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# Collaborative wildlife–snow science: Integrating wildlife and snow expertise to improve research and management

**Adele K. Reinking[1] | Stine Højlund Pedersen[1,2] | Kelly Elder[3] | Natalie T. Boelman[4] | Thomas W. Glass[5,6] | Brendan A. Oates[7] | Scott Bergen[8] | Shane Roberts[8] | Laura R. Prugh[9] | Todd J. Brinkman[10] | Michael B. Coughenour[11] | Jennifer A. Feltner[12] | Kristin J. Barker[13] | Torsten W. Bentzen[14] | Åshild Ø. Pedersen[15] | Niels M. Schmidt[16] | Glen E. Liston[1]**

[1]Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, Colorado, USA

[2]Department of Biological Sciences, University of Alaska Anchorage, Anchorage, Alaska, USA

[3]US Forest Service, Rocky Mountain Research Station, Fort Collins, Colorado, USA

[4]Lamont-Doherty Earth Observatory, Columbia University, Palisades, New York, USA

[5]Wildlife Conservation Society, Fairbanks, Alaska, USA

[6]Department of Biology and Wildlife, University of Alaska Fairbanks, Fairbanks, Alaska, USA

[7]Washington Department of Fish and Wildlife, Ellensburg, Washington, USA

[8]Idaho Department of Fish and Game, Pocatello, Idaho, USA

[9]School of Environmental and Forest Sciences, University of Washington, Seattle, Washington, USA

[10]Institute of Arctic Biology, University of Alaska Fairbanks, Fairbanks, Alaska, USA

[11]Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, Colorado, USA

[12]Wildlife Biology Program, University of Montana, Missoula, Montana, USA

[13]Department of Environmental Science, Policy, and Management, University of California Berkeley, Berkeley, California, USA

[14]Alaska Department of Fish and Game, Fairbanks, Alaska, USA

[15]Norwegian Polar Institute, Fram Centre, Tromsø, Norway

[16]Department of Bioscience and Arctic Research Centre, Aarhus University, Aarhus, Denmark

**Correspondence**
Adele K. Reinking
Email: adele.reinking@colostate.edu

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**Abstract**

For wildlife inhabiting snowy environments, snow properties such as onset date, depth, strength, and distribution can influence many aspects of ecology, including movement, community dynamics, energy expenditure, and forage accessibility. As a result, snow plays a considerable role in individual fitness and ultimately population dynamics, and its evaluation is, therefore, important for comprehensive understanding of ecosystem processes in regions experiencing snow. Such understanding, and particularly study of how wildlife–snow relationships may be changing, grows more urgent as winter processes become less predictable and often more extreme under global climate change. However, studying and monitoring wildlife–snow relationships continue to be challenging because characterizing snow, an inherently complex and constantly changing environmental feature, and identifying, accessing, and applying relevant snow information at appropriate spatial and temporal scales, often require a detailed understanding of physical snow science and technologies that typically lie outside the expertise of wildlife researchers and managers. We argue that thoroughly assessing the role of snow in wildlife ecology requires substantive collaboration between researchers with expertise in each of these two fields, leveraging the discipline-specific knowledge brought by both wildlife and snow professionals. To facilitate this collaboration and encourage more effective exploration of wildlife–snow questions, we provide a five-step protocol: (1) identify relevant snow property information; (2) specify spatial, temporal, and informational requirements; (3) build the necessary datasets; (4) implement quality control procedures; and (5) incorporate snow information into wildlife analyses. Additionally, we explore the types of snow information that can be used within this collaborative framework. We illustrate, in the context of two examples, field observations, remote-sensing datasets, and four example modeling tools that simulate spatiotemporal snow property distributions and, in some cases, evolutions. For each type of snow data, we highlight the collaborative opportunities for wildlife and snow professionals when designing snow data collection efforts, processing snow remote sensing products, producing tailored snow datasets, and applying the resulting snow information in wildlife analyses. We seek to provide a clear path for wildlife professionals to address wildlife–snow questions and improve ecological inference by integrating the best available snow science through collaboration with snow professionals.

