Looking beyond wildlife: using remote cameras to evaluate accuracy of gridded snow data

Alexej P. K. Sirén1,2, Marcelo Somos-Valenzuela1,3, Catherine Callahan4, Jillian R. Kilborn4, Timothy Duclos1,2, Cassie Tragert2 & Toni Lyn Morelli1,2,5

1Department of Environmental Conservation, University of Massachusetts, Amherst, Massachusetts, USA
2Department of Interior Northeast Climate Adaptation Science Center, University of Massachusetts, Amherst, Massachusetts, USA
3Agricultural and Forestry Sciences Department, Universidad de La Frontera, Temuco, Chile
4New Hampshire Fish and Game Department, Concord, New Hampshire, USA
5U.S. Geological Survey, Amherst, Massachusetts, USA

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Abstract
The use of remote cameras is widespread in wildlife ecology, yet few examples exist of their utility for collecting environmental data. We used a novel camera trap method to evaluate the accuracy of gridded snow data in a mountainous region of the northeastern US. We were specifically interested in assessing (1) how snow depth observations from remote cameras compare with gridded climate data, (2) the sources of error associated with the gridded data and (3) the influence of spatial sampling on bias. We compared daily observations recorded by remote cameras with Snow Data Assimilation System (SNODAS) gridded predictions using data from three winters (2014–2016). Snow depth observations were correlated with SNODAS predictions for sites ($R^2 = 0.20$) and regions ($R^2 = 0.16$), yet we detected factors associated with SNODAS bias at both scales. Specifically, SNODAS underpredicted depths at high elevations, at sites with higher solar radiation, and within conifer-dominated forest. Depths were most underpredicted at highest elevations, up to 44 and 26 cm on average at the site and region scales, respectively. Bias was greatest when predictions were lowest, occasionally predicting snow absence when depths were >100 cm at camera sites. We also detected breakdowns in accuracy when certain environmental conditions varied within the 1 km$^2$ SNODAS grid cells. For example, underprediction was greatest when the solar radiation values of camera stations increased relative to the mean of the SNODAS grid cells. This relationship was most prominent in mountainous regions, suggesting that factors which influence solar radiation (e.g. topographic complexity) contribute to SNODAS inaccuracy. We caution using gridded snow data for ecological studies when bias is unknown. We suggest increased sampling to adjust for errors associated with gridded data products that arise from factors, such as forest cover and topographic variability. Increasing resolution and accuracy of climate data will improve predictions of species’ responses to climate change.

Introduction
Warmer temperatures and shifts in precipitation regimes are drastically changing snowpack conditions (Lute et al. 2015; Ning and Bradley 2015; Suriano and Leathers 2016). These changes are threatening wildlife species adapted to snow (Musante et al. 2010; Zimova et al. 2016) and have increased interest in understanding the ecological importance of winter (Williams et al. 2015). Remote cameras are a common tool for studying wildlife populations (O’Connell et al. 2011). They provide abundant data for behavioral studies and for estimating
distribution, abundance and community structure (Burton et al. 2015). In addition, advances in camera technology are allowing users to record environmental data, such as ambient temperature and barometric pressure, at defined intervals and ecological data within the range of view (e.g. plant phenology; Richardson et al. 2009). These site data can enable evaluation of fine-scale processes (e.g. catchment-scale hydrology; Floyd and Weiler 2008; Parajka et al. 2012) as well as address the growing need, catalyzed by climate change, for high resolution, on-terrestrial environmental data to understand current and future conditions (He et al. 2015).

