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Key Points:

- Winter snow duration, depth, and fractional cover in a boreal peatland is extremely sensitive to warming, especially above +4.5°C
- Warming-driven reductions in winter snowpack result in more frequent soil freeze-thaw cycles
- The snow-albedo feedback effect is estimated to increase maximum daily air temperature by $0.077 \pm 0.010^\circ\text{C}$ per $\text{MJ m}^{-2} \text{d}^{-1}$

Supporting Information:

Supporting Information may be found in the online version of this article.

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Experimental Whole-Ecosystem Warming Enables Novel Estimation of Snow Cover and Depth Sensitivities to Temperature, and Quantification of the Snow-Albedo Feedback Effect

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Abstract Climate change is reducing the amount, duration, and extent of snow across high-latitude ecosystems. But, in landscapes where persistent winter snow cover develops, experimental platforms to specifically investigate interactions between warming and changes in snowpack, and impacts on ecosystem processes, have been lacking. We leveraged a whole-ecosystem warming experiment in a boreal peatland forest to quantify how snow duration, depth, and fractional cover vary with warming of up to +9°C. We found that every snow-related quantity we examined declined precipitously as the amount of warming increased. The importance of deep, continuous snow cover for moderating shallow soil temperature is highlighted by an increase in soil temperature variance and the frequency of short-duration freeze-thaw cycles in the warmer plots. We used a paired-plot approach to estimate the magnitude of the snow-albedo feedback effect, and demonstrate that albedo-driven warming linked to reduced snow cover varies between December (+0.4°C increase in maximum air temperature) and March (+1.2°C increase) because of differences in insolation. Overall, results show that even modest future warming will have profound impacts on northern winters and cold-season ecosystem processes. Plot-level data from this warming experiment, and emergent relationships between warming and quantities related to snow cover and duration, could be of enormous value for testing and improving the representation of snow processes in simulation models, especially under future climate scenarios that are outside of the range of historically observed variability.

Plain Language Summary Climate change is reducing the winter snowpack in many northern ecosystems, but disentangling changes in winter precipitation from concurrent winter warming is challenging. We used data from an already-established ecosystem warming experiment to look at relationships between warming (up to +9°C) and changes in snow duration, depth, and fractional cover. Even modest levels of warming had severe negative impacts on each snow-related quantity we investigated. For example, warming of just +2°C was sufficient to reduce the number of winter days with a 5 cm snowpack by about 50%. Reductions in snow cover will have feedback effects on local winter climate because more shrub-covered ground reflects less solar energy than snow-covered ground. We estimate that because of this so-called “snow-albedo feedback,” maximum daytime air temperature will be elevated by up to about 1°C above snow-free ground, compared to snow-covered ground. Our results show how future warming, at levels consistent with IPCC projections, will result in transformative changes to the winter season in boreal peatlands, with impacts on how these ecosystems function, and how they impact the climate system.

1. Introduction

Historically, continuous and deep snow cover has been a defining characteristic of winter in many northern ecosystems. Snow is important in the context of ecosystem function, hydrology, human society, and climate system feedbacks (Callaghan et al., 2011; Lemke et al., 2007; Siirila-Woodburn et al., 2021; Thackeray

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et al., 2019). For example, snow is an insulator, protecting both vegetation and soils from extreme cold (Verry, 1991), thereby reducing mortality of leaves and fine roots, and influencing soil carbon dioxide (CO₂) and other biogeochemical fluxes. Snowmelt is typically the driving force behind springtime river discharge in snowy ecosystems. The volume of snowmelt influences nutrient and dissolved organic matter export (Sebestyen et al., 2008), as well as soil water content and water table depth. Importantly, snowmelt recharges storage water and influences plant-water availability into the growing season (Jones et al., 2023). As a source of water for drinking, irrigation, and hydroelectricity, snow is a critical economic resource; it is also vitally important for winter tourism in many regions and countries. Finally, snow plays a key role in regulating land surface feedbacks to the climate system because its high albedo has a strong cooling effect (the “snow-albedo feedback”; Lemke et al., 2007; Thackeray et al., 2019).

Rising global temperatures and altered precipitation regimes are resulting in less snowfall, with more winter precipitation falling as rain, faster rates of melting, and shorter duration of snow cover in many ecosystems (Berghuijs et al., 2014; Huntington, 2006). The rising trend in near surface air temperature is considered the dominant factor (Thackeray et al., 2019), and decreases in snow cover have been observed even in locations where wintertime precipitation is increasing (Lemke et al., 2007). Overall, springtime snow cover across the northern hemisphere is decreasing by about 2% per decade since the 1960s. These trends are observed at a range of scales from regional to hemispherical, although the spatial patterns are variable and there is some variation in trends across different observational data sets (Croce et al., 2018; Dahe et al., 2006; Groisman et al., 1994; Lemke et al., 2007; Mudryk et al., 2017; Nicholls, 2005; Thackeray et al., 2019; Vorkauf et al., 2021). But, some studies have suggested that future rates of snowmelt may be reduced as the snowmelt season shifts earlier in the year, when there is less available energy (Musselman et al., 2017).

Modeling analyses to estimate future changes in snow cover and duration are highly uncertain (Derksen & Brown, 2012; Krinner et al., 2018; Van Den Hurk et al., 2016; Zaremehrijardy et al., 2021). Poor model performance has been attributed to numerous uncertainties in model parameterization and structure. Unfortunately, high-quality site-level data on snow depth and cover are surprisingly rare, leading to few opportunities to test models against direct observations. And, remote sensing data are not much help because of tradeoffs between spatial (30 m–1 km) and temporal resolution (days–weeks) of the remotely sensed products, in comparison to the fine spatial (1–10 m) and temporal (hours–days) scales at which rapid change and heterogeneity in snow cover can occur. Thus, existing ground observations and satellite data offer limited potential for improving the model representation of the complex physics of snow processes.

Sanders-DeMott and Templer (2017) have argued that more experimental studies are needed to understand interactions between warming, changes in the depth and duration of snowpack, and associated ecosystem impacts. But, for over two decades, ecosystem warming experiments have been conducted using a variety of methods (Aronson & McNulty, 2009; Hanson & Walker, 2020). Our over-arching hypothesis is that some of these—fortuitously, even when not designed with a focus on winter or snow—could yield new and important insights into the effects of warming on different quantities related to snowpack, and provide data that may be valuable for evaluating snow processes in simulation models. Specifically, as climate change pushes systems outside the envelope of historical variability, data on snow cover, depth, and duration from these manipulative warming experiments might serve as valuable model constraints or validation data.

SPRUCE (“Spruce and Peatland Responses Under Changing Environments”), a long-term, multi-factor manipulative experiment situated in a boreal peatland forest in the Upper Midwest of the United States (Hanson et al., 2017) is one example. SPRUCE combines year-round whole-ecosystem warming treatments of up to +9°C with ambient and elevated CO₂ treatments in a regression-based experimental design. While most of the emphasis of SPRUCE research has been on biogeochemical responses to warming and CO₂ (Curtinrich et al., 2022; Hanson et al., 2020; Hopple et al., 2020; Iversen et al., 2023; Malhotra et al., 2020; Richardson, Hufkens, Milliman, Aubrecht, Furze, et al., 2018; Wilson et al., 2021) digital camera imagery collected within each experimental plot permits quantification of snow depth, fractional snow cover, and snow cover duration in relation to warming.

Field experiments exploring the response of snow characteristics to manipulated air temperature are scarce (Sanders-DeMott & Templer, 2017) and generally limited to short-stature ecosystems where experimental temperature manipulation is more feasible. Modeling experiments are more abundant, and tend to report fairly dramatic changes in snow water equivalent with climate warming (Räsänen & Eklund, 2012; Steger et al., 2013),

though intermodel variability can be quite large. Moreover, these studies do not often describe changes in snow depth and snow cover, despite the fact that these two variables impact ecosystem function in different ways (e.g., snow depth regulates soil temperature, snow cover regulates albedo and associated feedbacks with temperature). Based on the limited amount of available information, we expect that snow cover and snow depth will decrease non-linearly with increasing air temperature (e.g., more rapid declines when air temperature is especially high). However, to our knowledge, the SPRUCE experiment is the first experiment to permit quantification of ecosystem-scale responses of snow cover and depth to gradients in air temperature.

Using data from the first 6 y of the SPRUCE experiment (2015–2021), we asked the following questions:

- (1) What are the relationships between ecosystem warming and the amount and duration of snow cover?
- (2) How do changes in snow cover impact soil temperature, and the amount and depth of soil freezing?
- (3) How do changes in snow cover impact soil moisture in winter and spring?
- (4) What are the impacts of changes in snow cover on surface energy balance and albedo, and can we estimate the magnitude of snow-albedo feedback effects on temperature?

Our data show that the most dramatic effects of warming on snow cover and depth will occur immediately, with any further warming above ambient—there is no “safety margin.” Indeed, the observed relationships tend to flatten only at warmer temperatures, when snow cover has already virtually disappeared. We discuss key implications for plants and soils, feedbacks to the climate system, and the potential for testing and improvement of snow processes in complex earth system models.