**KEYWORDS**
collaboration, data–model fusion, interdisciplinary, snow data, snow modeling, SnowModel, wildlife ecology, wildlife management, wildlife research, wildlife–snow, winter

# MOTIVATION

The physical properties of snow, and their spatial distribution and temporal evolution, influence many ecological processes (Figure 1). For wildlife, snow properties can impact individuals by affecting movements and behaviors (Balkenhol et al., 2020; Berman et al., 2019; Boelman et al., 2017; Chimienti et al., 2020; Coady, 1974; Droghini & Boutin, 2018; Mahoney et al., 2018; Oliver et al., 2018; Oliver et al., 2020; Pedersen et al., 2021); predator–prey interactions (Horne et al., 2019; Nelson & Mech, 1986; Peers et al., 2020; Sirén et al., 2021); energetics related to foraging (Dumont et al., 2005; Fancy & White, 1985), locomotion (Fancy & White, 1987; Gurarie et al., 2019; Lundmark & Ball, 2008; Parker et al., 1984), and thermoregulation (Karniski, 2014; Pruitt Jr., 1957; Thompson III & Fritzell, 1988); forage accessibility (Hupp & Braun, 1989; Takatsuki et al., 1995; Visscher et al., 2006; White et al., 2009); as well as ground (Boelman et al., 2016) and subnivean habitat use (Bilodeau et al., 2013; Glass et al., 2021; Petty et al., 2015). Additionally, the effects of snow on individual survival (Hurley et al., 2017; Reinking et al., 2018; Shipley et al., 2020) and reproduction (Apollonio et al., 2013; Barnowe-Meyer et al., 2011; Liston et al., 2016; Schmidt et al., 2019) can ultimately alter population-level demographics (Apollonio et al., 2013; Berteaux et al., 2017; Boelman et al., 2019; Cosgrove et al., 2021; Desforges et al., 2021; Van de Kerk et al., 2018; Van de Kerk et al., 2020). Effective evaluation of such wildlife–snow relationships requires identification, acquisition, and incorporation of appropriate and relevant snow property information.

Many wildlife professionals have an in-depth knowledge of how snow influences the species or communities

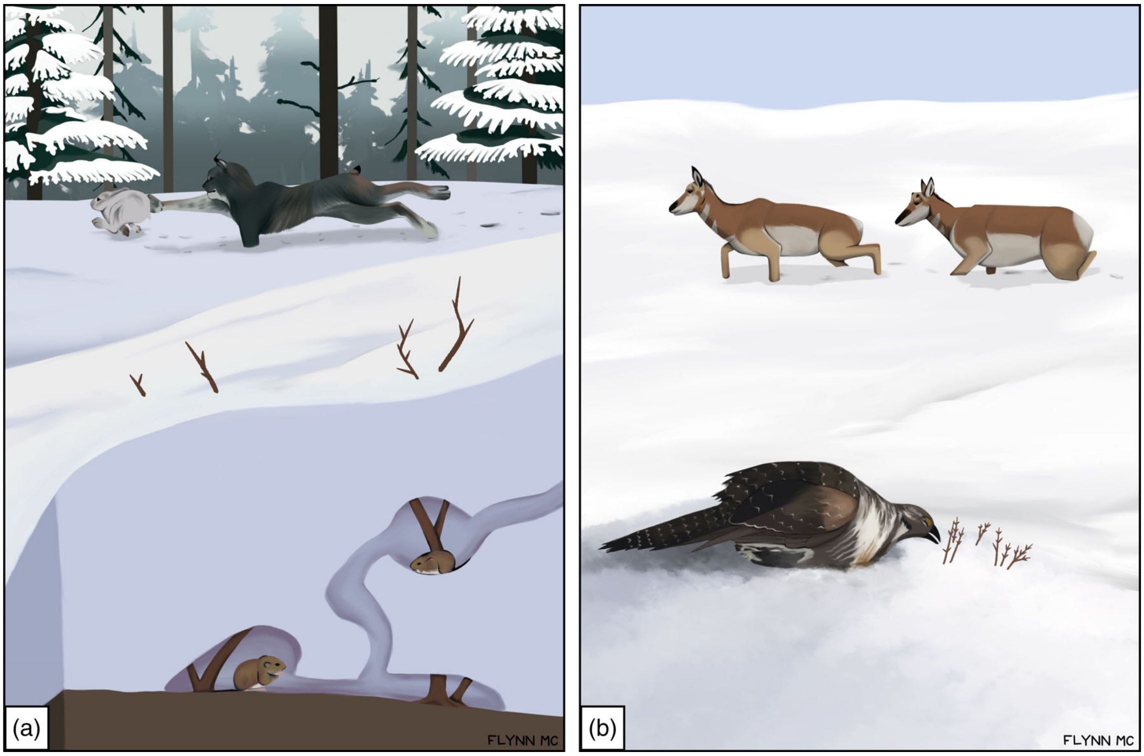


**FIGURE 1** Example wildlife–snow interactions. (a) Predator–prey (Canada lynx–snowshoe hare [*Lynx canadensis*–*Lepus americanus*]) interactions in snow and subnivean habitat use by meadow vole (*Microtus pennsylvanicus*). (b) Ungulate (pronghorn [*Antilocapra americana*]) movement through snow and forage accessibility above the snowpack for greater sage-grouse (*Centrocercus urophasianus*). Graphic courtesy of Flynn Melendy-Collier

