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Extracting Signals of Snowmelt From the Surface Energy Budget at a Rocky Mountain Eddy Covariance Site

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Key Points:

- Analysis of the surface energy budget can reveal unobserved hydrologic processes, improving confidence in energy budget measurements
- Seasonal changes in the observed surface energy budget reflect latent heat flux from melting snow in subalpine environments
- Springtime energy imbalance can reveal snowmelt dynamics without direct snow measurements

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Abstract Snowmelt is a dominant hydrologic process in mountainous watersheds and western river systems, yet automatic logging of snowpack properties such as depth, density, and internal energy fluxes, especially during melt, is not done at many Rocky Mountain surface flux sites. In this study, we show that springtime variations in the surface energy budget imbalance can be used to estimate snowpack energy fluxes. Using observations from the US-GLE AmeriFlux site, we demonstrate a data-driven method to extract springtime energy budget anomalies and show that 83% of this anomaly is explained by the latent heat flux of melting snow when computed at a 6-hour resolution. Additionally, we demonstrate that our model can explain this latent heat flux while preserving the statistical structure of the energy imbalance observed during the rest of the year. Our findings suggest that analysis of the surface energy budget, when tightly constrained, can reveal latent hydrologic processes, improving confidence in surface energy budget measurements and offering a low-cost, data-driven method for estimating snowmelt dynamics at existing flux sites without additional instrumentation.

1. Introduction

Snow-dominated mountain watersheds provide a majority of the runoff for many major river systems in the U.S. and throughout the world, establishing these watersheds as important regions of study (Stewart et al., 2004; Viviroli et al., 2007). The recent uptick in disturbances and other climate change impacts in the Rocky Mountains of the western United States (Peterson, 2018) make it imperative for us to understand how these changes will affect hydrologic, forest, and agricultural resources. The Rockies are home to many surface flux monitoring sites established to provide data on the environmental and ecological behavior. Continuous measurements of evapotranspiration and surface energy fluxes are used to evaluate water availability, ecosystem productivity, and resilience of these watersheds (Jung et al., 2017; Pastorello et al., 2020; Webb et al., 2024; Williams et al., 2012). Data collected at these sites are used to drive and validate landscape-scale ecological models used to inform land management and policy decisions (Desai et al., 2007; Jung et al., 2019; Maneta & Silverman, 2013).

In many snow-dominated ecosystems, a seasonal snowpack accumulates over the winter and melts in the spring snowmelt season. Of particular interest is the springtime, when liquid water from melting snow enters the ground. The mass flux of meltwater inputs (MWI) in these watersheds supplies the majority of the water used in runoff and evapotranspiration for the rest of the year (Li et al., 2017; Schlaepfer et al., 2014) and is an important determinant of ecosystem health and resilience (Westerling, 2016). Additionally, variations in the intensity of MWI over the course of the spring have implications for stream baseflows, annual runoff generation, and growing season evapotranspiration (Barnhart et al., 2016; Webb et al., 2024). Springtime MWI in snow-dominated regions remains poorly characterized because direct measurement of snowmelt at landscape scales is challenging.

Snowmelt occurs in three phases: warming, ripening, and runoff (Dingman, 2015). During warming, the snowpack's average temperature is below freezing and any net energy fluxes entering the snowpack decrease the snowpack's cold content (CC) until cold content is near 0 and the snowpack begins to ripen. During ripening, a slow-moving wetting front of meltwater begins to move downwards through the snowpack over several days, and most of the energy absorbed by the snowpack becomes latent heat of fusion. During the runoff phase, the snowpack can no longer hold on to its stored meltwater, resulting in a decrease in the snow-water equivalent (SWE) of the snowpack as meltwater leaves. Ice and water can evaporate and sublimate directly off the snow surface during all three phases. During the runoff phase, vegetation transpires meltwater that enters the soil (Hajji et al., 2021; Molotch et al., 2007). Measuring the mass flux of meltwater out of the snowpack is difficult. Common approaches include using soil moisture-based modeling techniques (Dobre, 2017), snowpack process models

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(Bartelt & Lehning, 2002; Lehning et al., 2002), or direct measurements of MWI through lysimetry (Kattelmann, 2000) or stream gauging (Suecker et al., 2000). In-situ snow measurements using snow pillows or manual surveys can quantify snowpack ablation, but cannot partition this ablation into MWI or ET. Additionally, the resources required for continuous monitoring (through surveys) or landscape-scale monitoring (through snow pillows) are often prohibitive (Rice & Bales, 2010). Many surface flux sites in the Rocky Mountains and other snow-dominated mountain regions therefore do not report snowpack or even precipitation measurements (Webb et al., 2024).

1.1. Surface Energy Budget

Direct observations of the surface energy budget at the surface typically take the form shown in Equation 1,

$$R_n + G + \lambda E + H - S + I_{\text{obs}} = 0 \quad (1)$$

where R_n is net radiation, λE and H are the turbulent latent and sensible heat fluxes, G is heat flux conducted into the ground, and S is storage flux, which includes the latent and sensible heat storage fluxes within the air column ($S_{\lambda E}$ and S_H), ground heat storage above the topmost ground heat flux sensor (S_G), heat storage flux in biomass (S_B), and the energy storage in biomass associated with photosynthesis (S_P). I_{obs} is the energy imbalance that remains after accounting for all other observed fluxes, which may include some or all of the ones listed above.

This study uses the sign convention that fluxes are positive when they carry heat toward the plane of the soil surface and storage fluxes are positive when their storage of heat increases. For example, net evaporation constitutes negative λE , heat conducted from deeper soil layers to the surface constitutes positive G , and an increase in the temperature of the air column constitutes positive S_H . By referencing the direction of fluxes to the plane of the ground surface, this sign convention allows for easier and more intuitive manipulation of energy budget terms.

The seasonality of snowpack and other synoptic-scale meteorological processes drives a cycle in the surface energy budget of these ecosystems. Energy fluxes have high magnitudes in the summertime, with high turbulent, radiative, and conductive heat fluxes. In the wintertime, low air temperatures and low sunlight suppress aboveground energy exchange while the snowpack insulates against heat conduction into the ground (Burns et al., 2014). The springtime serves as a transitional period between these two extremes: the presence of a snowpack suppresses ground heat fluxes, but higher net radiation and sensible heat flux inputs drive turbulent latent heat flux by melting snow (Cline, 1997; Cox, Adler, et al., 2025; Cox, Intrieri, et al., 2025).

Unexplained imbalances in the surface energy budget can make up a large portion of the overall energy budget. Within the FLUXNET network, this imbalance accounts for approximately 20% of a site's energy budget on average (Wilson et al., 2002). Common contributing factors to this imbalance include atmospheric conditions unfavorable to eddy covariance such as advective flows and large-scale convection (Foken, 2008), landscape heterogeneity within the flux footprint (Inagaki et al., 2006; Stoy et al., 2013; Wanner et al., 2022), mismatches between turbulent and non-turbulent (point) measurements (Foken, 2008), time lags between the absorption and release of energy in different pools (Massman, 1992; Reed et al., 2018), difficulties with measuring high frequency wind velocities (Frank, Massman, & Ewers, 2016; Foken et al., 2019; Kaimal, 1978) and gas concentrations (Burba et al., 2008; Fratini et al., 2018; Ibrom et al., 2007), or fundamental stochastic processes in nature (Chen et al., 2015; Wyngaard, 2010). However, it is still common to assume that energy imbalance is a product primarily of issues with turbulent flux measurements. This has resulted in the widespread adoption of forced energy budget closure, whereby turbulent sensible and latent heat fluxes are increased in flux data products, since complete energy budget closure is often a requirement for process-based ecosystem, hydrologic, and climate models (El Maayar et al., 2008; Pastorello et al., 2020; Ukkola et al., 2022). More broadly, the “energy budget closure problem” is often seen as an obstacle to obtaining high-quality measurements. Observed departures from energy-budget closure may reflect hydrologic signals from otherwise unobservable physical processes, such as snowmelt.