2. Materials and Methods

2.1. Study Site and Experimental Design

The SPRUCE experiment is located within the S1 bog at the Marcell Experimental Forest (47° 30.171' N, 93° 28.970' W) (Kolka et al., 2011), approximately 40 km north of Grand Rapids in north-central Minnesota, USA. The climate (Sebestyen, Lany, et al., 2021) is subhumid continental: mean annual temperature (1961–2019) is 3.5°C, mean annual precipitation is 787 ± 104 mm (mean $\pm$ 1 SD), and extreme temperatures range from -46°C to $+38^{\circ}\text{C}$ (Sebestyen et al., 2011).

The S1 bog is an ombrotrophic peatland with a perched water table (Verry et al., 2011), with trees approximately 5–8 m in height. The open canopy is dominated by *Picea mariana* (Mill.) B.S.P. (black spruce), with additional contributions from *Larix laricina* (Du Roi) K. Koch (eastern tamarack or larch). The understory is dominated by the evergreen shrubs *Rhododendron groenlandicum* (Oeder) Kron and Judd (Labrador tea) and *Chamaedaphne calyculata* (L.) Moench (leatherleaf), and a bryophyte layer dominated by *Sphagnum* spp.

SPRUCE experimental temperature (0 to $+9^{\circ}\text{C}$, in 2.25°C increments for both air and deep soil) and CO_2 (ambient and elevated) treatments are being applied through the use of large (approximately 12 m wide, 8 m high) open-topped octagonal enclosures. Forced-air blowers distribute heated air efficiently throughout each enclosure, and soil warming at a depth of 2 m is achieved through low-wattage resistance heaters (Hanson et al., 2017). The five temperature treatments are crossed with two CO_2 treatments, yielding 10 enclosures (the CO_2 treatments are turned off during the dormant season, and CO_2 as a factor is not considered further in this analysis). Each enclosure is hydrologically isolated from the rest of the bog by a sheet pile corral, driven 3–4 m through the peat into the underlying ancient lake sediments. Outflow pipes allow for lateral drainage from each enclosure (Sebestyen & Griffiths, 2016). Warming of the deep soil began in June 2014, while aboveground warming was initiated in August 2015. Two “reference” plots (ambient conditions, without constructed enclosures), tend to run about 1.6°C cooler than the “control” plots (constructed enclosures, but no added warming), but this temperature differential is dependent on radiation inputs and snow cover. Data from both reference and control plots are included in the analysis here.

The enclosure design, detailed performance metrics for the above- and below-ground warming, are assessed by Hanson et al. (2017); potential limitations include the effects of warming treatments on vapor pressure deficit, as well as impacts of the enclosures on longwave energy balance and precipitation inputs. Observed temperature differentials in the warmed enclosures have been consistent with the nominal warming targets (generally to within 0.5°C). These differentials have been sustained over time and are similar during the December–March winter

season and the rest of the year. Here, temperature treatments are expressed as realized temperature differentials, relative to the mean of the two control plots (Table S1 in Supporting Information S1).

2.2. Digital Camera Imagery

Beginning in August 2015, we installed digital cameras, or “phenocams” (Brown et al., 2016; Richardson, 2019), at a height of 6 m within each enclosure (“whole-plot cameras”), to observe the progression of the experiment over its planned 10 y course, and to track phenological responses of the two tree species, and the shrub layer, to warming (Richardson, Hufkens, Milliman, Aubrecht, Furze, et al., 2018). In November 2017, a second set of cameras was installed in all plots at a height of 1.5 m with a more limited field of view focused on the shrub layer (“shrubs layer cameras”). These cameras were used to observe shrub layer phenology, and to monitor snow cover and snow depth.

Cameras (NetCam model SD130BN, StarDot Technologies, Buena Park, CA) were configured and installed following standard protocols of the PhenoCam network (Richardson, Hufkens, Milliman, Aubrecht, Chen, et al., 2018). Minimally compressed JPEG images are uploaded every 30 min via FTP (file transfer protocol) to the PhenoCam server; a local copy is also maintained on a server at SPRUCE. The filename of every image identifies the enclosure in which the picture was recorded, as well as a date and time stamp in local standard time. Imagery is posted and publicly available in near-real time on the PhenoCam page (<https://phenocam.nau.edu/webcam/network/search/?group=spruce>).

2.3. Snow Detection

Previous studies have identified snow in PhenoCam images using subjective (visual assessment by a human observer; Kosmala et al., 2018; Seyednasrollah et al., 2021) and automated (deep learning; Bowling et al., 2018; Kosmala et al., 2018) methods. Fractional snow cover has also been estimated using indices based on the blue band and monochrome VIS + NIR band (Caparó Bellido & Rundquist, 2021). Here, we used visual methods to judge snow presence and depth, and a simple image processing routine based on pixel-level distance from white to estimate fractional cover.

To quantify the *presence* of snow, we visually examined mid-day images (August 2015 through May 2021) from each whole-plot camera to evaluate whether there was snow on the ground. As a lower limit, “snow on ground” was detected when more than $\approx 10\%$ of the ground area was covered by snow. The end-of-winter “snowmelt” date was identified as the last day with visually detectable snow on the ground until the following autumn.

To quantify *snow depth*, we visually examined each mid-day image from each shrub layer camera and assessed the depth of snow, to the nearest 5 cm, using the depth gauge (Part SI45780, SI Manufacturing, Newmarket, Ontario, Canada) within each camera’s field of view. Depth gauges were installed in late November 2019. To generate complete data for winter 2019–2020, depths were visually estimated without a gauge for October and early November 2019 when there was relatively little snow, especially in the warmed plots. For validation of this method, see Figure S1 in Supporting Information S1.

To quantify *fractional snow cover*, we computed the RGB (red, green, and blue color channels) sample variance, s^2 , or each pixel in the image:

$$\mu_{DN} = \frac{(R_{DN} + G_{DN} + B_{DN})}{3} \quad (1)$$

$$s^2 = \frac{1}{2} \times \left((R_{DN} - \mu_{DN})^2 + (G_{DN} - \mu_{DN})^2 + (B_{DN} - \mu_{DN})^2 \right) \quad (2)$$

where DN is the digital number characterizing the intensity of each color channel for each pixel, and μ is the mean DN across all three channels. This variance is a measure of the distance from white/gray, which is defined as an equal mix of each channel. We used four images per day (13:30, 14:00, 14:30, 15:00 hr), which were stacked. We then calculated the pixel-mean DN for each color channel, resulting in a single “daily mean” image. The stacked image was created to mitigate the effects of over- (saturated) or under-exposed (dark) pixels, for which the RGB signature may not be well-characterized. In addition to the daily average image, we computed the local DN range as $\max(\mu_{DN}) - \min(\mu_{DN})$ across a moving 3×3 pixel window centered on the pixel of interest, and then used these

windows to calculate the average range across each image. The local DN range is an expression of image homogeneity; a low local DN range tended to indicate a higher likelihood of snow in the image. Finally, the camera's internal temperature (typically elevated by 20–30°C above ambient) was used as an additional filter; when the camera temperature was above a threshold value, the likelihood of snow was low and the maximum distance from what would still be classified as snow was reduced. The threshold temperature was parameterized based on a correlation analysis between camera temperature and a visual inspection of the snow classification performance across the studied sites. The *Snowgreen* MATLAB code to conduct this analysis is publicly available (Westergaard-Nielsen, 2024; <https://zenodo.org/records/10677903>).

2.4. On-Site Environmental Data

We measured air temperature and relative humidity (HUMICAP, model HMP-155, Vaisala, Vantaa, Finland) at 2 m above the peat surface within each plot (three replicate sensors), and recorded 30-min mean values. Likewise, we recorded peat temperature every 30 min across three replicate depth profiles from 0 to 200 cm depths. Volumetric water content (model 10HS Moisture Sensor, Meter Group, Pullman WA, USA) was measured across three replicate locations at +20 cm height above hollows (laterally inserted into the hummocks) or from 0 to –20 cm depth vertically down into the hollows. Due to large differences in peat bulk density that confound water content sensor response due to air gaps (primarily in the hummocks), the measurements were standardized by placing the moisture sensors into peat-packed mesh cylinders of known bulk density (0.1 g cm^{-3}), thus providing a consistent, relative measurement of volumetric water content across the plots. For our analysis we used data from sensors installed vertically into the hollow as these integrate water content in the upper peat and surface layers. Quality-assured SPRUCE environmental data are available through Hanson et al. (2016).

Frost depth (ice thickness) has been measured periodically within hollows in each plot during late winter and spring using an electric drill with a long-shank, 1 cm masonry bit to estimate the distance until resistance to drilling decreased in the underlying unfrozen ground (2.5 cm resolution); this method has been used elsewhere at Marcell Experimental Forest since 2012 (Sebestyen et al., 2021).