that they study or manage. However, the complex and constantly changing nature of snow makes its inclusion in wildlife research and management projects challenging. Effective evaluation of wildlife–snow relationships, and monitoring of these relationships through time, requires identifying and understanding the specific snow properties that are relevant for each unique application and appropriately applying data that represent that property in analyses. Snow properties ranging from depth (i.e., the height of the snow surface above the ground surface) to more complex properties, such as strength (i.e., the ability of the snow surface to support the force an animal exerts upon it), impact wildlife across ecosystems (Crupi et al., 2020; Pozzanghera et al., 2016; Sivy et al., 2018) and are often highly dynamic in space and time. Accounting for this complexity demands an intimate knowledge of snow science beyond that of most practicing wildlife professionals.

To use biologically relevant snow data in their analyses, wildlife professionals must specify dataset: (1) *spatial and temporal domains* (e.g., multiple study areas and historical, current, or future snowpacks), (2) *spatial and temporal resolutions* (e.g., several spatial scales and hourly, daily, monthly, or yearly snow conditions), and (3) *unique snow variables* (e.g., depth, number of rain-on-snow events each year, or strength). The technical expertise required to make these decisions relies on specific knowledge of the physics driving snow property evolution, field measurement procedures, snow remote-sensing datasets, and programming environments and modeling tools to which wildlife professionals may not have access. These challenges can be further confounded by limited project funding and logistical constraints and can lead to the inclusion of easily accessible, but less biologically meaningful, snow information in wildlife research and management efforts (as described in Brennan et al., 2013; Magoun et al., 2017). We believe that by leveraging the discipline-specific expertise of professionals from both the wildlife and snow fields, we can overcome these obstacles and advance our understanding of how snow influences wildlife.

## Incentive for collaboration

Across science and management fields, interdisciplinary and diverse collaboration produces stronger, more innovative outcomes (Hong & Page, 2004; Schmidt et al., 2017). This innovation can be crucial in addressing major societal challenges, such as climate change and loss of biodiversity, and may provide additional benefits, including greater citation impact (Yegros-Yegros et al., 2015), cost-sharing of resources, and simultaneous advancement across fields. Nearly 175 years ago, this principle was advocated by prominent philosopher, John Stuart Mills, when he emphasized,

> "It is hardly possible to overrate the value … of placing human beings in contact with persons dissimilar to themselves, and with modes of thought and action unlike those with which they are familiar … Such communication has always been, and is particularly in the present age, one of the primary sources of progress. (Mills, 1848)"

Today, such multi-institutional, cross-disciplinary research is encouraged and frequently required by research funding bodies. For example, the United States National Science Foundation (NSF) lists collaboration as a "core value," and often solicits research projects evaluating interdisciplinary questions (NSF, 2018). Despite the well-recognized benefits of and frequent financial support for collaboration, integration of different scientific backgrounds, particularly in ecological studies, remains challenging; this is usually because scientific outlets (e.g., conferences and journals), physical workplaces, and programmatic education structures remain broadly segregated by discipline (Campbell, 2005; Mair et al., 2018; Schmidt et al., 2017). We seek to facilitate collaboration by providing a formalized structure to address wildlife–snow questions through a stronger integration of wildlife and snow sciences.

## Moving forward together

We describe a five-step, systematic protocol to identify, access, and apply the most appropriate snow information: (1) identify relevant snow property information; (2) specify spatial, temporal, and informational requirements; (3) build the necessary datasets; (4) implement quality control procedures; and (5) incorporate snow information into wildlife analyses. To demonstrate the practical utility of these five steps, we apply them to an example investigation of the fitness consequences of snow roosting by ruffed grouse (*Bonasa umbellus*; Boxes 1–5: Ruffed grouse example). We use the terms "wildlife professionals" and "snow professionals" throughout, with the intention of encompassing all researchers and natural resource managers spanning the disciplines of wildlife ecology and snow science, including research biologists, field biologists, wildlife managers, conservationists, climate modelers, hydrologists, avalanche forecasters, and others. By working with snow professionals, wildlife professionals can take advantage of the wealth of snow information that has, until now, remained largely within the snow science community to answer important questions that have previously been elusive. This collaborative framework can be applied to a variety of objectives, from basic ecological research and monitoring to the development of wildlife management strategies.