Temporal variations in the surface energy imbalance can occur in systematic ways. Previous studies have shown that such variability can reveal hydrologic processes such as changes in surface moisture or heat flux partitioning (Reed et al., 2018; Wang et al., 2021). These findings suggest that energy budget imbalances are not necessarily symptoms of poor measurement, but may instead represent meaningful hydrologic signals. Building on this idea, our analysis explores whether similar patterns in energy-budget closure can also indicate snowmelt processes.

1.2. Hypothesis

In snow-dominated mountain regions, the snowpack represents a major component of the water cycle and has the capacity to absorb and release large amounts of energy. However, in situ snow measurements are uncommon at surface flux sites, and directly measuring soil meltwater inputs at landscape scales remains challenging. We hypothesize that latent heat fluxes carried by meltwater inputs at snow-dominated surface flux sites contribute to seasonal variations in the springtime energy imbalance. In this study, we develop a method to isolate anomalies in the observed energy imbalance and quantify landscape-scale MWI at a sub-daily timescale. We test this method at US-GLE, an Ameriflux site located in a high-elevation subalpine forest in the Medicine Bow Range in southeast Wyoming, USA (Frank et al., 2021).

2. Methodology

We can decompose the imbalance observed in the surface energy budget Equation 1 into three separate components Equation 2: a physically meaningful but unobserved hydrologic signal (f), a baseline term with predictable structure ($\bar{\epsilon}$), and short-term stochastic noise (ϵ'):

$$I_{\text{obs}} = f + \bar{\epsilon} + \epsilon' \quad (2)$$

A method that can predict any measurement biases $\bar{\epsilon}$ and reduce measurement uncertainties ϵ' independently of a hypothesized hydrologic signal f would allow us to characterize that signal.

Our hypothesis predicts that I_{obs} contains a signal (f) from unobserved snowmelt energy fluxes. Starting from the control volume that defines the energy budget of the entire ecosystem Equation 1, we divide that control volume into separate components: one control volume spans from the height of the topmost heat flux plate to the soil surface, a second control volume spans from the top of the snow surface to the height of the eddy covariance sensors and net radiometer, and a third control volume spans from the surface of the soil to the top of the snowpack. The energy budget of this third control volume is expressed in Equation 3.

$$\lambda \text{MWI} + S_{\lambda \text{MWI}} - S_{\text{CC}} = f \quad (3)$$

Here, λMWI gives the latent heat flux carried across the top and bottom boundaries of the snowpack by soil by meltwater inputs, as would be measured by a hypothetical lysimeter placed at the ground surface or a water presence sensor on the snowpack surface. The water that carries this energy is carried out of the snowpack into the soil or onto the snow surface by melt or into the snowpack as rain. $S_{\lambda \text{MWI}}$ gives the storage of latent heat of fusion within the body of the snowpack, carried by changes in the liquid water content of the snow matrix. S_{CC} is the storage flux of cold content in the snowpack, carried by changes in internal temperature of the snowpack. In this study, we use the storage flux nomenclature from Lee et al. (2004), which is the standard in micrometeorology. During the warming phase, the majority of energy within the snowpack is through S_{CC} . During the ripening phase, $S_{\lambda \text{MWI}}$ is the dominant term, as liquid water accumulates in the snowpack without being expelled. During the runoff phase, $\lambda_f \text{MWI}$ is dominant, as meltwater is expelled across the top and bottom boundaries of the snowpack.

To test our hypothesis Equation 3, we must devise a methodology to (a) minimize the random uncertainty ϵ' in the observed energy imbalance by ensuring high-quality measurements of the observable components of the energy budget (§2.1), (b) accurately quantify the temporal structure of the baseline energy imbalance $\bar{\epsilon}$ (§2.2), and (c) devise an independent model of the snowpack energy budget, which we will use to validate our calculation of f (§2.3).

2.1. Micrometeorological Data

We used measurements from the Ameriflux BASE data product for the US-GLE site for our study. The site is located in southeast Wyoming in the Medicine Bow range (41.3665 °N, −106.2399 °W) and sits in a high-elevation (3,197 mASL) subalpine forest dominated by a 17 m high canopy of lodgepole pine, subalpine fir, and engelmann spruce (Figure 1). The site receives 1,200 mm of precipitation per year, mostly as snow (Frank et al., 2021). The primary eddy covariance instruments are located 23 m above the ground and consist of an open-path LI-7500, closed-path LI-7200 (LI-COR Biosciences, Inc., Lincoln, NE, USA) and an ATI Vx-style 3D sonic



Figure 1. Map of the region around the US-GLE Ameriflux site. The points indicate the locations of the various sensor installations. Orange: main micrometeorology tower, green: soil heat flux plates, blue: snow depth and temperature probes, red: Brooklyn Lake SNOTEL site. The Orange polygon gives the 90% flux footprint for eddy covariance data at US-GLE. 5 m contour intervals are shown as white lines. The location of the site within the U.S. state of Wyoming is shown in an inset on the bottom left.

anemometer (Applied Technologies, Inc., Longmont, CO, USA). Additionally, the site hosts several additional sensors for collecting ancillary data, including soil heat flux plates, a four-channel net radiometer, an ultrasonic snow-depth sensor, and an array of thermocouples for measuring snow temperature. Further information than what is described in this study on the data collection and ecosystem at US-GLE can be found in Frank et al. (2014, 2019) and through the Ameriflux Management Project (Frank et al., 2021). All of our calculations rely only on data available through the Ameriflux BASE data product (Chu et al., 2023).

2.1.1. Turbulent Flux Post-Processing

We applied a despiking filter (Frank et al., 2014) to measurements of turbulent carbon flux data to remove extreme outlier datapoints before moving on to subsequent steps. To despike the data, we binned measurements by hour. In each hourly bin, we considered points in a 48 days running window and computed their median-absolute-deviation ($MAD = \text{median}(|x_i - \text{median}(x)|)$). We removed points where $|x_i - \text{median}(x)|/MAD > 5$.

US-GLE reports λE data collected with both an open-path LI-7500 and a closed-path LI-7200 infrared gas analyzer (LI-COR Biosciences, Inc., Lincoln, NE, USA). Since open path gas analyzers are known to give better water flux measurements than closed path gas analyzers (Ibrom et al., 2007), we used λE collected on the LI-7500, which we gapfilled by inserting data from the LI-7200.