2.5. Historical Snowpack and Precipitation Data

Snowpack depth and snow water equivalent have been surveyed at Marcell Experimental Forest since 1962 (Sebestyen, Verry, et al., 2021a). Since 1983, 10 replicate snow courses (10 measurement points per course), spanning a range of cover types, have been surveyed consistently. Snow depth was measured using a Mount Rose (Federal) Snow Tube (2.5 cm resolution). The mass difference between an empty and full snow tube was used to determine snow water equivalent. Measurements every 2 weeks were begun in February when the snowpack was typically deepest, and continued through the disappearance of snow, which occurred in March or April. “Snowmelt” was estimated to occur mid-way between the final completed snow survey and the first “skipped” survey 2 weeks later.

There are three long-term meteorological stations in the Marcell Experimental Forest; we used daily precipitation data (measured since 1961) from the South (S2) Met Station (Sebestyen, Verry, et al., 2021b), approximately 1.5 km northwest of the S1 bog where the SPRUCE experiment is situated. A Belfort Universal Recording Precipitation Gauge (chart recorder) was used prior to 2010, when it was replaced with a digital NOAA IV total precipitation gauge (ETI Instrument Systems, Ft. Collins, CO). In winter, antifreeze and oil are added to the receiving bucket for the measurement gauge to melt snow and limit evaporation. The linear correlation of monthly precipitation measured at the South Met Station with monthly precipitation measured since 1962 at the North (S5) Met Station, located approximately 7 km to the north, is $r = 0.97$, suggesting these data should also be representative of the (closer) S1 bog.

These datasets are freely available and described more fully by Sebestyen, Lany, et al. (2021).

2.6. Energy Balance and Climate System Feedbacks

To estimate the impact of warming-driven reductions in snowpack on the surface energy balance, we combined surface albedo ($\alpha = R_g^\uparrow / R_g^\downarrow$, where R_g is the flux of shortwave (global) solar radiation, and the $\uparrow$ and $\downarrow$ symbols denote upwelling and downwelling, respectively) data from the Environmental Monitoring plot together with

phenocam-derived estimates of fractional snow cover. We found that the mean surface albedo during wintertime is about 50% when the shrub layer is snow-covered, but only 10% when there is little or no snow on the ground, leading to a simple linear scaling relationship between fractional snow cover (C) and albedo (α) at time t :

$$\alpha_t = 0.1 + 0.4 \times C_t \quad (3)$$

Using fractional snow cover data from the reference plots and the +9°C plots, we estimated the seasonal course of albedo in each plot from December through March. Albedo estimates were then multiplied by the measured $R_g^{\downarrow}$ (30-min means, W m^{-2} , aggregated to daily values, $\text{MJ m}^{-2} \text{d}^{-1}$) to calculate the impact of reduced snow cover on reflected and (by difference) absorbed shortwave radiation. Daily values were then aggregated over the months of December to March for each winter.

Additionally, we used the paired-plot method of Scherrer et al. (2012) to directly estimate the magnitude of the snow-albedo feedback effect on air temperature. For this, the reference and control plots provide a unique opportunity: while PID (proportional integral derivative) temperature control of the heated plots is designed to maintain a consistent temperature offset from the control plots, no heat is added to the control plots. Differences in energy balance thus drive temperature differences between reference plots (ambient conditions, no constructed enclosures) and control plots. We estimated the magnitude of the snow-albedo effect by considering that control plots are warmer than the reference plots because energy retained by the constructed enclosure warms the air by a (a) fixed amount, as well as (b) a varying amount that is dependent on incident shortwave radiation; which (c) is further increased by a snow-albedo effect that is driven by the difference in snow cover between the control (less snow) and the reference (more snow) plots, but is also dependent on incident radiation.

$$\Delta T_{\text{air}} = \beta_0 + \beta_1 \times R_g^{\text{daily}} + \beta_2 \times (R_g^{\text{daily}} \times \Delta C) + \varepsilon \quad (4)$$

Here, ΔT_{air} is the (positive) difference in air temperature between the control (warmer, because of the enclosure) and the reference (cooler, no enclosure) plots, R_g^{daily} is the daily incident shortwave radiation ($\text{MJ m}^{-2} \text{d}^{-1}$), ΔC is the (negative) difference in fractional snow cover between the control (less snow) and the reference (more snow) plots, and ε is the regression residual. The intercept, β_0 (units of °C), accounts for differences between the reference and control plots that result from (a) while the first multiplicative term, with a slope of β_1 (°C per MJ m^{-2}), accounts for (b). The second multiplicative term, with a slope of β_2 (°C per MJ m^{-2} per unit ΔC ; quantifying the snow-albedo effect) accounts for (c).

To estimate parameters for Equation 4, we used a number of temperature differential metrics: $\Delta T_{\text{air}}^{\text{max}}$ (difference in daily maximum air temperature), $\Delta T_{\text{air}}^{\text{4pm}}$ (difference in air temperature at 4 p.m.), and $\Delta T_{\text{air}}^{\text{range}}$ (difference in daily temperature range, $T_{\text{air}}^{\text{max}} - T_{\text{air}}^{\text{min}}$). We conducted this analysis using data from months when one or both plots had at least some snow cover (October through April), in SAS OnDemand for Academics (<https://welcome.oda.sas.com>).

2.7. Statistical Analysis

To characterize relationships between temperature treatments and the quantities of interest (e.g., mean snow depth, duration of snow cover, etc.), we used linear regression, with the realized temperature differential in each plot (Table S1b in Supporting Information S1) as the explanatory variable. Regression slopes give the temperature sensitivity, for example, change in cm snow depth per 1°C, or change in days with snow cover per 1°C. When relationships were not well-described by a straight line, we used a second- or third-order polynomial. For these nonlinear relationships, the temperature sensitivity changes as a function of temperature and we therefore report the derivative at two or more temperature differentials for illustrative purposes. In all figures with regression lines, the shaded area around each regression line indicates the 95% confidence bands of the best-fit line. Analyses were conducted in Prism v10 (GraphPad Software, Boston MA).

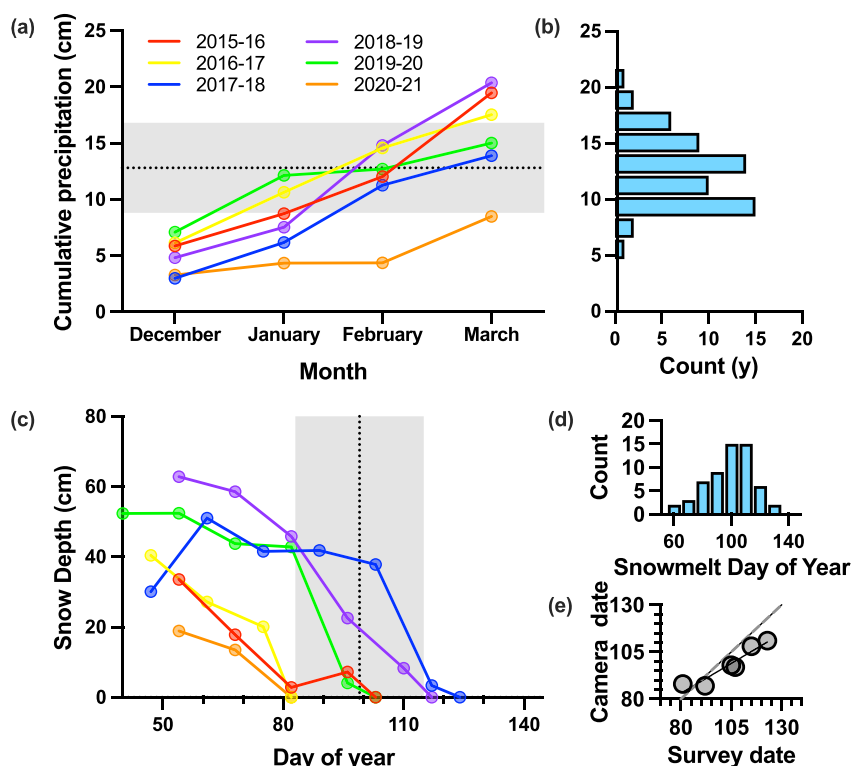


Figure 1. Winter precipitation and snow depth during 2015–2021, in the context of longer-term interannual variability at Marcell Experimental Forest. (a) Cumulative precipitation during the winter months December through March; (b) Histogram of total winter precipitation over December–March, based on data recorded at Marcell since 1962; (c) Biweekly manual survey measurements of snow depth across a series of permanent snow courses at Marcell; (d) Histogram of snowmelt dates, based on snow course survey data recorded at Marcell since 1962; (e) Scatter plot showing comparison of estimated snowmelt dates, based on snow course surveys and PhenoCam imagery, using data from 2015 to 2016 through 2020–2021 ($n = 6$). In (a) and (c), dotted line with gray shading shows mean ± 1 SD, based on long-term Marcell data, and years are colored from warmest (red) to coldest (purple) winter temperature.