Ecological studies commonly use gridded climate products (e.g. temperature, precipitation, snow depth) to evaluate wildlife-environment associations (see review in introduction of Brennan et al. 2013). However, these data are often developed for other uses (e.g. hydrological modeling; Di Luzio et al. 2008). Although gridded data may be useful for capturing relative changes in population parameters, scales improperly matched to a species’ behavior can compromise inference (McCann et al. 2014). For example, although roe deer (Capreolus capreolus) preferentially select shallow snow sites, remotely sensed MODIS snow data were a poor predictor of fine-scale habitat use (e.g. Ossi et al. 2015). Similarly, simulated models of elk predation based on remotely sensed snow water equivalent (SWE) were biased and less precise than those based on field estimates of SWE (Brennan et al. 2013). These scale-dependent relationships are especially important to consider for species with narrow climate niches (e.g. wolverine (Gulo gulo): Schwartz et al. 2009) or those with specific threshold responses (e.g. snowshoe hare (Lepus americanus): Sultaire et al. 2016).

In addition to scaling problems, gridded climate data also have biases (McEvoy et al. 2014; Oyler et al. 2015). Climate models utilize data from sparsely distributed weather stations typically located in lowland developed areas (Lundquist et al. 2015). Notably, the western US has better coverage of high elevation areas (e.g. SNOTEL: www.wcc.nrcs.usda.gov/snow), which has contributed important insights of snowpack dynamics in mountainous areas (Knowles 2015). Although variables such as elevation and latitude are used to model precipitation and temperature (Thornton et al. 1997; Daly et al. 2008), few studies validate model predictions with field observations to evaluate bias (Lundquist et al. 2015). Importantly, landscape features such as forest cover type and management can influence snow depth and persistence (Dickerson-Lange et al. 2015). Further, landforms such as mountains influence the spatial formation of clouds and local weather, creating variance not captured by interpolated data (e.g. snow shadows: Daly et al. 2008; Brennan et al. 2013). Increased monitoring will improve understanding of local factors that influence climate and benefit several science fields (Oyler et al. 2015).

One such example of a gridded climate dataset commonly used by wildlife researchers in the US (e.g. Zielinski et al. 2010; Holbrook et al. 2017; Reed et al. 2017) is the Snow Data Assimilation System (hereafter SNODAS: Barrett 2003) produced by the National Oceanic and Atmospheric Administration. SNODAS combines output from the numerical weather prediction models (downscaled from 13 to 1 km²) with observed values from ground stations, airborne surveys and satellites (Barrett 2003). Factors that influence snow accumulation such as elevation, forest cover type, slope, aspect and solar radiation are also used to model depth predictions (Barrett 2003; Carroll et al. 2006). Although SNODAS was developed for several science fields, including ecology (Barrett 2003), recent studies indicate that it can be biased in some regions (Clow et al. 2012; Brennan et al. 2013), which is consequential for effectively understanding climate–wildlife dynamics. Biases may arise from numerous sources, including infrequent and sparsely distributed ground observations and forest cover which can block aerial and satellite observations (Barrett 2003; Carroll et al. 2006).

We developed a novel approach to collect daily snow depth data with remote cameras in a mountainous region of the northeastern US. We used our method to evaluate the relative contributions of local environmental factors on SNODAS bias. We were specifically interested in (1) how daily snow depth observations recorded by remote cameras compared with gridded SNODAS predictions, (2) the sources of bias associated with SNODAS data and (3) how the spatial scale of our sampling influenced interpretations of SNODAS bias. We hypothesized that elevation, latitude, solar radiation and forest type/structure would explain the difference between our camera observations and SNODAS predictions of snow depth. We chose these factors for three reasons: (1) they are used to develop SNODAS data (Carroll et al. 2006); (2) they also likely explain disparities between predictions and observations as there are fewer weather stations in mountainous and northern regions of the northeastern US (see Burakowski et al. 2008) and (3) local variability of sun exposure and forest conditions influence snow depth (Clow et al. 2012; Hedrick et al. 2015). Although we frequently observed a disparity between SNODAS predictions and our camera and direct observations of snow depth, we did not predict the direction or magnitude these factors would have on the SNODAS bias. Instead, we explored the influence of local environmental factors on SNODAS bias and the extent to which our design was representative of the SNODAS grid cells to identify key breakdowns in SNODAS accuracy.
Materials and Methods