We applied a u^* filter to λE and H using a threshold value of $u^* = 0.2 \text{ m} \cdot \text{s}^{-1}$ determined by visual inspection of the nighttime $u^* \sim FC$ relationship (Barr et al., 2013), where FC is the net turbulent carbon flux measured through eddy covariance. Atmospheric turbulence at US-GLE is among the highest in the Ameriflux network (Frank et al., 2014), so this filtering only removed 4.5% of daytime turbulent flux data across all seasons, 12% of nighttime turbulent flux data between October and March, and 24% of nighttime turbulent flux data between April and September. We gap-filled carbon, water, and sensible heat flux following the method of Liu et al. (2025) using air temperature, relative humidity, soil moisture, soil temperature, photosynthetic photon flux density, net radiation, year, cyclically encoded DOY, and cyclically encoded time of day as predictors. We used a histogram-based gradient-boosting regression tree implemented in scikit-learn v1.2.2 (Pedregosa et al., 2011) as our gap-

filling model and used scikit-optimize v0.8.1 (The scikit-optimize developers, 2025) to optimize its hyperparameters.

2.1.2. Storage Flux Post-Processing

We computed S_H and $S_{\lambda E}$ using measurements of ambient air temperature, pressure, and humidity. Since the height of the volume of air beneath the sensor can change with the height of the snow pack, we applied the Leibniz integral rule for differentiation under the integral sign according to Equations 4–6, which we evaluated using trapezoidal integration with heights of $z = 6.5$ and $z = 23.4$ m above the ground.

$$S(t) = \frac{d}{dt} \int_{d(t)}^h g(t, z) dz = \int_{d(t)}^h \frac{\partial f}{\partial t} dz - g(t, d(t)) \frac{dd(t)}{dt} \quad (4)$$

$$S_H : g(t, z) = c_p(t, z) \rho_a(t, z) T_K(t, z) \quad (5)$$

$$S_{\lambda E} : g(t, z) = \lambda_e(t, z) \rho_v(t, z) \quad (6)$$

where T_K is the air temperature in kelvins, c_p is the specific heat capacity of moist air under constant pressure, ρ_a is the density of moist air, ρ_v is the density of water vapor in the air, λ is the latent heat of vaporization, h is sensor height, and $d(t)$ is the height at the top of the snowpack. We used the latent heat of vaporization rather than of sublimation because our method accounts for the latent heat of fusion separately as a part of snowmelt. When a snowpack was present, we assumed air temperature at $z = d(t)$ to be the minimum of the air temperature at 6.5 m and 0°C.

We computed heat stored in the top soil layer (above the topmost soil heat flux plate) according to Equation 7.

$$S_G(t) = \frac{\partial}{\partial t} \int_{z_{G0}}^0 c_v(t, z) T_s(z, t) dz \quad (7)$$

T_s is the soil temperature, z_{G0} is the depth of the topmost soil heat flux plate, and c_v is the volumetric heat capacity of the soil, computed from the mineral and water fractions of the soil according to Equation 8.12 of Campbell and Norman (2000).

We opted not to compute S_B , which was found to be negligible at US-GLE (Frank et al., 2019).

2.1.3. Non-Turbulent Flux Post-Processing

We recorded snow depth on an ultrasonic snow depth sensor (Judd Communications LLC, Salt Lake City, UT, USA) located 150 m South of the main tower at US-GLE (Figure 1). Depth measurements from ultrasonic depth sensors can be very noisy (Ryan et al., 2008), especially during deposition or blowing snow events. To address this, we smoothed the snow depth measurements using a 3-hour running median and clamped all observations below 5 cm to 0.

To measure snow temperature, we established four vertical profiles of type-T thermocouples (Figure 1) sensors at 40 cm intervals from the ground (at 40, 80, 120, 160, and 200 cm). To avoid accidentally reporting air temperature instead of snow temperature, we filtered snow temperature profile measurements in three stages. First, we computed the degree of correlation between each snow temperature sensor and the ambient air temperatures in one-day blocks: tight correlation between snow and air temperature could indicate that the snow temperature thermocouple was exposed. We removed datapoints when $R^2 > 0.9$ between snow and air temperature and when the thermocouple height was within 30 cm of the reported snow depth. Second, we removed any temperature measurements taken < 4 cm below the reported top of the snowpack. We then averaged the four profiles to give mean snow temperature at each depth. Finally, we filtered out all snow temperature measurements over 0.05°C.

We computed net radiation as $R_n = SW_{in} + LW_{in} - SW_{out} - LW_{out}$, where SW is shortwave radiation, LW is longwave radiation, in is downwelling radiation, and out is upwelling radiation, measured using a four-channel net radiometer located on the US-GLE main tower (Figure 1). We observed incoming shortwave radiation at US-GLE to have been decreasing over time, likely due to clouding of the down-welling sensor. To correct this drift we

compared the observed monthly maximum value of incoming shortwave radiation to its theoretical value computed using SolarPy 0.1.3 (AeroPython Team, 2019). We found the drift to be 1% per year, which we corrected.

We measured ground heat flux using the average of measurements taken by soil heat flux plates in five separate profiles at a depth of 2 cm below the soil surface. Four of these profiles were located 20 m North of the main tower at US-GLE, and one was located 150 m South (Figure 1).

2.2. Baseline Energy Imbalance

We used a neural network to quantify the temporal structure of the long-term bias $\bar{\epsilon}$ in the surface energy imbalance. We trained the network on observations of I_{obs} during the winter and summer. During midwinter and summer, snowmelt is expected to be near zero, so a model of I_{obs} effectively captures just this bias component. We opted for a neural network as our averaging function over other methods such as block-averaging or running-window-averaging because it can both capture nonlinear trends in $\bar{\epsilon}$ and generate predictions for $\bar{\epsilon}$ during the springtime.

Our analysis requires identifying periods when snowmelt contributes meaningfully to the surface energy budget. In situ observations (e.g., snow pillows, manual SWE surveys, or snowpack temperature profiles) can be used to constrain these ablative periods. Although such data are available at US-GLE, we do not rely on them here in order to develop an approach i.e. transferable to sites lacking continuous snow observations. Instead, we develop a physically informed heuristic to identify the onset and termination of the snow ablation period using variables available at most flux tower sites. This approach is tailored to subalpine evergreen needleleaf forests in the Rocky Mountains (e.g., US-GLE); application to other ecosystems will require modification to account for differences in snowpack dynamics and canopy–snow interactions.

Following Monson et al. (2005), we considered springtime to start 3 weeks before the first day of the calendar year when sustained net carbon uptake (FC) was observed. We defined net carbon uptake to be “sustained” when mean $\text{FC} < 0$ within a 7-day averaging window Equation 8. We considered summer to start once ground heat flux transitioned from upwelling to downwelling (averaged across all five soil pits). We defined this transition to occur halfway between the date when ground heat flux first became negative in the calendar year and the date when ground heat flux reached its minimum for the calendar year Equation 9. We chose this metric because the heterogeneous nature of snowpack and snowmelt meant that some soil pits melted out earlier than others. Choosing a date halfway between these two gives a date when most of the snow has disappeared from the landscape. These two metrics are good for the beginning and end of the snowmelt period: the snowpack insulates the ground surface, blocking any movement of heat until it disappears (Bowling et al., 2024), and photosynthesis typically starts as soon as the snowpack enters the ripening stage in subalpine evergreen needle-leaf Rocky Mountain ecosystems such as US-GLE (Monson et al., 2005).

$$\text{doy}_{\text{springstart}} = \min \left\{ \text{doy} \left| \frac{1}{7} \int_{\text{doy}-7/2}^{\text{doy}+7/2} \text{FC}(t) dt < 0 \right. \right\} - 21 \text{ days} \quad (8)$$

$$\text{doy}_{\text{summer start}} = \frac{1}{2} \left[\min \{ \text{doy} | G(\text{doy}) < 0 \} + \arg \min_{\text{doy}} G(\text{doy}) \right] \quad (9)$$

For our neural network, we used a multi-layer perceptron regressor with one hidden layer of 50 tanh-activated neurons trained on cyclically encoded day-of-water-year and the water year, implemented in scikit-learn v1.2.2 (Pedregosa et al., 2011). We asked the network to then predict values of $\bar{\epsilon}$ during the springtime to generate a reference baseline energy imbalance for our hypothesis.