3. Results

3.1. SPRUCE in a Climatological Context

Long-term data recorded since 1961 document the high variability of winter weather at Marcell Experimental Forest. Over six decades, total wintertime (December through March) precipitation averaged 12.8 ± 4.0 cm (mean ± 1 SD; range 4.3–22.5 cm) while mean wintertime temperatures averaged $-10.5 \pm 2.3^\circ\text{C}$ (range -5.2°C to -16.2°C). By comparison, the six SPRUCE winters analyzed here, from 2015 to 2016 through 2020–2021, tended to be both wetter and warmer than average. The winters of 2015–2016 and 2018–2019 (19.5 and 20.4 cm, respectively) were among the wettest in the last 60 y, while 2020–2021 was not only substantially drier (8.5 cm) but also just the second year in the last 10 with wintertime precipitation below the long-term average (Figures 1a and 1b).

The winters of 2017–2018 and 2018–2019 were climatologically average, but markedly colder than the other years since SPRUCE was initiated. By comparison, with a mean temperature of -5.4°C , the winter of 2015–2016 was much warmer (Table S1a in Supporting Information S1) and among the warmest on record. The other three winters were intermediate (but still more than 1 SD above the long-term mean), with mean temperatures of about -7.2°C . To put the experimental treatments in perspective, we note that during the warm winter of 2015–2016, conditions in the $+9^\circ\text{C}$ enclosures were hardly even “winter-like”, with mean temperatures of 5.0°C (Table S1a in Supporting Information S1). By comparison, the mean wintertime temperature in Kansas City, Missouri—over 900 km to the south—was marginally colder, at 4.3°C (GHCND station USW00003947, Kansas City International Airport).

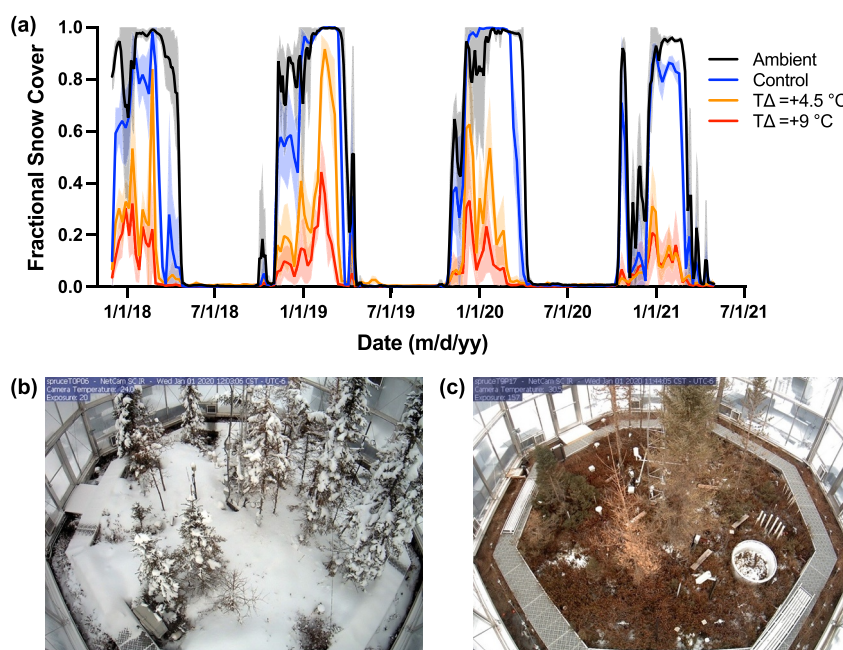


Figure 2. Impact of SPRUCE warming treatments on fractional snow cover. (a) Seasonal patterns in relation to warming treatments (data from $+2.25^{\circ}\text{C}$ to $+6.75^{\circ}\text{C}$ warming are excluded for clarity). Lines indicate the mean across $n = 2$ replicate temperature treatment plots and shading indicates ± 1 SD. Data have been smoothed with a 7-day gliding window; (b) and (c) PhenoCam imagery (ca. 12 noon on 1 January 2020) illustrating the difference in fractional snow cover between an unheated control plot (enclosure 6) and a $+9^{\circ}\text{C}$ treatment plot (enclosure 17). Note: For the version of the image shown in panel (b), image brightness was manually adjusted to compensate for under-exposure of the original, although the time series shown in panel (a) were derived using the original, unadjusted images.

As a result of differences in both precipitation and temperature across years, late-winter snow depth patterns and snowmelt timing were also highly variable (Figure 1c). Over the long-term record, estimated snowmelt occurred, on average, on April 8 (day of year 99, 1 SD = 16 days), with a 2-month range between the earliest (day of year 59) and latest observed dates (day of year 129) (Figure 1d). The comparatively wet winter of 2016–2017 and the comparatively dry winter of 2020–2021 both had shallow snowpacks and earlier-than-normal snowmelt (Figure 1c). Deeper snowpack and later-than-normal snowmelt were observed in the relatively cold winters of 2017–2018 and 2018–2019.

3.2. Impact of Warming on Snow Presence, Fractional Cover, and Depth

Warming treatments progressively reduced the number of days with snow present, from a mean of 120 days/winter in the control plots and 90 days/winter in the $+2.25^{\circ}\text{C}$ plots to about 40 days/winter in the $+9^{\circ}\text{C}$ plots (Figure S2 in Supporting Information S1). Based on a second order polynomial fit to the multi-year mean for each enclosure, the sensitivity to warming was -15.0 days with snow per 1°C increase in temperature at $+0^{\circ}\text{C}$, but only -8.8 days per 1°C at $+9^{\circ}\text{C}$. The relationship between air temperature differential and number of days with snow present was close to linear in the wet and cold winter of 2018–2019 (high snowpack) but nonlinear in the dry and warmer winter of 2020–2021 (low snowpack).

The amount and duration of snow cover was also dramatically reduced by warming (Figure 2). Whereas the reference plots and the control plots both had extended periods where fractional snow cover was $>80\%$ in every winter, in the $+4.5^{\circ}\text{C}$ plots fractional snow cover rarely exceeded 60% and in the $+9^{\circ}\text{C}$ plots fractional snow cover rarely exceeded 30% (Figure 2a). Warming treatments thus resulted in more shrub layer leaf area being exposed to ambient air temperatures for a longer period throughout the winter. Indeed, the pronounced difference between virtually 100% fractional snow cover in a control plot (Figure 2b) and—at the same time, 12 noon on 1 January 2020—almost 0% fractional snow cover in one of the $+9$ plots (Figure 2c) highlights the impact of the warming treatments (Figure S3 in Supporting Information S1).

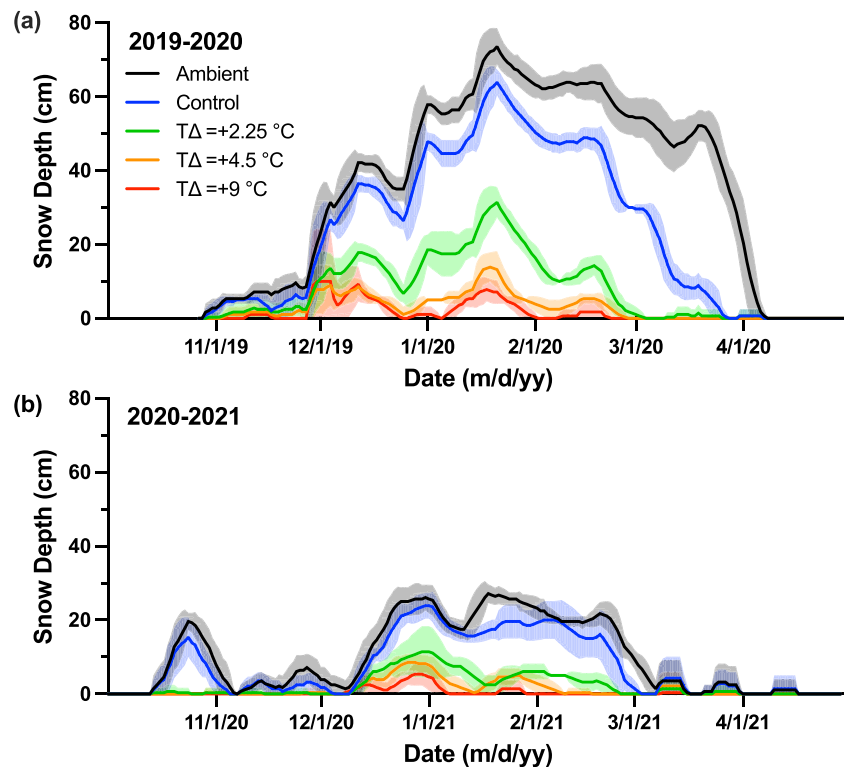


Figure 3. Seasonal patterns of snowpack depth across SPRUCE warming treatments. Lines indicate the mean across $n = 2$ replicate temperature treatment plots; shading indicates ± 1 SD. Data have been smoothed with a 7-day gliding window. (a) Winter of 2019–2020, a winter with average precipitation; (b) Winter of 2020–2021, a very dry winter. Data for the $+6.75^{\circ}\text{C}$ treatment have been excluded for clarity.