Study site

We conducted our study in the New England-Acadian Forest of New Hampshire and Vermont, US (Fig. 1). This region is classified as the transition zone between the northern hardwood and boreal forests and is mountainous with elevations ranging from sea level to 1906 m (Davis et al. 2013). The climate is influenced by maritime air masses, characterized by mild, wet summers and cold, snowy winters with mean annual temperature and precipitation ranging from 3 to 6.5°C and 100–160 cm, respectively (Davis et al. 2013). The snowpack varies considerably (snowfall: 244–406 cm; Kelly et al. 2009) with high elevation and northern latitudes typically have deep and low-density snow (Dingman 1981). The area is home to many wildlife species such as Canada lynx (Lynx canadensis), bobcat (Lynx rufus), American marten (Martes americana) and snowshoe hares that are sensitive to changes in snowpack (Hoving et al. 2005; Zimova et al. 2016; Reed et al. 2017; Sirén et al. 2017).

Camera trap method

We established 80 camera sites along elevational (335–1452 m) and latitudinal (43.906–45.283°) gradients (Fig. 1). Sites were placed in non-overlapping 2 × 2 km grids to meet sampling requirements for a concurrent wildlife study. We recorded daily snow depth using a combination of camera brands (Moultrie, Bushnell Trophy Cam, Reconyx HC500 Hyperfire, and ScoutGuard) that were programmed to take pictures at fixed intervals or in response to triggers (e.g. animal presence). We positioned cameras on a tree facing north to reduce false triggers from solar exposure, 1.5–2 m aboveground, and pointed at a slight downward angle toward a snow stake with 4 cm increments placed 3–5 m from the camera (Fig. 2). Cameras were shifted upwards 0.2–0.5 m during mid-winter to accommodate maximum snow depths. To minimize measurement bias, we chose sites that were (1) relatively flat, (2) not prone to wind loading and (3) in areas that were representative of the canopy cover in the surrounding forest (e.g. Fig. 2). Camera sites were checked 3–7 times/year (2–4 times/winter) during 2014, 2015, and 2016 to download data and ensure cameras were working properly.

SNODAS correlation and bias analyses

We took a multistage modeling approach to evaluate our hypotheses. First, we evaluated SNODAS accuracy by testing for correlation between camera observations and SNODAS predictions. The aim of our second analysis was to identify potential sources of SNODAS bias using site
variables that are known to influence snow accumulation and also used to develop SNODAS predictions. Our third analysis was to determine how representative our site variables were of the SNODAS grid cells and if the differences between the site and grid level parameters indicated breakdowns in SNODAS accuracy. Lastly, we conducted a coarse-scale analysis to see if bias trends persisted at broader spatial scales.

We used daily snow depth observations collected by 80 remote cameras ($n = 3485$) that operated for 43.56 ± 5.35 (5–234) days to test for correlation and bias of SNODAS predictions. Specifically, we matched daily snow depth, extracted manually from pictures, with snow depth predictions from 1 km$^2$ resolution SNODAS rasters that corresponded with camera station locations. We calculated bias as the difference between snow depth predictions and observations and used these data to model the influence of elevation, solar radiation, canopy cover, percent conifer forest and biomass on SNODAS bias. The elevation (m) and daily solar radiation values (watt hours per square meter; Wh/m$^2$) of camera stations were extracted from a 10-m digital elevation model (DEM) from the National Elevation Dataset (Gesch et al. 2009). We used a global calculation, which incorporates direct and diffuse solar radiation and uses slope and aspect from the DEM to derive radiation values (Fu and Rich 2002). Canopy cover (0–100%) and percent conifer forest (0–100%) of camera stations were extracted using a 30-m National Land Cover dataset (Homer et al. 2015). Canopy cover is a measurement of horizontal forest structure with higher values indicating greater coverage of the forest floor (Walker et al. 2007; Homer et al. 2015). To provide a plausible size of forest that would influence snow depths, we extracted the percentage of conifer forest within a 50-m radius of the camera station. We also calculated aboveground live forest biomass (metric tons/ha) at camera stations using a 30-m raster dataset provided by McGarigal et al. (2017). The forest biomass layer was created using Forest Inventory and Analysis data and recent forest cover change imagery (Hansen et al. 2013) to provide a predictive map of forest disturbance and succession (McGarigal et al. 2017). Finally, we included the latitude of the camera trap sites as a covariate. All spatial analyses were conducted using ArcMap 10.4 (Environmental Systems Research Institute, Inc., Redlands, CA, USA).