2.3. Snowpack Energy Budget Model

We modeled the snowpack energy budget using SLF-SNOWPACK v.3.7.0 (Lehning et al., 2024). SLF-SNOWPACK is a complex process-based snowpack evolution model that can simulate the accumulation, ablation, internal layering, and the energy budget of a snowpack over the course of a winter (Bartelt & Lehning, 2002; Lehning et al., 2002).

We drove SLF-SNOWPACK using observations of air temperature, relative humidity, wind speed, incoming short and longwave radiation, precipitation, air pressure, snow depth, and ground surface temperature. We provided SLF-SNOWPACK with land surface characteristics including LAI, canopy throughfall of snow, and canopy height (Frank et al., 2019, 2021).

SLF-SNOWPACK simulates a number of snow processes including cold content storage flux, meltwater storage flux, and meltwater discharge flux, which we hypothesized comprise the unobserved signal in the springtime energy imbalance Equation 3. We numerically optimized any fixed parameters we did not have direct measurements for or to which we suspected the model may have been sensitive (LAI, direct canopy throughfall, and canopy height) by training it to match observations of the snow temperature profile. We also loosely evaluated model predictions by comparing SLF-SNOWPACK-simulated SWE to SWE measurements at the nearby Brooklyn Lake SNOTEL site. However, since the Brooklyn Lake SNOTEL site lies 900 m SE of the US-GLE tower and outside of its flux footprint (Figure 1), we did not use SNOTEL measurements in our optimization procedure, only as a loose reference point to make sure that final, predicted SWE values were not radically different from nearby measurements.

To minimize the compute time associated with running SLF-SNOWPACK, we used an alternative data assimilation method to the more common Markov Chain Monte Carlo (MCMC) or gradient descent methods. Such methods may require hundreds or thousands of model iterations to converge, amounting to several days of compute time. To address this, we employed a surrogate optimization approach to efficiently calibrate SLF-SNOWPACK. Instead of directly searching for the global minimum of the objective function (in this case, the $-R^2$ of SLF-SNOWPACK's simulated vs. observed snow temperatures as a function of LAI, canopy height, and direct canopy throughfall), surrogate optimization first constructs a computationally inexpensive machine learning model that approximates the true objective function (called an *emulator*). The emulator can then be optimized much more quickly using gradient descent to identify the parameter set that minimizes the approximate objective function.

Similar to Lee et al. (2011), we chose to use a Gaussian Process Regressor (GPR) as the surrogate model. GPRs are well-suited for this task because they provide a Bayesian posterior distribution as output, including both the predicted mean and uncertainty of their predictions (Wang, 2023). This property allows GPRs to make confident predictions even with limited training data. We trained our GPR to predict the quality of SLF-SNOWPACK's outputs ($-R^2$ of observed vs. modeled snow temperature) as a function of LAI, direct canopy throughfall, and canopy height parameters using results from 15 SLF-SNOWPACK simulations as training data. We took the parameter values found by the emulator to minimize the predicted $-R^2$ of SLF-SNOWPACK and used them to run SLF-SNOWPACK a final time to generate modeled snow temperature and MWI.

We implemented the emulator in scikit-learn (Pedregosa et al., 2011) and chose optimal parameter values by minimizing the approximate objective function it produced using gradient-based optimization in SciPy (Virtanen et al., 2020). LAI and canopy height measurements are available for US-GLE (Frank et al., 2021); however, process uncertainty in the SLF-SNOWPACK canopy model led to inaccurate snowpack temperature predictions when using them directly. Consequently, we treated LAI and canopy height as tunable parameters, with observational data providing bounds.

2.4. Statistical Methods

To evaluate the performance of our energy budget residual method against our snowpack model, we performed an ordinary linear regression between springtime values for $I_{\text{obs}} + \varepsilon'$ and $\lambda \text{MWI} - S_{\text{CC}}$. Additionally, we compared the residual structure of springtime ε' both with and without modeled snowmelt to summer and wintertime ε' using a Kolmogorov-Smirnov test.

To investigate the accuracy of this approach at multiple timescales, we repeated this analysis for energy budgets block-averaged at intervals of 0.5, 1, 2, 3, 4, 6, 12, and 24 hr, and at intervals of 2–10 days.

2.5. Computational Tools

We implemented all post-processing, numerical, statistical, and visualization methods in Python v3.11.13 with NumPy v1.24.3 (Harris et al., 2020), SciPy v1.10.1 (Virtanen et al., 2020), Pandas v2.0.2 (McKinney, 2010),

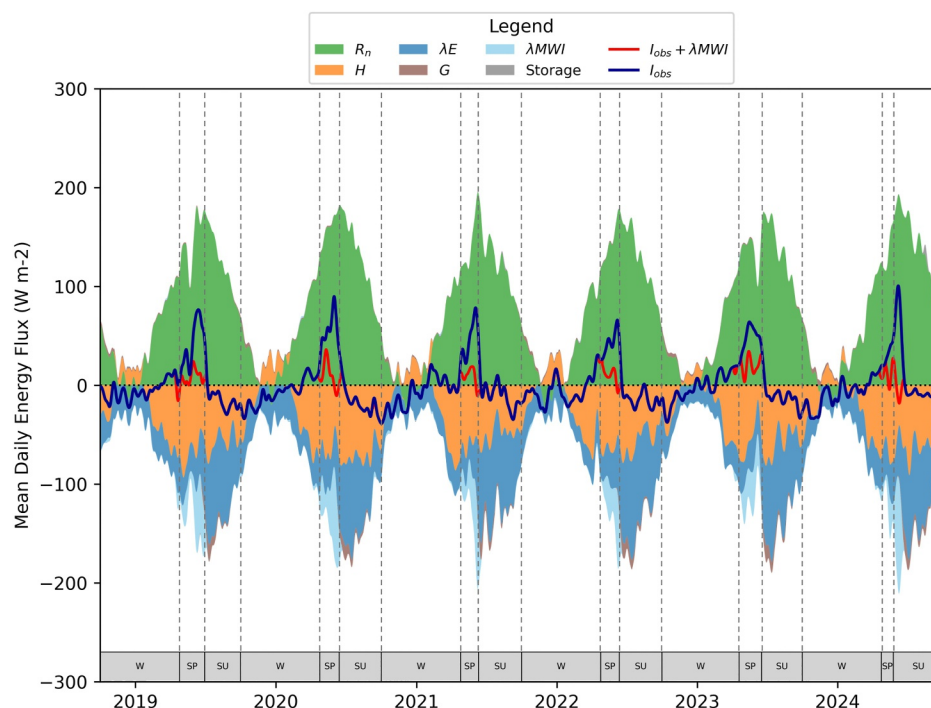


Figure 2. Timeseries of the energy budget at US-GLE, smoothed with a 14 days running Hann window for legibility. The shaded regions represent a decomposition of the energy budget (R_n : net radiation, G : ground heat flux, λE : turbulent latent heat flux, H : turbulent sensible heat flux, λMWI : latent heat flux of meltwater inputs). The thickness of each shaded region represents the magnitude of that flux. The dark blue line represents the observed energy imbalance (I_{obs}). The red line represents the energy imbalance when considering meltwater inputs ($I_{obs} + \lambda M$). The gray bar at the bottom indicates the season (W: winter, SP: spring, SU: summer) and the vertical gridlines indicate the season boundaries.