Maximum snow depth and the duration of deep snow were both substantially reduced by warming (Figure 3). During the winter of 2019–2020, which had average temperature and snowfall, the snowpack was more than 40 cm deep within both the reference plots and the control plots for much of the winter, but rarely more than 10 cm deep within the $+4.5^{\circ}\text{C}$ and warmer plots (Figure 3a). Snowpack was greatly reduced in all plots during the dry winter of 2020–2021: even in the control plots, snow was rarely deeper than 20 cm, and in the $+4.5^{\circ}\text{C}$ and warmer plots it was never deeper than 10 cm (Figure 3b).

Across all 4 years, mean fractional snow cover declined nonlinearly with increasing warming, from a multi-year mean of more than 80% fractional snow cover in the reference plots to less than 20% fractional snow cover in the $+9^{\circ}\text{C}$ plots (Figure 4a). The rate of change in mean fractional cover with warming decreased from -11.3% per $^{\circ}\text{C}$ at $+0^{\circ}\text{C}$ to -0.6% per $^{\circ}\text{C}$ at $+9^{\circ}\text{C}$. This result is not because the impacts of warming are reduced at warmer temperatures, but rather because at $+9^{\circ}\text{C}$ snow hardly accumulates and never lasts long, even in years with abundant snowfall under ambient conditions. Within individual years, the relationship between mean fractional snow cover and warming tended to be more linear in high-snowpack years (e.g., 2018–2019 and 2019–2020) and more nonlinear in low-snowpack years (e.g., 2017–2018 and 2020–2021). But, whereas the number of winter days with fractional cover $>10\%$ declined linearly at a rate of -10.6 days per $^{\circ}\text{C}$, with increasing fractional cover thresholds the decline became progressively more nonlinear (Figure 4b). Nonlinearity was particularly pronounced for the number of winter days with fractional cover $>90\%$, because with warming above $+4.5^{\circ}\text{C}$, the frequency of days with this amount of cover was essentially nil.

Maximum and mean snow depth likewise varied nonlinearly with warming, although the nonlinearity was stronger for the winter of 2019–2020, a high-snow year, than the winter of 2020–2021, a low snow year (Figure 4c). The number of days where snow depth exceeded a range of thresholds was linear for low threshold values and nonlinear as the threshold was increased (Figure 4d). For example, the number of days with >0 cm of snow on the ground at midday decreased linearly at -10 days/yr per $^{\circ}\text{C}$. By comparison, the number of days with

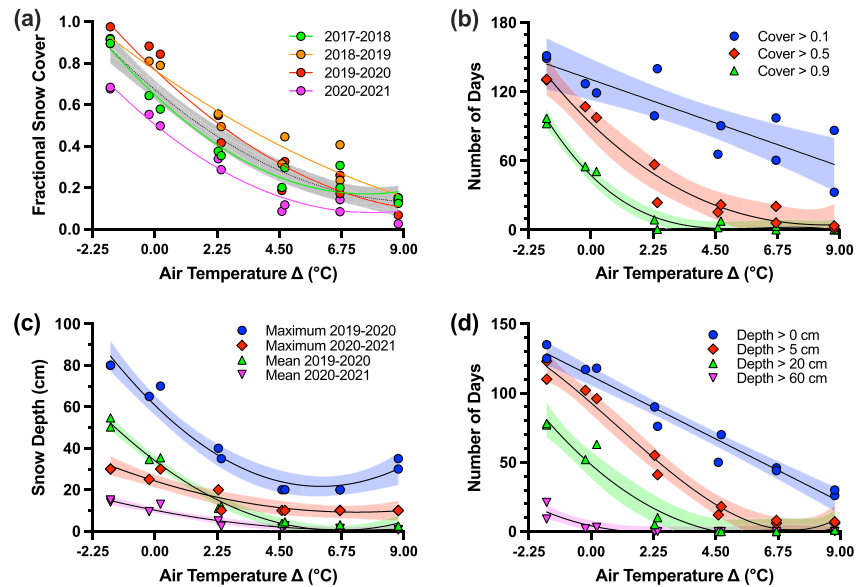


Figure 4. Effects of SPRUCE warming treatments on integrated measures of snow cover and snow depth. (a) Variation across treatments and years in mean wintertime (December through March) fractional snow cover. Best fit line (black) is a second order polynomial fit to the mean (per plot) across all years; (b) Variation across treatments in the number of days where fractional snow cover exceeded different cover thresholds, from 10% to 90%. Regression lines are linear for 10% threshold and third order polynomials for 50% and 90% thresholds; (c) Variation across treatments in maximum and average wintertime (December through March) snow depth, separated by year (2019–2020 was a winter with average precipitation, whereas 2020–2021 was a very dry winter). Regression lines are second order polynomials; (d) Variation across treatments in the number of days where snow depth exceeded different depth thresholds. Regression line is linear for depth >0 cm but a third order polynomial for all other depth thresholds. Shading around best-fit lines indicates 95% confidence bands of the regression.

>20 cm of snow declined from 48 days/yr in control plots to 0 days/yr at +4.5°C; the rate of change was −17 days/yr per °C at +0°C but essentially 0 days/yr per °C at +4.5°C and above.

3.3. Implications for Soil Temperature

The effects of whole-ecosystem warming on the soil thermal environment varied over the year, but were mediated by snowpack in winter. Shallow soil temperatures were higher in the warmed plots than in the control plots during the summer months (Figures 5a and 5c). But, while winter air temperature closely tracked the warming treatments, mean winter soil surface temperature and soil temperature at a depth of 10 cm did not (Figure 5b). Mean winter soil temperatures were coldest at moderate levels of warming (between +2.25 and +4.5°C; Figure 5b).

Longer-term averages obscure some of the higher frequency variability in soil temperature that was observed in warmed plots with negligible snow cover. There were instances even during the winter of 2019–2020, a year with a deep snow pack, when the shallow soil temperatures (soil surface and 10 cm depth) were as cold, if not colder, in the +9°C plots than the reference or control plots (Figure 5a). Notably, there were at least three extended periods when the soil surface in the +9°C plots experienced a hard freeze. In each instance (10–18 December 2019, 8–16 January 2020, and 4–20 February 2020), there were 3 or more days where the daily mean soil surface temperature dropped below −5°C. These periods of hard freeze were followed by a period of thaw when the soil surface temperature rose to at least +2°C. The conditions that enabled these freeze-thaw cycles were thin (or discontinuous) snowpack, daytime lows below −10°C during the freeze period, and daytime highs near 10°C during the thaw period. By comparison, soil surface temperatures in the reference and control plots remained below freezing from late November through at least early March; during this period, these plots were covered by an insulating blanket of snow and daytime temperatures rarely rose above +5°C. Thus, warming treatments tended to exacerbate the frequency and severity of freeze-thaw cycles, which are known to cause damage to fine roots, by dramatically reducing the snowpack.

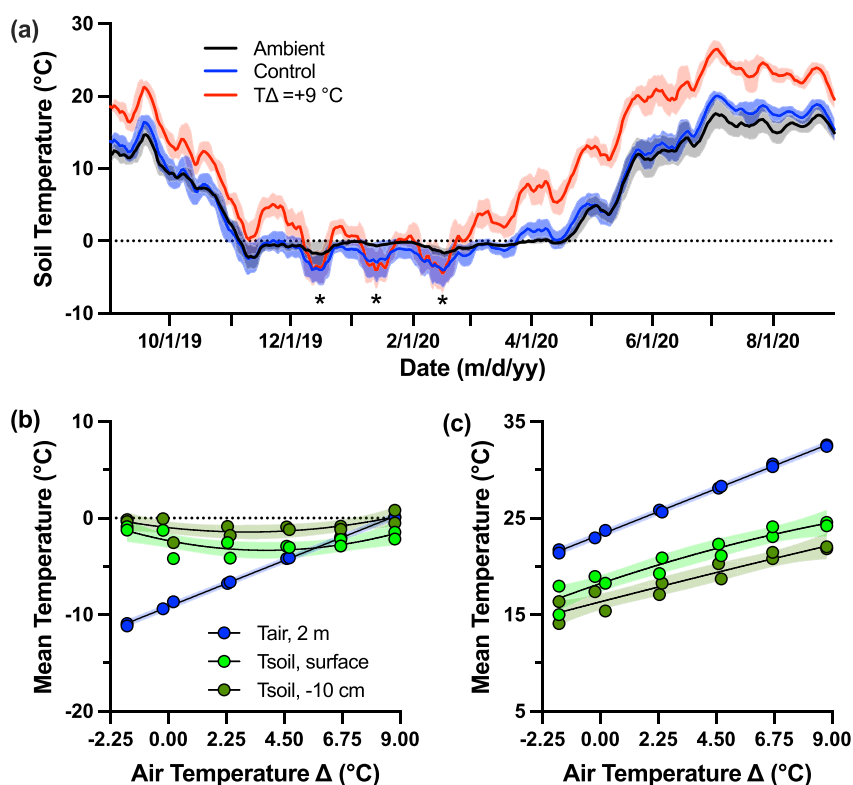


Figure 5. Effects of SPRUCE warming treatments on soil thermal environment varied across seasons. (a) Time series of soil surface temperature (0 cm depth). Daily plot means calculated from $n = 3$ sensors per plot. Lines show means, across $n = 2$ replicate plots per treatment, calculated over a 7-day gliding window, with shading indicating ± 1 SD calculated over the same window. Asterisks on the x-axis indicate periods when soil surface temperature in the $+9^{\circ}\text{C}$ plots was as cold as, if not colder than, the soil surface temperature in the control plots and in each instance reached -5°C ; (b), (c) Relationship between warming treatments and mean air temperature (T_{air}), soil surface temperature and soil temperature at a depth of 10 cm, calculated during the months of (b) February 2020 and (c) July 2020. Best-fit regressions (linear for air temperature, quadratic for soil temperature) are shown in black; shading indicates 95% confidence bands of the regression.