To evaluate our hypotheses, we used two approaches: As a preliminary step, we calculated Pearson’s correlations and mean bias between corresponding camera and SNODAS grid cells to identify the strength of the relationship for individual sites. To evaluate trends and factors influencing bias over the entire study area, we used generalized linear mixed effects models (GLMM) with a Gaussian distribution and the identity link function with the ‘nlme’ R package (Pinheiro et al. 2016; R Development Core Team 2016). Because cameras were collecting data repeatedly within a snow season and across years, we included camera within year as a random intercept to account for potential correlations and varying effort among sites (Bolker et al. 2009). Prior to bias modeling, we evaluated continuous covariates for collinearity using correlation plots and variance inflation factors (VIF), removing those with VIF scores >2 from the same model (Zuur et al. 2009).

We also plotted continuous covariates versus bias to evaluate linear and quadratic relationships. We retained six covariates with VIF scores <2, including elevation, latitude, solar radiation, canopy cover, percent conifer forest and biomass; solar radiation was specified as a quadratic term due to non-linearity. All covariates were scaled and centered prior to modeling to improve parameter estimation (Zuur et al. 2009). We evaluated our hypotheses using second order Akaike Information Criteria (AICc) to correct for small sample size with the ‘AICcmodavg’ R package (Mazerolle 2017). If top models were within 2 AICc units, we calculated the natural average of all possible model combinations to ensure a balanced model set (Burnham and Anderson 2002; Giam and Olden 2016); the significance of the parameter estimates was evaluated at the 95% confidence level. To evaluate the strength of models, we also calculated marginal $R^2$ values, which describe the proportion of variance explained by the fixed effects for GLMMs (Lefcheck 2016).

We checked for violations of temporal and spatial independence by visually inspecting autocorrelation function plots, semivariograms and bubble plots (Zuur et al. 2009). Because we detected strong temporal autocorrelation (TAC) for the SNODAS correlation and bias models, we evaluated a suite of correlation structures for data that contain an incomplete chronosequence (Zuur et al. 2009). We also had an incomplete chronological time series of snow data because some of our cameras were not capable of recording data at daily intervals and/or batteries would occasionally expire during the sampling period. We suspected that the TAC was due to the frequency of snow events in the region which contributed to correlated snow depth observations over short time frames (e.g. 3–5 days). To account for these factors, we created a variable to describe the form of the correlation structure, which included the year and the day for each observation. We used this variable to test five correlation structures (exponential, Gaussian, linear, rational, spherical) for the correlation and bias models using AICc and selected the function which resulted in the lowest AICc (Zuur et al. 2009). We chose this approach because we did not know a priori the shape or function of the correlation structure.
The model with an exponential correlation structure had the lowest AICc score [$\Delta$AICc = −2.2 compared to the second closest model (spherical model) and $\Delta$AICc = −4601.8 compared to the model without a correlation structure]. Finally, we conducted a Moran’s I test on the full model to evaluate spatial autocorrelation (SAC) in the residuals. We failed to detect SAC (Moran’s I statistic = −0.00003, $P = 0.67$); therefore, we proceeded to use this structure for modeling SNODAS correlation and bias.