SolarPy v0.1.3 (AeroPython Team, 2019), Matplotlib v3.7.1 (Hunter, 2007), scikit-learn v1.2.2 (Pedregosa et al., 2011), and scikit-optimize v0.10.2 (The scikit-optimize developers, 2025).

During the preparation of this work the authors used Perplexity (Perplexity AI, San Francisco, CA) and ChatGPT (OpenAI, San Francisco, CA) to help conduct literature review, organize manuscript structure, and suggest edits to improve the clarity of existing writing. After using these tools the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

3. Results

3.1. Direct Observations at US-GLE

At US-GLE, when computed with a 2-week running mean, the observed energy budget imbalance slides between -30 and $+100 \text{ W m}^{-2}$ over the course of a year, with a strong positive (toward the ground surface) imbalance between March and July and a slight negative imbalance between August and February (Figure 2). Between March and November, the energy budget is dominated by R_n , which is the primary source of energy input to the ecosystem during that time: H , λE , and G are all negative during this time. During the winter between December and March, the energy imbalance is slightly negative or zero, with R_n , H , and λE alternating signs and rarely exceeding 50 W m^{-2} . During this time, G is consistently positive and near zero, slowly adding energy to the snowpack, rarely exceeding 10 W m^{-2} . Between March and July, λE appears to be suppressed, rarely exceeding 50 W m^{-2} until suddenly rebounding along with G in mid-late July.

3.2. Modeled Snowpack Energy

Snow depth peaked between March 15 and April 15 each year, while modeled SWE peaked between April 15 and May 1. Measurements of the snowpack temperature profile show that the snowpack typically reached isothermal status between April 5 and April 15. The final day of snowmelt as measured by a snow depth sensor typically

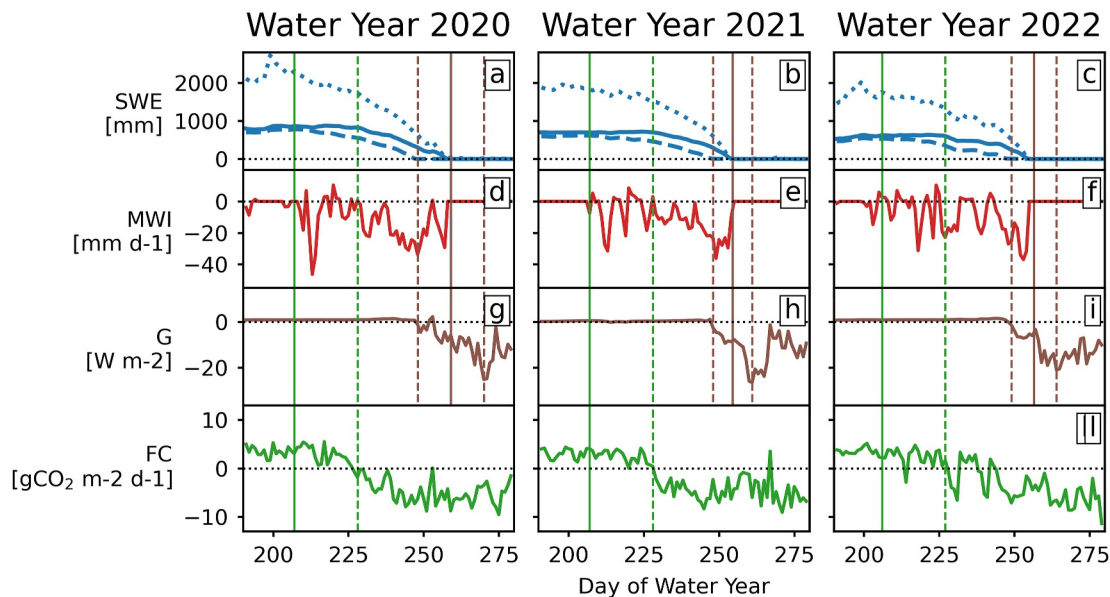


Figure 3. Results from the spring snowmelt season identification heuristic for three example water years (WY2020–2022). (a–c) Measured snow depth (dotted) and modeled snow water equivalent (solid) at US-GLE and measured snow water equivalent (dashed) at Brooklyn Lake SNOTEL. (d–f) Daily meltwater input (MWI) computed by SLF-SNOWPACK. (g–i) Observed daily mean ground heat flux (G). (j–l) Observed daily carbon flux (FC). Solid vertical lines mark the starts of spring (green) and summer (brown) as identified by the heuristic (Equations 8 and 9). The dashed green line indicates the first date of net carbon uptake (21 days after spring onset). Dashed brown lines indicate the first day of negative G and the day of minimum G. The horizontal dashed line marks zero. The arrows serve as a visual aid.

occurred between DOWY 258–274 (Figures 3a–3c). Relative to in situ observations of snow temperature and snow depth, the heuristic identified the onset of snowmelt approximately 5 days earlier. The end of snowmelt was also identified earlier by an average of 5 days, although this bias was strongly influenced by WY2024, during which the heuristic indicated an end date 24 days earlier than observed. Excluding WY2024, the heuristic accurately identified the end of snowmelt to coincide with the observed date (Figure 3).

Through our surrogate optimization method, we found optimal parameters for SLF-SNOWPACK to be $LAI = 1.25$, direct canopy throughfall = 98%, and canopy height = 23.5 m. The GPR surrogate optimizer predicted that the SLF-SNOWPACK model with these parameters would produce snow temperatures having $R^2 \sim \text{Normal}(\mu = 0.77, \sigma = 0.03)$ when compared with observations. The actual R^2 value when using these parameters was $R^2 = 0.74$, within the reported uncertainty of the GPR predictions.

During springtime, modeled λMWI represented a significant portion of the energy budget, equaling up to 25% of the magnitude of the observed energy flux of the landscape during high melt days (Figure 2). Snow depth typically peaked around 2500 mm, and SWE typically peaked around 800 – 900 mm.

3.3. Energy Budget Residual

During the winter and summer, our neural network model for the long-term bias $\bar{\epsilon}$ in the energy imbalance captured the long-term mean of the observed energy imbalance I_{obs} when trained on 6-hour averages of energy flux measurements. As expected, $I_{\text{obs}} - \bar{\epsilon}$ had a strong positive bias in the springtime, where we hypothesized snowmelt to be a major component of the energy budget (Figure 4c). Regressing the observed energy imbalance I_{obs} (Figure 4a, orange shaded region) against $\lambda MWI + \bar{\epsilon}$ (Figure 4a, red dots), we found a good correspondence between the two with a slope of 0.83, an intercept of 15.58 W m^{-2} , and a correlation of $R^2 = 0.58$ (Figure 4b).