There are other examples of the many ways in which the soil thermal environment was modified by warming. Warming treatments had an impact on the mean number of days each winter with frozen soil at 10 cm, which declined linearly at a rate of -8.6 days/yr per $^{\circ}\text{C}$ (Figure S4a in Supporting Information S1). The impact of warming on the longest continuous period of soil frost each year was even more pronounced and nonlinear, decreasing from 83 days/yr in control plots to 14 days/yr at $+9^{\circ}\text{C}$. The rate of change decreased from -15 days/yr per $^{\circ}\text{C}$ at $+0^{\circ}\text{C}$ to -1 day/yr per $^{\circ}\text{C}$ at $+9^{\circ}\text{C}$. Thus, metrics related to specific soil temperature thresholds better captured the impacts of warming on the soil environment than monthly or seasonal mean temperatures.

Manual measurements of ice thickness in surface hollows have been made periodically in late spring at SPRUCE. Data for April and May (Figure S4b in Supporting Information S1) show 25 cm or more of ice in the control plots, but 5 cm or less of ice in the $+9^{\circ}\text{C}$ plots.

3.4. Implications for Soil Hydrology

By altering snow cover and depth, the timing of snowmelt, and the soil thermal regime and soil freezing, the warming treatments also influenced soil hydrology in winter and spring. However, impacts on soil moisture varied among years depending on the amount and timing of winter precipitation, and the depth of soil freezing. The wet winter of 2018–2019, when there was less freezing at 20 cm (the depth of water content measurements) than other years, provides an instructive case study. In that year, snow cover was declining by mid-late February in the warmest plots, but not until late March in the reference and control plots. The resulting inputs of water into the soil column increased volumetric water content at 20 cm from 0.40 to 0.90 in the $+9^{\circ}\text{C}$ plots between early March and mid-April (>0.9 is saturated); a comparable rise took place with some delay and over a longer time in

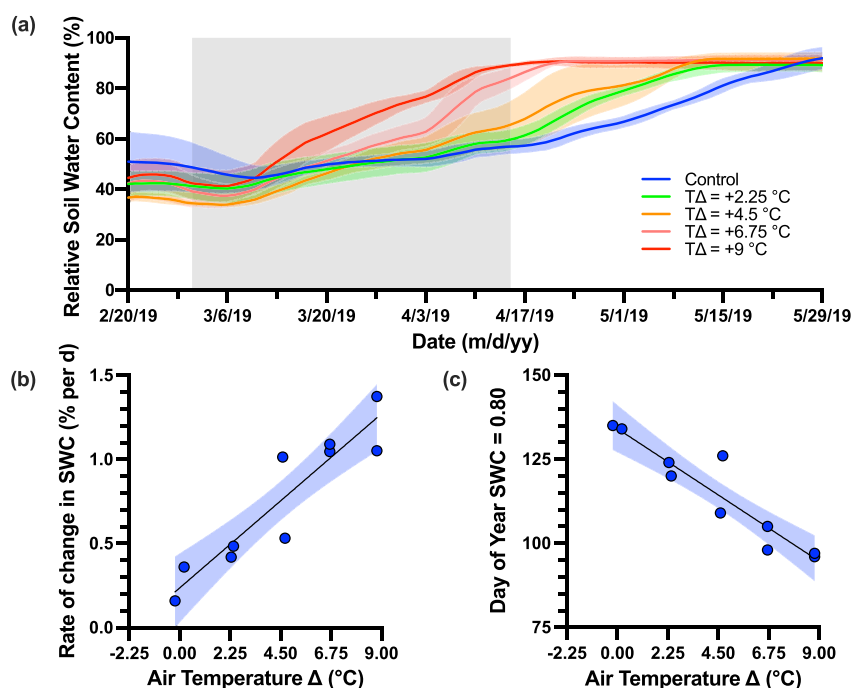


Figure 6. Hydrological impacts of SPRUCE warming treatments during the winter of 2018–2019, a wet but relatively cold winter. (a) Soil water content at 20 cm in winter and early spring across warming treatments. Solid lines show treatment means, shading indicates ± 1 SD. Means were first calculated across $n = 3$ sensors per plot, and then averaged across $n = 2$ plots per treatment. Minor x-axis tick marks are at 1-week intervals; (b) rate of change (slope, in % per day) of soil water content increase over time, calculated between March 1 and April 15 (shaded zone in panel [a]), in relation to warming treatments; (c) day of year soil water content reached 80% (an arbitrary threshold) for the first time, in relation to warming treatments. In (b) and (c), black lines indicate best-fit linear regressions, and shading indicates 95% confidence bands of the regression.

plots that were warmed less (Figure 6a). The rate of increase in volumetric water content during the month of March was strongly correlated ($r = 0.93$, across $n = 10$ plots with experimental enclosures) with the observed temperature differentials (Figure 6b), as was the date at which volumetric water content reached an arbitrary threshold value of 0.80 ($r = 0.94$, Figure 6c). Thus, warming treatments—which have already been shown to have advanced the date of spring onset across a range of plant functional types (Richardson, Hufkens, Milliman, Aubrecht, Furze, et al., 2018)—resulted in increased water availability to support plant growth in early spring, although the slope of the best-fit line in Figure 6c is -4.4 ± 0.6 days/°C, which is somewhat faster than the observed rates of phenological change.

3.5. Implications for Climate System Feedbacks

Analysis of the wintertime surface energy balance at SPRUCE shows that whereas on average the reference plots reflected 345 MJ m^{-2} of incident wintertime (December–March) shortwave radiation (corresponding to mean, time-integrated and flux-weighted albedo of $\bar{\alpha} = 0.47$), the $+9^\circ\text{C}$ plots reflected only 95 MJ m^{-2} ($\bar{\alpha} = 0.13$). The difference, 250 MJ m^{-2} (enough energy to evaporate $11 \text{ cm H}_2\text{O m}^{-2}$), is about one-third of the average incident shortwave radiation during this 4-month period, 740 MJ m^{-2} , and thus represents an enormous change in wintertime energy input.

We used a method similar to that proposed by Scherrer et al. (2012) to estimate the magnitude of the snow-albedo effect, but our analysis accounted for day-to-day differences in insolation (R_g^{daily}). With $R^2 = 0.58$ ($n = 751$) more than half of the variance in observed $\Delta T_{\text{air}}^{\text{max}}$ is explained by R_g^{daily} and differences in snow cover between reference and control plots (Figure 7). Indeed, our model (Table S2 in Supporting Information S1) shows that the snow-albedo effect is highly dependent on R_g^{daily} : the expected difference in daily maximum air temperature between fully snow-covered plot and a snow-free plot ($=\beta_2 \times R_g^{\text{daily}}$) is only $0.38 \pm 0.05^\circ\text{C}$ (mean ± 1 SE) on a typical

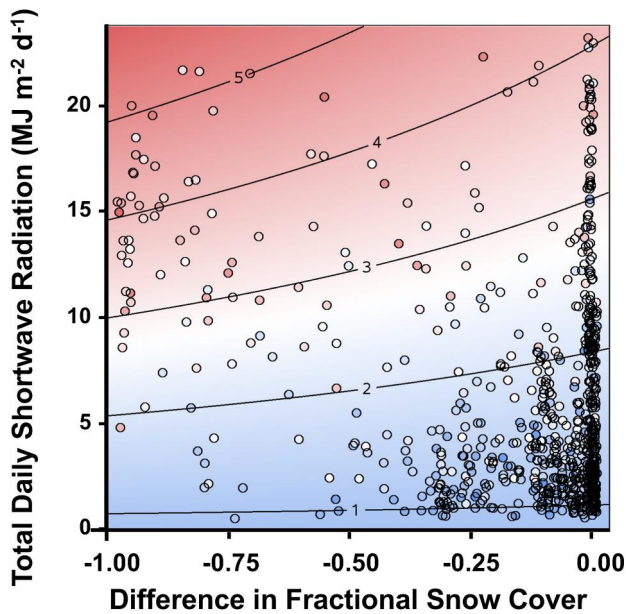


Figure 7. Differences in daily maximum temperature between reference and control plots at SPRUCE vary as a function of incident shortwave radiation and differences in fractional snow cover. Isoclines show temperature difference in $^{\circ}\text{C}$, which is also indicated by background shading (red = warmer, blue = cooler), estimated from the model in Equation 4. From this analysis, the snow-albedo effect is estimated at $0.077 \pm 0.010^{\circ}\text{C}$ per MJ m^{-2} per unit ΔC , for example, compared to 100% snow cover, the snow-albedo effect warms air temperature by $0.8 \pm 0.1^{\circ}\text{C}$ on a snow-free day with incident shortwave radiation of $10 \text{ MJ m}^{-2} \text{ d}^{-1}$.