We also were interested in how representative our site predictors were of the SNODAS grid cells and if the differences between them could help us understand breakdowns in SNODAS accuracy. To evaluate these relationships, we calculated the mean elevation, latitude, biomass, canopy cover, per cent conifer forest, and solar radiation of the SNODAS grid cells and subtracted these values from those of corresponding camera sites (e.g. site elevation – grid cell elevation; hereafter referred to as differential variables). We visually examined the differential variables using histograms and bubble maps to determine if the site characteristics were representative of the grid cells and if there were any spatial biases, and also to provide a tabular summary of differences. We fit univariate models using each variable as a predictor of SNODAS bias to determine if any of the differential variables had predictive power.

To determine whether SNODAS predictions and camera observations were correlated at coarser scales, we performed a post hoc analysis using regions with ≥4 camera sites ($n = 7$; Fig. 1), and only selected data when at least four cameras were operating on the same day. Because the dataset was considerably smaller than the local scale analysis ($n = 279$), and it was not appropriate to model certain variables at the regional scale (e.g. solar radiation), we performed a linear mixed regression of regional SNODAS predictions versus cameras observations. We included ‘region’ as a random intercept to account for potential correlations from repeated measurements and varying effort among regions (Bolker et al. 2009). We detected TAC and incorporated the same correlation structure as the local scale (i.e. ’corExp’). Similarly, we did not detect SAC of the residuals.

**Results**

**SNODAS correlation and bias analyses**

Individual correlations (Pearson’s $r$) between SNODAS predictions and observed depths for corresponding grid cells and camera sites ranged from −0.04 to 1.00 and averaged 0.85, indicating high trends at local scales (Table S1). However, SNODAS commonly underpredicted depths, often ≥30 cm on average, especially at high elevation sites (Table S1). The strength of the correlation was lower (marginal $R^2 = 0.20$) when including all data and adjusting for autocorrelation at multiple levels and this relationship was significantly positive ($\beta = 0.41 \pm 0.01$, $t = 38.01$, $P < 0.0001$). SNODAS sometimes predicted no or trace amounts of snow when depths at cameras were >100 cm, yet overprediction was just as common, especially when depths were intermediate and deep (Fig. 3).

The spatial distribution of SNODAS bias varied greatly over the study area (Fig. S5). There were five models with $\Delta$AICc scores <2, which contained nested combinations of the full model (Table S4). The variance of SNODAS bias was moderately explained by the model-averaged parameters (average marginal $R^2 = 0.31$) with elevation, latitude, solar radiation and per cent conifer forest all having strong effects (Table S4, Table 1). Specifically, SNODAS overpredicted depths up to 12 cm at elevations <590 m and underpredicted depths up to 44 cm higher than this elevation (Fig. 4A). Similarly, there was a negative relationship between latitude and SNODAS bias (Table 1). However, this effect was likely spurious, despite low multicollinearity (VIF scores <2), and due to a moderate correlation with elevation ($r = 0.4$), as the univariate latitude model was comparable to the null model (Table S4). We detected a curvilinear relationship for solar radiation where bias plateaued, yet always remained negative (SNODAS underpredicted), at around 1327 Wh/m² and sharply declined to 17 cm at the highest values of solar radiation (6000 Wh/m²; Fig. 4C). SNODAS also underpredicted snow depths up to 10 cm when sites had >27% conifer forest (Fig. 4C). Depths were overpredicted
only up to 4 cm when sites were primarily comprised of deciduous trees (Fig. 4D).

Our sites were representative of the grid cells for most differential variables (elevation, latitude, per cent conifer forest, solar radiation and canopy cover), except for biomass which was biased in some regions (Figs. S2 and S3). The only differential variables to influence SNODAS bias were solar radiation and biomass (Table S2). Specifically, underprediction increased as solar radiation values for camera sites increased relative to SNODAS grid cell values (\( \beta = -0.46 \pm 0.10, \ t = -4.43, \ P < 0.0001 \); Fig. S4). Although solar radiation values of the sites were relatively similar to those of SNODAS grid cells (Fig. S2), areas with the greatest positive solar radiation differences (i.e. where site > grid cell solar radiation) were in mountainous regions (Table S3, Fig. S3). Decreasing differences in biomass between sites and SNODAS grid cells had a marginal positive effect on SNODAS bias (i.e. bias decreased) (\( \beta = 3.71 \pm 1.99, \ t = 1.87, \ P = 0.065 \); Fig. S4), especially for sites with lower biomass than grid cells, which commonly occurred in mountainous regions (Table S3, Fig. S3). Most sites, however, had slightly greater or similar biomass than that of the grid cells (Figs. S2 and S3).