To explore the statistical similarity between the snowmelt-corrected energy imbalance in the spring and the observed energy imbalance during the summer and winter (when snowmelt is expected to be insignificant), we compared the observed energy imbalance anomaly ($I_{\text{obs}} - \bar{\epsilon}$) during the summer + winter (a) to the same during the spring (b) and to the same during the spring with the addition of modeled snow energy fluxes (λMWI) (3). According to a Kolmogorov-Smirnov test, the distributions of (a) and (b) differed substantially ($KS = 0.31$,

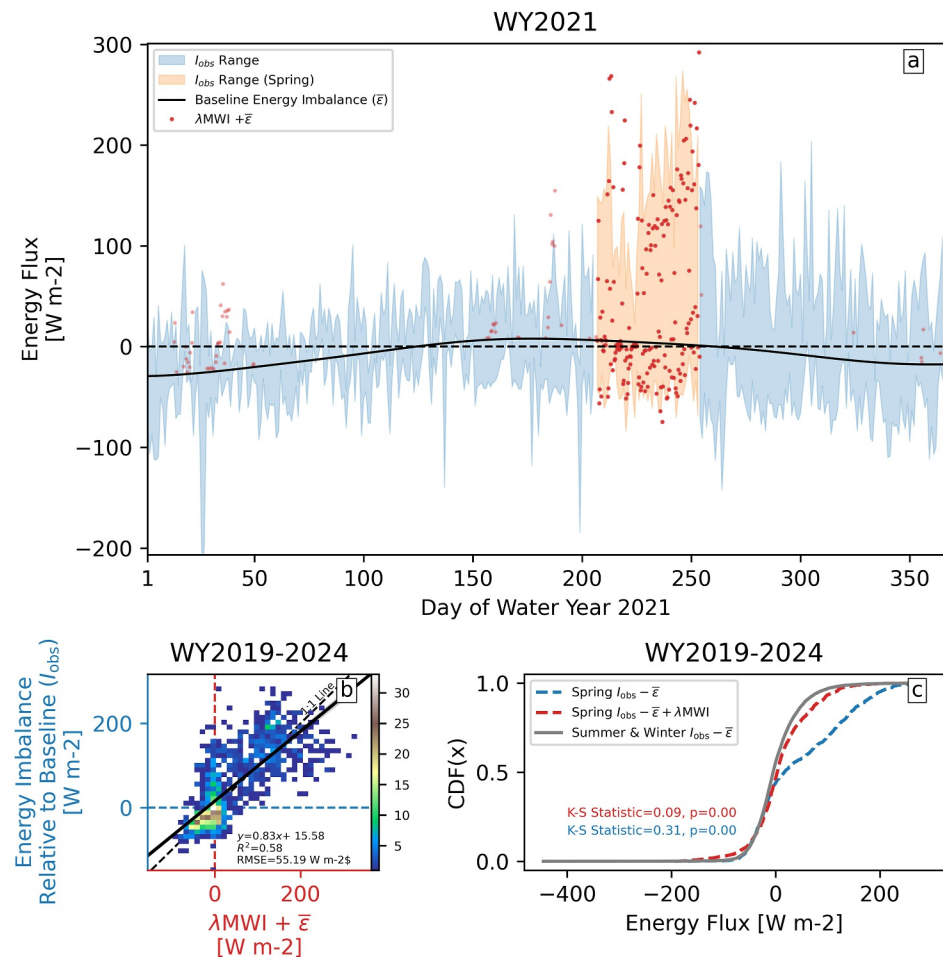


Figure 4. Comparing modeled snowmelt to the energy budget residual. (a) Timeseries data for water year 2021. Shaded regions: daily range of the observed daily energy imbalance I_{obs} during the spring (orange) and the rest of the year (blue). Black line: baseline component of the energy imbalance ($\bar{\epsilon}$). Red dots: modeled snowmelt from SLF-SNOWPACK, added to the baseline imbalance ($\lambda MWI + \bar{\epsilon}$). (b) Heatmap histogram of $\lambda M + \bar{\epsilon}$ versus I_{obs} computed in 6-hour chunks with a regression line (solid black) and a 1:1 line (dotted black) for all available water years (WY2019-2024). Color indicates the number of points in each pixel-bin. (c) Results of the two-sided Kolmogorov-Smirnov (K-S) Test comparing the distributions of $I_{obs} - \bar{\epsilon}$ during the winter and summer (gray) to the same during the spring (blue) and to the same plus modeled meltwater inputs (red) for all available water years (WY2019-2024).

$p < 0.001$). Residuals (a) and (c) were much more similar ($KS = 0.09$) but still significantly different ($p < 0.001$) (4c).

Repeating this analysis with other averaging windows changed our results. Our snowmelt model had the closest relationship with I_{obs} and energy budget residual K-S scores were the lowest when we averaged half-hourly fluxes in blocks of 2–6 hr. However, we observed the tightest correlation with I_{obs} when we used averaging windows exceeding a day (Figure 5).

4. Discussion

4.1. Main Findings

On 6-hour timescales, our snowmelt model predicted 83% of the mean observed springtime energy imbalance anomaly and brought springtime energy balance residuals closer to those observed during the winter and summer (Figures 4b and 4c). This indicates that anomalies in the observed energy imbalance at US-GLE can arise from latent heat flux carried by meltwater input events, and that poor energy budget closure during the springtime at this site is largely explained by snowmelt.

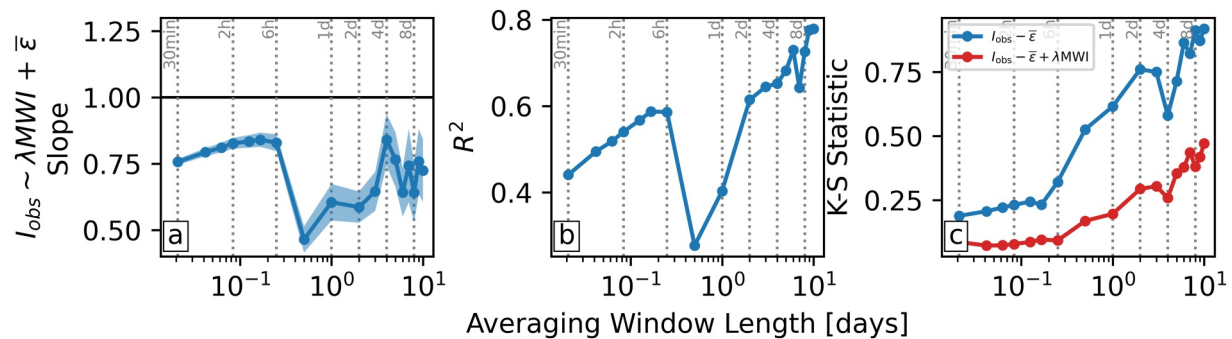


Figure 5. Model performance plotted against averaging window length. (a, b) Model validation slope and R^2 (Figure 4b). Shaded envelope in (a) represents the 89% CI. (c) Statistic of the Kolmogorov-Smirnov test for the modeled snowmelt-corrected (red) and uncorrected (blue) spring energy budget residual.