December or January day ($R_g^{\text{daily}} = 5 \text{ MJ m}^{-2} \text{ d}^{-1}$), but $1.16 \pm 0.15^{\circ}\text{C}$ on a sunny day in late March or early April ($R_g^{\text{daily}} = 15 \text{ MJ m}^{-2} \text{ d}^{-1}$). Generally comparable results were obtained using different metrics to define ΔT_{air} ; notably, however, estimates of the β_2 coefficient were only $\approx 40\%$ as large when daily mean air temperature was used (Table S2 in Supporting Information S1).

Our estimates of the snow-albedo effect can be also used to quantify the additional warming that would result under future “no snow” scenarios, relative to the actual snow cover observed over the years 2017–2021. With no snow, the mean daily maximum temperature in March would be increased by $0.65 \pm 0.28^{\circ}\text{C}$ (mean ± 1 SD, across 4 years of data), with large variability in this value resulting from the much earlier snow melt in 2021 than in other years (i.e., 2021 was a low-snow year to begin with). By comparison, the lack of snow would increase the mean daily maximum temperature in January by only $0.20 \pm 0.03^{\circ}\text{C}$, and even less in November and December ($\approx 0.13^{\circ}\text{C}$).

4. Discussion

Results from the SPRUCE whole-ecosystem warming experiment suggest that future warming will bring far-reaching changes to the winter environment in northern Minnesota, and by extension much of the southern boreal region in North America. Contrary to expectations, the temperature sensitivity of snow cover, depth, and duration tended to decrease with increasing temperature, as greater reductions in snow occurred with warming from 0 to $+2.25^{\circ}\text{C}$ than with warming from $+6.75$ to $+9.0^{\circ}\text{C}$. Our results are consistent with Steger et al. (2013) who reported 40%–80% reductions in snow water equivalent with 2–4 $^{\circ}\text{C}$ of warming (see also Räisänen & Eklund, 2012). We found that warming treatments of $+2.25^{\circ}\text{C}$ were sufficient to reduce mean

wintertime fractional snow cover by about half (Figure 4a), reduce the number of days with snow cover $>50\%$ by about half (Figure 4b), reduce maximum and average snowpack depth by at least a third (Figure 4c), and reduce the number of days with more than 5 cm snow pack by more than half (Figure 4d). With additional warming, even greater reductions in snow cover and snow pack are to be expected, to the point where winter is almost unrecognizable, at least compared to winters during the past 60 y: in the long-term snowcourse data from Marcell, maximum annual snowpack depth averaged almost 50 cm over the last 6 decades, and most years there was still snow on the ground in mid-April. Our results show that *any* future warming will seriously reduce the amount and duration of snow on the ground in northern Minnesota. Projected future (2081–2100) mean wintertime temperatures are expected to rise by more than 4°C under the RCP 4.5 emission scenario, and by about 7°C under the RCP 8.5 emissions scenario (University of Minnesota Climate Adaptation Partnership, 2022)—suggesting that SPRUCE’s $+4.5^{\circ}\text{C}$ and $+7.75^{\circ}\text{C}$ warming treatments may provide reasonable analogs for end-of-century conditions in northern Minnesota.

We discuss these results in the context of three themes: (a) implications for plants and soil; (b) implications for climate system feedbacks; and (c) possible applications of these data to improve simulation models.

4.1. Impacts on Vegetation and Soils

Snow plays a critical role in insulating above and belowground organisms from temperature extremes, and changes in the amount and duration of snow cover are expected to have critical effects on vegetation, soils, and ecosystems (Kreyling, 2010; Kreyling & Henry, 2011; Rixen et al., 2022; Sanders-DeMott & Templer, 2017). For example, snowmelt timing is an important driver of alpine plant phenology (Jerome et al., 2021), and it likely has impacts on microsite characteristics and phenology in other ecosystem types. Other studies document how snow cover is related to plant stress: in a recent review, Slatyer et al. (2022) found a consistent impact of reduced snow cover was an increase in plant mortality, injury, or damage. But, Taulavuori et al. (2011) observed that even when snow cover was lacking, *Vaccinium* did not necessarily show obvious visual signs of freezing damage per se, although high solar loading together with frozen soils resulted in desiccation and sustained photo-inhibition.

Likewise, Neuner et al. (1999) reported that snow cover not only enabled *Rhododendron* foliage to maintain a higher efficiency of photosystem II (as measured by chlorophyll fluorescence F_v/F_m) through the winter, it also enabled faster recovery of photosystem II in spring, and could improve plant water relations if snow cover was sufficient to maintain soil temperatures above -3°C . Because this kind of physiological damage may not be obvious to the human eye, its extent and severity may be under-estimated in many studies.

Whether damage results from freezing or photoinhibition, the risk of both clearly becomes larger with the effect of warming temperatures on snowpack, given the trends we documented in snow depth and cover (Figures 2–4, Figure S2 in Supporting Information S1; see also Bokhorst et al., 2009). And, while other factors may be involved, observational data at SPRUCE anecdotally support this risk. Following the low-snow winter of 2020–2021 at SPRUCE, ground phenology surveys noted extensive *Chamaedaphne* shoot dieback by early April in both of the $+6.75^{\circ}\text{C}$ plots and both of the $+9^{\circ}\text{C}$ plots, but not in any of the reference, control, or $+2.25^{\circ}\text{C}$ plots (Heiderman et al., 2018). Snow in the $+9^{\circ}\text{C}$ plots had largely disappeared by the beginning of February, but this was followed by extreme cold (minima below -20°C) for 10 days mid-month, and then episodic freezing events with nighttime lows below -5°C in early March, mid-March, and early April, all of which could have contributed to foliar damage on plants that were either not insulated by snow, or had prematurely lost frost hardiness. Foliar damage is expected to have many trickle-down effects on ecosystem function (Gu et al., 2008), including reduced primary productivity resulting from a reduction in photosynthetically active leaf area, altered nutrient budgets resulting from plants being unable to translocate nitrogen and other essential elements from damaged foliage, less carbon available to support growth and reproductive efforts, and reduced flowering and fruiting to support pollinators and frugivores. As warming increases the likelihood of winter damage, it is certainly plausible that carry-over effects from damage in previous years—progressively increasing stress, reduced nonstructural carbohydrate reserves, and nutrient deficiency—may rapidly compound to have severe impacts on vegetation health, productivity, and reproductive success. On top of the 2016 spring freeze which damaged foliage of black spruce (*Picea*) trees in the warmest SPRUCE enclosures (Richardson, Hufkens, Milliman, Aubrecht, Furze, et al., 2018), the results presented here highlight the potential for increasing plant stress in winter as an indirect product of warming.

At the same time, reduced snow cover resulting from ongoing warming is expected to have “profound” (Brooks et al., 2011) effects on the soil environment, as well as impacts on ecosystem carbon and nitrogen cycling (Zhao et al., 2022). In snow removal experiments, soil freezing has been previously shown to result in root mortality, reduced rates of soil nutrient cycling, and accelerated nutrient export (Groffman et al., 2001; Sanders-DeMott & Templer, 2017). Our data provide some experimental support for the surprising hypothesis of “colder soils in a warmer world” (Groffman et al., 2001), although they also highlight some of the subtleties associated with this aphorism. But, snow removal experiments alone cannot fully represent future low- or no-snow conditions; it is well-established that as air temperatures rise, deep soil temperatures will also become warmer as they reach a new equilibrium with new mean annual air temperature (Baxter, 1997; Hu & Feng, 2003). Importantly, we found that freeze-thaw cycles at the soil surface were much more prevalent in the $+9^{\circ}\text{C}$ plots than in the reference or control plots, and there were numerous instances where surface soil in the $+9^{\circ}\text{C}$ plots was colder than in any other treatment. However, freezing was still less common in the warmest plots (Figure 5a). These results contrast somewhat with those from the classic snow removal experiment described by Groffman et al. (2001) in which snow removal (without warming) was associated with mild but extended freezing. Snow removal experiments (Sanders-DeMott & Templer, 2017) have also repeatedly shown the critical importance of snow cover for moderating soil temperatures (see also Liu et al., 2023; Rixen et al., 2022). Our data show that as warming air temperatures reduce snow depth, cover, and duration, shallow soil temperatures become much more variable during the winter, despite deep soil temperatures that are also warmer. This supports Verry’s (1991) observation that soil surface temperature in winter is much more tightly regulated by the depth and extent of insulating snow cover than it is by air temperature.