SNODAS predictions and camera observations were significantly correlated at the regional scale (marginal \( R^2 = 0.16; \beta = 0.39 \pm 0.03, \ t = 11.95, \ P < 0.0001 \)). SNODAS under- and overpredicted snow depth in certain regions (Fig. 5). A closer examination at this scale indicated that SNODAS primarily underpredicted snow depths sometimes \( \geq 26 \) cm at high elevation regions (CLNA, Kinsman, Twin and Zealand; Fig. 6). SNODAS also underpredicted depth at these sites when depths were lower, and shallow snow conditions are typical during the beginning and end of winter.

Table 1. Model-averaged parameter estimates (\( \beta \)), including SE, Wald’s z values (z-value) and probability statistics (\( P \)) of SNODAS prediction bias.

| Parameter       | \( \beta \)     | SE     | z-value | \( P \)     |
|-----------------|-----------------|--------|---------|-------------|
| (Intercept)     | -6.119          | 1.662  | 3.681   | 0.000       |
| Elevation       | -13.876         | 2.108  | 6.583   | \(<0.001\)  |
| %Conifer        | -4.029          | 2.015  | 2.000   | 0.045       |
| Latitude        | -6.867          | 2.116  | 3.245   | 0.001       |
| Solar radiation | -1.011          | 0.623  | 1.622   | 0.105       |
| Solar radiation \(^2\) | -0.815        | 0.301  | 2.708   | 0.007       |
| Canopy cover    | -2.017          | 1.542  | 1.309   | 0.191       |
| Biomass         | -1.431          | 1.763  | 0.812   | 0.417       |

The parameters highlighted in bold had 95% confidence levels that did not overlap zero. SE, standard errors; SNODAS, Snow Data Assimilation System.

Discussion

Remote cameras are established tools for monitoring wildlife populations; our study indicates that they can also be used to collect local climate data. Our local measurements of snow depth provided a unique opportunity to evaluate the biases associated with gridded snow data products such as SNODAS. We documented moderate to strong correlations between our observed depth measurements and SNODAS predictions at multiple scales, indicating SNODAS tracked trends in snowpack. However, we detected systemic biases at the local and regional scale. Although we did not formally model bias at the regional scale, our regression analysis indicated that regions where SNODAS underpredicted depths were at high elevations. Potentially, these trends are due to the paucity of regional ground-based snow stations which are used to update the predictions (Carroll et al. 2006). The northeastern US, and the region of this study in particular, has considerably fewer high elevation snow stations (\( n = 4 \)), unlike the western US which has numerous SNOTEL stations in mountainous regions (Knowles 2015). This may have contributed to the higher correlation and lower bias between SNODAS predictions and ground observations in Colorado (Clow et al. 2012). However, a study in Wyoming found strong positive bias (i.e. overprediction), especially in areas with snow shadows despite an extensive SNOTEL network (Brennan et al. 2013). Further, over-prediction at high elevation was associated with large-scale circulation patterns in the Sierra Nevada range (Lundquist et al. 2015). Bias trends in mountainous regions may indicate a poorly performing model estimation of temperature change with elevation or accumulation/ablation algorithm for the region (Roth and Nolin 2017). Although the northeastern US has considerably less mountainous terrain, it would be prudent to increase ground observation sites in high elevation areas to correct for biases in SNODAS predictions.