4.2. Day-to-Day Uncertainty

Our model was able to accurately capture mean trends in the energy imbalance during the springtime (Figure 4b), but was not able to capture all of the statistical variance from the mean (Figure 4c). This is to be expected, since there are a number of stochastic processes that influence energy budget closure that still persist once snowmelt is accounted for (Foken, 2008; Wanner et al., 2022). Accounting for snowmelt processes can remove some of this variance, but our method is fundamentally limited to producing an energy budget with variance ϵ' that is consistent throughout the winter-spring and spring-summer transition, which it succeeds at on timescales shorter than a day.

Our method shows very high agreement at very long timescale (4 days or longer) (Figure 5), but this likely reflects a regression to the mean over long timescales: the springtime only lasts between 6 and 8 weeks at US-GLE, so weekly or longer timescale begin to limit the amount of available data. Nevertheless, this behavior supports our method's ability to accurately capture the total energy required to melt the snowpack on seasonal timescales. Our method also shows very poor agreement at intermediate (24–48 hr) timescales, contrary to what we would expect for a typical eddy covariance site. This behavior could be due to drainage flows from the uniquely complex terrain surrounding US-GLE, leading to energy storage fluxes that do not balance on diurnal cycles (Leuning et al., 2012).

4.3. On the Computation of $\bar{\epsilon}$

In our study, I_{obs} represents observations of the energy imbalance, which we decompose into a physically meaningful hydrologic signal f , a persistent baseline $\bar{\epsilon}$, and short-term stochastic noise ϵ' Equation 2. This decomposition works best with a tightly constrained energy budget in which systematic biases are well-characterized and random fluctuations are minimized. While many environmental variables (e.g., atmospheric stability and surface characteristics) can influence the quality of instrument observations (Burns et al., 2014; Reed et al., 2018; Stoy et al., 2013), we intentionally model $\bar{\epsilon}$ using only time-based features. Our goal is not to predict the energy imbalance as precisely as possible, but to quantify the structure of its residual components after all the observed fluxes have been constrained. Including physically relevant predictors like u^* might improve predictive performance (Anderson & Wang, 2014), but would risk attributing physically meaningful variation in the observed fluxes to the residual effects, masking any observational uncertainty or real signals. Instead, we treat the residual structure as a reflection of any unresolved measurement error, and address known drivers of flux quality at the level of flux processing through filtering (Barr et al., 2013; Lee et al., 2004), gapfilling (Liu et al., 2025), and instrument correction (Burba et al., 2008; Frank, Massman, Swiatek, et al., 2016; Foken et al., 2019; Ibrom et al., 2007; Kaimal, 1978). This approach ensures that any remaining variation in I_{obs} not explained by observed fluxes or snowmelt dynamics can be taken at face value. However, we can and should investigate possible causes of this remaining energy imbalance introduced by our methods.

4.4. Uncertainty in Point Measurements

Our snowpack model introduces some of this unexplained variance. Measurements of snow depth from sonic range finders can be biased by air temperature, local ground/snow surface variability, and internal electronic

processes, and can vary from manual measurements by 1–7 cm depending on conditions (Ryan et al., 2008). Additionally, snow depth can vary wildly across a landscape. The footprint of the US-GLE site consists of wetlands, forest, open meadows, and roads, all of which accumulate and melt snow at different rates (López-Moreno & Stähli, 2008). In particular, snow that persists within the tower footprint but not directly below the snow depth sensor could lead to a significant mismatch between turbulent and non-turbulent measurement footprints (Foken, 2008), and could explain the large spike in the energy budget imbalance that we observe in early summer (Figure 2), when SLF-SNOWPACK predicts the complete ablation of the snowpack. This is evidenced by the mismatch between the date of final melt-out observed at US-GLE and at the Brooklyn Lake SNOTEL site, where the date of final melt-out was offset by up to a week (Figure 3). Future work expanding on our method could address this issue by taking advantage of a fully distributed hydrologic snowmelt model such as Alpine3D (Lehning et al., 2006).

4.5. Uncertainty in SLF-SNOWPACK Predictions

We provided high-quality meteorological driver data to SLF-SNOWPACK (Bartelt & Lehning, 2002; Lehning et al., 2002) consisting of observations of precipitation, net radiation, wind speed, and snow depth. These drivers tightly constrain process uncertainty around snowpack height and accumulation. Additionally, our choice to optimize SLF-SNOWPACK's parameters against observed snow temperature profiles further constrains how the model simulates internal heat fluxes (Viallon-Galinier et al., 2020). While it would have been beneficial to focus our parameterization efforts on additional components such as turbulent fluxes into the snowpack or the snow surface radiation balance, direct measurements of these quantities were unavailable: only above-canopy turbulent fluxes were recorded at US-GLE for the full study period, and the measurement height of 7 m used in sub-canopy observations remains within the canopy and is therefore not representative of fluxes at the snow surface. However, uncertainty remains in SLF-SNOWPACK's predictions. SLF-SNOWPACK reproduced the measured snowpack temperature profile with an R^2 of 0.74 and generally overestimated diurnal internal temperature variance. This limits our confidence in simulated energy fluxes, particularly on sub-daily timescales. Such uncertainties can propagate into errors in the timing and magnitude of melt events, because snow temperature is strongly coupled to the turbulent exchange of latent and sensible heat (Burns et al., 2014). Structural limitations of SLF-SNOWPACK contribute to this uncertainty. As a one-dimensional point model (Lehning et al., 2002), SLF-SNOWPACK does not resolve lateral redistribution processes such as wind-driven transport or small-scale variability in accumulation, for which coupling with a fully distributed model is required (Lehning et al., 2006). Consequently, scaling SLF-SNOWPACK outputs to the scale of a flux tower footprint introduces additional uncertainty into both hydrological flux predictions and the representation of snowpack energy dynamics.

4.6. Other Energy Budget Uncertainties

Additionally, there are processes inherent to the observed portion of the energy budget that can contribute to random uncertainty, which our method can never account for. These processes include slow convergence of turbulence statistics (Wyngaard, 2010), footprint mismatch (Foken, 2008), and advective fluxes and large scale circulations (Mather, 2024; Wanner et al., 2022). However, these factors should not behave differently in the springtime than they do in the summer. Atmospheric stability at US-GLE is close to neutral year-round (Frank et al., 2019).

However, there are specific concerns regarding energy flux measurements over isothermal snowpacks. During the springtime, the snowpack surface never exceeds 0°C, while the air temperature is usually above freezing. This establishes a strong temperature gradient in a thin, highly stable surface layer above the snowpack, typically under 20 cm in height (Cox, Adler, et al., 2025). This stable layer can lead to flux divergence in upwelling radiation (Garratt & Brost, 1981; Helgason & Pomeroy, 2012). However, this effect is small except in the most extreme cases, and is expected to remain under 20 W m^{-2} (Hoch, 2025). Additionally, above-canopy longwave radiation sensors capture canopy thermal radiation as well as ground surface radiation, further decreasing this effect. However, this consistent underestimation of R_n may introduce a slight positive bias in our results. Additionally, this stability results in a cool layer of air that is only occasionally refreshed by surface renewal processes, rather than by the usual turbulent processes expected by the eddy covariance technique (Cox, Adler, et al., 2025). This

process can be accurately measured through eddy covariance; however its behavior may be different when atmospheric turbulence is low, introducing potential uncertainty into gap-filled data from low-turbulence time periods. Given that atmospheric conditions at US-GLE are often sufficiently turbulent (92% of half-hourly blocks were above the $u^* = 0.2$ m/s threshold), we believe that this effect is relatively minor.

