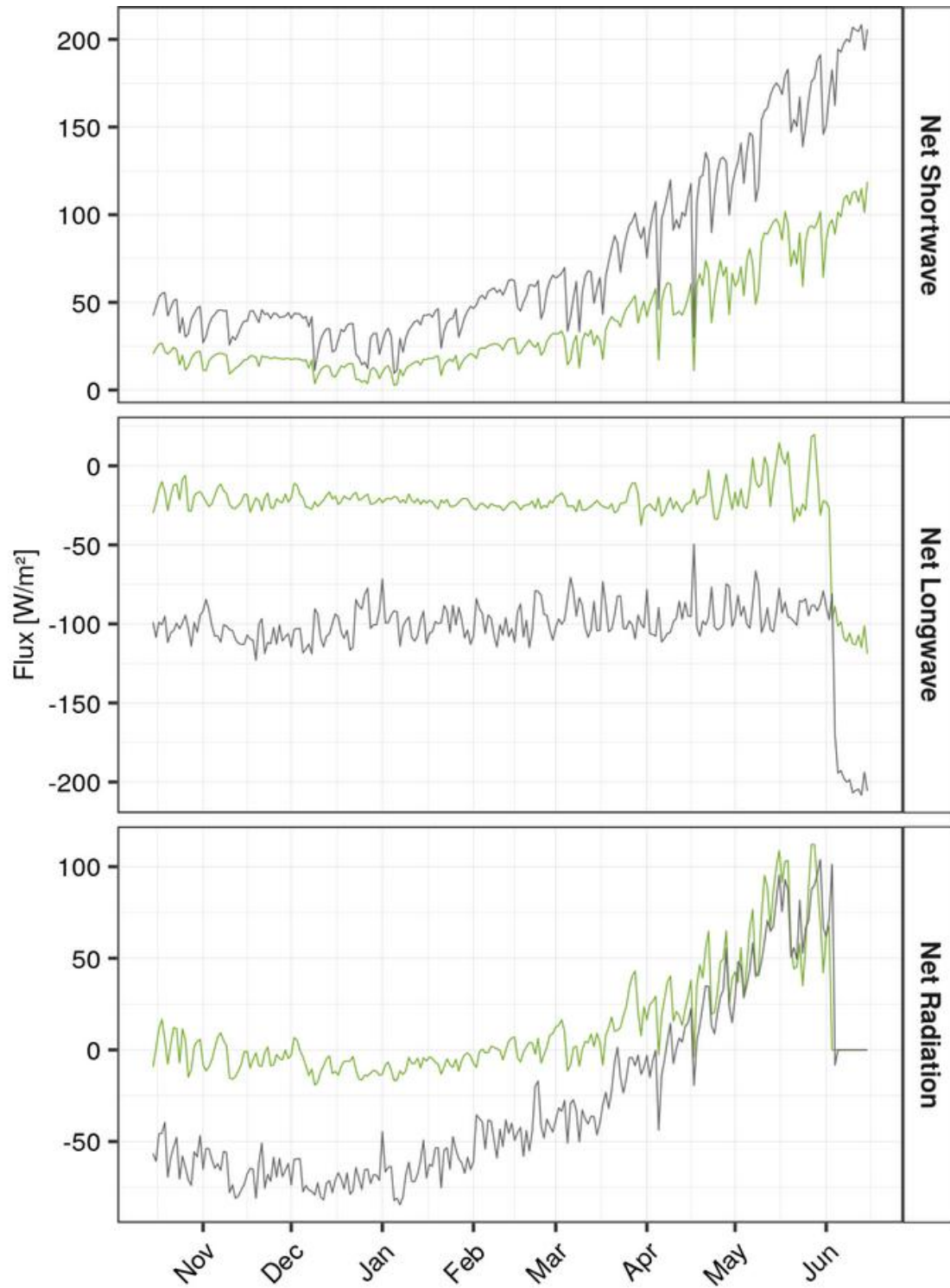


Figure A8. Radiation components for the vegetation recovery scenarios. The Excellent scenario is shown in green and the Poor scenario is shown in gray.