Forest cover type is another factor that contributed to snow depth bias. We found SNODAS underpredicted snow depth in forests with a higher proportion of conifers, possibly due to known challenges modeling snowpack characteristics in these types of environments (Dickerson-Lange et al. 2015) and known uncertainty in SNODAS predictions where trees are present (Barrett 2003). Forests with an intermediate proportion of conifers (i.e. mixedwood forest) can have deep and low-density snow (Halpin and Bissonette 1988; Sirén 2013) due to low snow interception from deciduous trees and insulative properties from conifers (Halpin and Bissonette 1988; Essery et al. 2003). Alternatively, conifer-dominated forests may block satellite observations which make it difficult to estimate depths (Dickerson-Lange et al. 2015),
especially when temperature varies above and below freezing (Lundquist et al. 2013). Both of these factors can lead to greater uncertainty and potentially explain why SNODAS increasingly underpredicted depths in conifer forest. Clow et al. (2012), however, found that SNODAS predictions were accurate in conifer-dominated montane forest in Colorado. These forests are generally more open with simple structure (e.g. homogenous species composition) and have fewer hardwood species than mesic forests in the northeastern US (e.g. Berg et al. 2012) in which case snow depths may be more uniform and easier to predict. However, the study area of Clow et al. (2012) had a high density of snow stations, which may have increased the accuracy of SNODAS predictions. Alternatively, their binary classification of land cover (i.e. montane/alpine) may have been too coarse and masked biases occurring at finer thematic resolutions (e.g. Zhou et al. 2014).

Furthermore, our study revealed a bias that might not be detected at coarser scales. For example, remote camera surveys allow for daily observations over the course of a snow season. SNODAS bias was greatly influenced by solar radiation which varied spatially and temporally, suggesting an inability to detect local variability. Indeed, solar radiation is more variable in areas with topographic complexity (Kang et al. 2002), which also influences snowpack dynamics (Ellis et al. 2013). Our differential analysis revealed that SNODAS bias increased when sites had higher than average solar radiation values than grid cells, which primarily occurred at higher elevations (see Table S3). SNODAS predictions are assumed to represent average conditions within the 1 km cell (Barrett 2003), yet when conditions are highly variable at finer resolutions, predictions may be less reliable. SNODAS also underpredicted depths when snow was shallower which is
a typical characteristic of shoulder seasons. We detected these trends at the local and regional scale, where, for example, depths were 100 cm greater than SNODAS predictions (Fig. 3) and occurred most often at high elevation regions (e.g. CLNA, Twin and Zealand; Fig. 5).

Both solar radiation, which varies spatially and temporally, and forest cover interact in complex ways to influence snow accumulation and ablation (Ellis et al. 2013; Dickerson-Lange et al. 2017). These factors are highly variable in areas with topographic complexity (e.g. mountainous areas) which has cascading impacts on snowpack (Roth and Nolin 2017). Further, changes in temperature and forest cover, especially conifer forest, can interact to influence snow melt and accumulation and vary considerably along elevation gradients (Lundquist et al. 2013; Roth and Nolin 2017). Our findings indicate that all three of these factors (i.e. solar radiation, forest cover and elevation) greatly influenced SNODAS accuracy, and that mountainous sites/regions, in particular, were associated with the highest underpredicted depths. Our findings also support recent studies that more knowledge is required to identify the spatial and temporal factors that influence snow accumulation and ablation in mountainous regions (Dickerson-Lange et al. 2017; Roth and Nolin 2017).

The northeastern US, in particular, would benefit from a better understanding of snowpack dynamics in mountainous regions given the paucity of ground stations. This knowledge is critical for end users such as wildlife ecologists that work with species that are sensitive to changes in snow phenology (e.g. snowshoe hares: Zimova et al. 2014; Sultaire et al. 2016). Further, increasing the spatiotemporal accuracy of climate products will help scientists and natural resource managers to identify climate change refugia (Morelli et al. 2016). Because snow depths at high elevation were highly underestimated in our region, refugia for snow-adapted species may be overlooked if bias is not well understood. These considerations are also important for evaluating resources that are important ecosystem services (e.g. water from snowmelt) that are expected to be altered from land use and climate change (Ellis et al. 2013; Lundquist et al. 2013).