4.7. Identifying the Start and End of Snowmelt

One challenge of this approach is properly identifying when snowpack ripening begins and when final meltout ends, since those two dates are needed to determine the start and end of springtime in the absence of direct snow observations. In our method, we used the first day of net carbon uptake (around May 15 at US-GLE) to mark the beginning of snowmelt ripening (Monson et al., 2005) and a day halfway between the first day of downward heat flux (around June 15 at US-GLE) and the date of maximum downward ground heat flux (around July 7 at US-GLE) to mark the date of final meltout (Bowling et al., 2024) (Equations 8 and 9). Our heuristic for the end of snowmelt correctly identified the final day of melt-out in all years except WY2024, where it was 24 days early. We attribute this to a short-lived melt-out event that temporarily uncovered one of the five soil heat flux pits at US-GLE on 24 May 2024, causing a spike in downward heat flux at that sensor, while the rest of the sensors remained covered by snow (Figure 3). This behavior further highlights the problems associated with point measurements of snow properties.

While these heuristics work very well at a site like US-GLE with a reliable, persistent winter snowpack, they are less transferable to sites with intermittent winter snowpacks. Evergreen forests with snowpacks that disappear and reappear over the course of a winter can have year-round photosynthesis (Biederman et al., 2017), invalidating the method from Bowling et al. (2024). Additionally, the time required for the snowpack and soil column to reach thermal equilibrium may be longer than the time it takes for the snowpack to accumulate and then ablate. This asynchrony would lead to similar errors as those introduced by time lag in heat fluxes between different soil layers as in Massman (1992). Under these alternative conditions, our heuristics for the start and end of the snowmelt period will be unreliable.

4.8. Seasonal Variation of the Energy Budget

In this study, we identified one contribution (snowmelt) to seasonal variations in the surface energy budget. However, in addition to real hydrologic processes, seasonal variations in energy budget closure have been shown to represent outside factors, such as measurement error: outside of the tropics, the dominance of net radiation over other energy budget terms in the summer gives rise to the same predictable sinusoidal behavior that we observe here (Figure 2), stemming from measurement biases between net radiation and other energy budget terms (Reed et al., 2018). In the tropics, variation in net radiation is less important, but the relative contributions of latent and sensible heat flux still change seasonally between wet and dry seasons, leading to predictable seasonal variations in energy budget closure, stemming from different measurement biases between sensible and latent heat flux measurements (Gerken et al., 2018). Surface flux sites consistently underestimate the magnitude of turbulent fluxes (Stoy et al., 2013), making them the main sources of error responsible for energy budget imbalances during the winter, when they dominate over net radiation. Calibration drifts, thermal effects, dome contamination, and installation errors affect the magnitude of net radiation measurements, making them the main sources of error responsible for energy budget imbalances during the summertime, when net radiation dominates the energy budget (Meloni et al., 2024). Further work could leverage the seasonal shifts in the dominance of H , λE , and R_n over and their relative measurement biases to further constrain the surface energy budget in long-term flux observations.

4.9. Benefits of This Approach

Obtaining a tightly constrained surface energy budget at flux sites is difficult, considering the wide range of possible errors and uncertainties present in every measurement. Solving the problem of reducing the energy imbalance to zero, dubbed the “energy budget closure problem,” is therefore extremely difficult. However, this analysis does not require a completely closed energy budget. Instead, it requires a highly constrained and precise energy budget: so long as the random uncertainty in the energy budget is minimized, the energy budget can be highly imbalanced and this analysis method will still work. The broad applicability of this approach means that future work could direct this method to constrain the energy budget and quantify meltwater inputs across multiple

sites and years of data, helping to build confidence in past and future observations and helping to quantify snowmelt processes across the Rocky Mountains.

Additionally, applications for this method are not limited to snowmelt processes. Any unobserved hydrologic flux that is coupled to the surface energy budget and exhibits seasonal structure distinguishable from a baseline could be isolated using this framework Equation 2. For example, Reed et al. (2018) identified that seasonal variations in surface water discharge in a temperate wetland produce interpretable anomalies in the surface energy imbalance, and proposed that a residual-based approach like ours could be used to characterize them. In arctic and subarctic climates, Wang et al. (2021) documented that seasonal soil freeze-thaw cycles generate latent heat exchanges within the soil column that produce seasonal anomalies in the surface energy budget—a signal structurally analogous to the snowmelt flux studied here. Whether our method can be applied to a given ecosystem will depend on local data availability and the dominant hydrologic processes at play, but the range of potential applications extends well beyond snowpack processes.

4.10. MWI and Runoff

Our model does not directly predict total runoff from the snowpack; rather, it resolves energy fluxes within the snowpack and between the snow and ground surface. In the spring, these fluxes drive the timing and magnitude of meltwater inputs to the soil. Since MWI represents the immediate liquid water supply to the ecosystem, it drives all subsequent hydrologic processes within a landscape. In many snow-dominated systems, especially in semi-arid mountain regions, the timing and rate of MWI are more critical to ecological and hydrological outcomes than total seasonal melt volume (Westerling, 2016). Rapid MWI events can saturate soils, trigger infiltration-excess runoff (Wilcox et al., 1997), elevate peak and base streamflow (Barnhart et al., 2016), accelerate seasonal evapotranspiration (Webb et al., 2024), and promote plant growth (Westerling, 2016).

By directly predicting a high-resolution MWI timeseries, our method enables new ways to drive ecosystem, streamflow, and groundwater models sensitive to direct soil water inputs. This capacity to resolve the temporal structure of meltwater delivery into the soil offers a pathway toward more mechanistic predictions of how mountain hydrology responds to climate change. The multi-year record at US-GLE enables a longer-term perspective on MWI variability. Expanding our method to the full historical record at US-GLE and to other flux tower sites in the Rocky Mountains would allow for a regional analysis of the intensity of meltwater inputs throughout the region, linking them to ecosystem processes and complementing existing evidence from streamflow and snowpack records that show systematic trends toward earlier snowmelt onset and reduced late-season water availability under a warming climate (Stewart et al., 2004). This capacity to resolve the temporal structure of meltwater delivery into the soil and directly link it to ecosystem processes offers a pathway toward more mechanistic predictions of how mountain hydrology responds to climate change.

5. Conclusions

These findings demonstrate that the springtime energy imbalance at snow-dominated flux sites serves as a useful proxy for snowmelt processes, even in the absence of direct snowpack or runoff measurements. By leveraging predictable seasonal patterns in the observed surface energy imbalance, we were able to estimate the magnitude and temporal behavior of the snowpack energy budget and meltwater fluxes. This approach provides a novel framework for tracking snowmelt dynamics in snow-dominated environments such as alpine, glacial, and arctic landscapes, improves the hydrologic utility of surface flux monitoring sites, and highlights how the perceived errors in surface flux measurements may actually contain useful hydrologic signals, and should not be ignored.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The data and scripts needed to reproduce the analyses and figures in this study are available through the AmeriFlux Network (Frank et al., 2021) at DOI:10.17190/AMF/1246056 and GitHub: <https://github.com/alextsfox/Snow-chapter-2025/releases/tag/WRR-Final>.

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