4.2. Impacts on Ecosystem Feedbacks to the Climate System

Snow plays a role in several ecosystem-climate system feedbacks. The most important of these is the snow-albedo feedback, but weaker feedbacks associated with soil moisture, latent heat flux, and surface insulation have also been identified (Lemke et al., 2007). For example, our analysis of the effect of snow cover on the shortwave component of the surface energy balance shows that with $+9^{\circ}\text{C}$ warming, reduced snow cover can be expected to lead to changes in albedo that result in a 75% reduction in reflected shortwave radiation over the winter months. As a result, one-third more of the incident shortwave radiation is absorbed. This then leads to a tremendous

increase in net radiation, which must be balanced by some combination of increased sensible and/or latent heat flux, ground heat flux, or outgoing longwave radiation. The potential for additional climate feedbacks is strong, if any of this energy goes toward below-ground warming. Results from SPRUCE have already shown that the underlying peat is highly susceptible to warming-induced degradation of soil organic matter and increased greenhouse gas production (Wilson et al., 2021). Globally, 24% of the boreal forest—or 330×10^6 ha—is covered by peatlands (Wieder et al., 2006). At the planetary scale, massive positive feedbacks to climate change could occur if albedo changes drive soil warming.

We leveraged the unique experimental design of SPRUCE to estimate the magnitude of the snow-albedo feedback effect on near-surface air temperature. This feedback is difficult to quantify from observational data, and is highly variable across different earth system models (Guo & Yang, 2022). Scherrer et al. (2012) estimated the magnitude of the feedback effect from paired plots, with and without snow, which we extend here. We note that in Scherrer's analysis, "paired" plots were a minimum of 15 km, and in some cases more than 50 km, distant from each other. Our approach instead relies on SPRUCE reference plots and (unheated) control plots, separated by (at most) hundreds of meters.

Scherrer et al. (2012) observed that "the daily mean 2-m temperature of a spring day without snow cover is on average 0.4°C warmer than one with snow cover at the same location." Our results show how the snow-albedo feedback effect critically depends on insolation, or incident shortwave radiation, so that there is more albedo-driven warming on an early spring day with high incident radiation than on a mid-winter day with low incident radiation. In early spring, where incident radiation is $15 \text{ MJ m}^{-2} \text{ d}^{-1}$, we estimated $T_{\text{air}}^{\text{max}}$ is elevated by more than 1°C above snow-free ground, compared to snow-covered ground. While the SPRUCE chamber infrastructure may induce unforeseen biases in these estimates, the similarity of results between our analysis based on $\Delta T_{\text{air}}^{\text{max}}$ and that based on $\Delta T_{\text{air}}^{\text{max-min}}$, where differencing against $\Delta T_{\text{air}}^{\text{min}}$ is intended to control for those artifacts (e.g., differential long wave cooling at night), suggests that our results are robust. Our approach yields an important new constraint on the magnitude of this effect.

Modeling studies have examined some of the earth system effects of snow loss at regional-to-global scales. For example, in an analysis focused on northern Sweden, a warming climate was found to reduce the duration of snow cover by 2–3 months, advance the date of spring increases in soil temperature by 2–3 weeks, and increase the frequency of soil freeze-thaw cycles by 30% by the end of the century (Mellander et al., 2007). In a more extreme example, CCSM3 model runs where precipitation falling as snow was converted to liquid water increased mean annual temperatures by 5 K and winter temperatures by 8–10 K at high latitudes in the Northern Hemisphere; this warming then also influenced global circulation patterns (Vavrus, 2007). The distribution across North America (as well as Scandinavia and Siberia) of boreal forest that are floristically and structurally similar to those at SPRUCE suggests that the results obtained here should be relevant across a wide geographic region, with potential for regional-to-global effects on the climate system.

4.3. Potential to Improve Models

Model-based projections of future changes in snow cover are challenged by the complexities of snow physics and uncertainties about how snowfall and snowmelt may be impacted by warming temperatures. CMIP5 model runs suggest that low-elevation, high-snow temperate regions are at high risk of large reductions in snow water equivalent with even small increases in warming (Kudo et al., 2017). But, these same models do a poor job of reproducing observed trends toward reduced springtime snow cover extent in recent decades (Thackeray et al., 2016), reducing confidence in model projections. A more recent analysis of CMIP6 models found that "simulated changes in snow depth may not be suitable for assessing associated impacts ... in future scenarios," leading to the conclusion that "CMIP6 models require more detailed and comprehensive treatments of snow physics to more accurately project snow cover" (Zhong et al., 2022). Indeed, the model representation of many snow-related processes is considered dated and simplistic, and specific deficiencies have been identified, including (a) poor representation of reductions in snow cover in response to warming (the "snow cover sensitivity," Thackeray et al., 2019); (b) high uncertainty in general circulation model (GCM) projections of temperature propagating through snow process models, and interacting with nonlinearities in those models (Kudo et al., 2017); and (c) uncertainty in the snow-albedo feedback (Hall & Qu, 2006; Qu & Hall, 2006).

While improved parameterizations of snow-related processes are needed (Qu & Hall, 2006), it is also readily apparent that better observational data are needed to validate model predictions of snow cover and snow cover dynamics (Collados-Lara et al., 2019). In spite of global coverage, the scale and resolution of satellite observations (Kosmala et al., 2018) may limit the use of these data for improving how the complex physics of snow processes are represented in models. Alternatively, it has also been suggested that existing snow process models could be improved by calibrating parameters to observational data sets (Huang et al., 2017; Kudo et al., 2017). Indeed, Thackeray et al. (2019) concluded that to better constrain projections of future changes in snow cover, ongoing model development needed to occur hand-in-hand with improved monitoring of snow cover and related variables (e.g., snow mass, snow depth, snow water equivalent) at the site level. These measurements would be particularly valuable if they were conducted simultaneously with comprehensive water and energy flux measurements, for example, as at FLUXNET, ICOS (Integrated Carbon Observation System), or NEON (National Ecological Observatory Network) sites.

We argue that the experimental data presented here, and in particular the relationships between different snow cover metrics and warming treatments, could be used for testing and improving the representation of snow and snow processes in simulation models. While the experimental data may not be a perfect representation of reality, the overall *patterns* across treatments represent a viable and defensible target for models to reproduce (i.e., *evaluation* rather than strict *validation*), especially if uncertainties can be realistically characterized and used in model evaluation. In fact, in one previous study, Huang et al. (2017) assimilated pretreatment SPRUCE data (soil temperature profiles, snow depth, water table depth, etc.) into the TECO model using the EcoPAD framework. They found that the forecast uncertainty was small for soil temperature but large for snow cover and depth of freezing. Sparse observations of snow cover (4 dates, January to March) from the first winter of experimental treatments were available for model testing; except when snow cover was 100% or 0%, the model performance was poor. With the fine-scale data provided here on relationships between warming treatments and snow depth, duration, and fractional cover, there is a new opportunity to test the representation of snow processes in simulation models. Furthermore, the fact that the experimental conditions vastly exceed the bounds of observed historical variability should provide extra power to falsify models, as was demonstrated by Schädel et al. (2023) in the context of phenological models.

5. Conclusions

One of the key impacts of climate change, affecting both ecosystem and earth system processes, is reduced snow cover and snow duration in cold, historically snowy, environments. Our analysis from the SPRUCE whole-ecosystem warming experiment enables quantification of the impacts of warming on snow cover, depth, and duration at the plot-level scale. Our results show that at best, further increases in temperature will have a negative but approximately linear effect on snow cover characteristics. In other instances, the effect of warming will likely be highly nonlinear, with the steepest (rate of change per 1°C of warming) reductions in snow-cover metrics (e.g., the number of days with deep snow cover) occurring immediately with *any* warming above ambient conditions. We also devised a method, leveraging the reference and control plots at SPRUCE, to quantify the snow albedo feedback effect and how it varies with incident solar radiation. The data presented here could be used to test or improve the realism of model representation of processes related to snow accumulation and melting under climate conditions that are representative of what is projected for the end of the 21st century, without having to make assumptions about the validity of space-for-time substitutions.

Data Availability Statement

PhenoCam imagery, data, and data products for the SPRUCE project are publicly available in near real-time through <https://phenocam.nau.edu/webcam/network/search/?group=spruce>, and imagery has also been archived at ORNL (Milliman et al., 2019) with documentation in (Seyednasrollah et al., 2019). SPRUCE environmental data (Hanson et al., 2016) and snow presence data (Schädel et al., 2022) have been archived, with documentation, at ORNL. SPRUCE snow cover and depth data have been archived at figshare (Richardson et al., 2023). Marcell Experimental Forest data for snow surveys and daily precipitation are available through the Environmental Data Initiative (Sebestyen et al., 2021a, 2021b), and described by Sebestyen et al. (2021). The *Snowgreen* code to perform the snow cover analysis has been archived at Zenodo (<https://zenodo.org/records/10677903>).

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