Increasing observation networks in areas that are underrepresented (e.g. high elevation) will be crucial for accurate modeling of wildlife populations and ecosystem services (Dickerson-Lange et al. 2015; He et al. 2015; Pepin 2015; Morelli et al. 2016). Understanding the mechanisms that create bias will allow for adjustments (see Clow et al. 2012), but also provide direction for future studies. Based on our results, we recommend future studies to (1) test the influence of forest structure on snow depth bias, (2) intensify sampling along elevation gradients, (3) integrate our method in other regions that have more ground-based observations and (4) increase the number of cameras per SNODAS grid cell. Finally, we suggest the integration of temperature readings with our camera method to evaluate indices such as winter severity (Notaro et al. 2014) or the impact of temperature and forest cover on snowpack along elevation gradients (e.g. Roth and Nolin 2017). This could be accomplished through the inclusion of a shielded thermometer within the range of view or using temperature readings recorded by remote cameras. Preliminary investigation of camera temperatures, however, indicates that certain brands and seasons influence the accuracy of
camera temperatures (A. Sirén, University of Massachusetts, unpubl. data).

The use of remote cameras by the general public and scientists is widespread in the US (Steenweg et al. 2017), which creates myriad opportunities for climate and wildlife monitoring that may fit well within a citizen science framework (Chandler et al. 2017). Developing a continent-wide array of camera observation networks would greatly increase our understanding of local and regional factors that influence climate and benefit multiple scientific disciplines and applications. Minimally, our method provides a cost-effective tool for improving our knowledge of factors that influence local snow depth which can be used to bias-correct gridded climate data.

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Conflict of Interest

The authors declare no conflict of interests.

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Supporting Information

Additional supporting information may be found online in the supporting information tab for this article.

Table S1. Sample size (n), elevation (m), mean (X), standard error (SE), and median bias (difference between SNODAS predictions and camera observations), and Pearson’s correlations (r²) between camera observations and SNODAS predictions for each camera site.

Table S2. Linear mixed models of differential variables versus SNODAS bias from camera surveys conducted in northern New England, USA, from 9 January 2014 to 9 March 2016.
Table S3. Summary of scaled differential (Dif) variables (Site value – grid value) and elevation (m) for 80 camera sites used to evaluate SNODAS bias in northern New England, USA, from 9 January 2014 to 9 March 2016.

Table S4. Linear mixed models of SNODAS bias from camera surveys conducted in northern New England, USA, from 9 January 2014 to 9 March 2016.

Figure S1. Plots of SNODAS predictions versus camera observations for each site. Note: Black diagonal line indicates 1:1 relationship between SNODAS versus camera observations.

Figure S2. Histograms of the differences between the camera site and SNODAS grid predictor variables used to evaluate SNODAS bias. All parameters were scaled and centered prior to analysis. Positive (green) and negative (blue) values indicate where camera site values were greater or less than SNODAS grid values, respectively. Larger bubbles indicate greater differences between sites and grids.

Figure S3. Bubble plots indicating the spatial distribution of the differences between the camera site and SNODAS grid predictor variables used to evaluate SNODAS bias. All parameters were scaled and centered prior to analysis. Positive (green) and negative (blue) values indicate where camera site values were greater or less than SNODAS grid values, respectively. Larger bubbles indicate greater differences between sites and grids.

Figure S4. Predictive plots of significant (solar radiation) and marginally significant (biomass) differential variables versus SNODAS bias. SNODAS bias negatively increased (i.e. SNODAS underpredicted snow depths) as the solar radiation values for sites became greater than grid values. Conversely, negative SNODAS bias occurred when grid biomass values were higher than site biomass values.

Figure S5. Bubble plots indicating the spatial distribution of SNODAS bias (difference between camera observations and SNODAS predictions). Positive (green) and negative (blue) values indicate where observed depths were greater or less than SNODAS predictions, respectively. Larger bubbles indicate greater differences between sites and grids.