Finally, to aid in the production of more impactful, higher quality research and management outcomes, we provide examples of using three types of snow information (field observations, remote sensing information, and modeled datasets) that can be employed when following this collaborative, systematic approach. We discuss these data types using an example of the Greater Yellowstone Ecosystem (GYE) wolf–elk (*Canis lupus*–*Cervus canadensis*) predator–prey relationship to showcase their potential use in real-world projects; for each type of snow information, we highlight the benefits of working collaboratively (Boxes 6–8: GYE example). In this review, we focus on time-evolving, spatially distributed information and methodologies, as opposed to point observations, since these former data better reflect the dynamic nature of wildlife–snow interactions and are usually of the greatest interest and utility to wildlife professionals. To this end, we present a detailed comparison of four snow modeling tools, chosen to exemplify the general range in complexity of such systems. These snow distribution and snow evolution modeling systems all assimilate (i.e., synthesize) snow observations as part of their simulation process, thereby pulling model results closer to observed snow characteristics; these tools are referred to as data–model fusion systems. A key component of this data–model fusion approach is that wildlife and snow professionals use their unique scientific backgrounds to work together to define, produce, and incorporate the most useful snow datasets for each specific wildlife–snow project.

# WILDLIFE–SNOW COLLABORATION IN FIVE STEPS

## Step 1: Identify relevant snow properties

The snow properties relevant to any wildlife application depend on the research questions and can be informed by literature review, Traditional Ecological Knowledge, field experience and measurements, model studies and outputs, and anecdotal evidence (Bélisle et al., 2018; Cuyler et al., 2020; Huntington, 2000; Sagarin &

Pauchard, 2010). In addition to identifying fundamental snow properties that are often important to consider, such as depth, a specific wildlife–snow application may also benefit from including value-added synthesis variables that better describe wildlife-relevant snow properties by combining multiple snow characteristics.

For example, consider the common hydrologic variable, snow water equivalent (SWE), which represents the depth of water produced if the snowpack is melted at a given point and time. From a hydrologic perspective, maximum winter SWE approximates the amount of meltwater that will be available as runoff in the spring (Li et al., 2017; Sexstone et al., 2021), and this variable represents one possible metric to characterize winter severity in terms of maximum winter snow accumulation. However, from a wildlife perspective, additional information may be required to define and quantify winter severity in a more meaningful way. Variables representing combinations of time and snow properties, such as the total number of days in the season with snow deeper than some depth threshold for a specific species (e.g., percent of limb length or shoulder height), may provide more relevant measures of snow season severity (Feltner, 2021). Other value-added, synthesis variables that are representative of winter severity in wildlife–snow applications might include a combination of spatially and temporally distributed variables such as snow depth, date of first snow accumulation, wind speed, temperature, length of the snow-covered period, and snow-free date.

Through interdisciplinary work and discussions (Figure 2), wildlife and snow professionals can collaboratively determine which snow properties should be defined and quantified to address research and management objectives. Moreover, it is crucial that sufficient time be devoted to ensuring that all team members understand the terminology being used to describe the snow variables of interest and the precise snow properties that are being characterized by those variables. This initial time investment can minimize breakdowns in communication that may cause problems later in the collaborative process. Step 1 is further illustrated in Box 1: Ruffed grouse example.

## Step 2: Specify spatial, temporal, and informational requirements

### Fit-for-purpose snow data

After identifying relevant snow properties, wildlife and snow professionals must determine the appropriate


FIGURE 2 (a) Wildlife and snow professionals conducting field research side-by-side to collaboratively collect data on wildlife–snow interactions. (b) Wildlife and snow professionals in subsequent discussion after a collaborative day in the field to develop, refine, and execute high-quality, interdisciplinary wildlife–snow science. Graphic courtesy of Flynn Melendy-Collier

**BOX 1 Ruffed grouse example**

In the northern portions of their range, snow can serve as important winter thermoregulation habitat and refugia from predators for ruffed grouse. Snow, as a roosting substrate, reduces winter metabolic requirements more than other roosting microsite types, minimizes physiological stress associated with low temperatures, and is preferred when available at sufficient depths (Shipley et al., 2019; Thompson III & Fritzell, 1988; Whitaker & Stauffer, 2003). Moreover, it provides cover from avian predators (Heinrich, 2017; Marjakangas, 1990). Therefore, snow roosting has fitness consequences for ruffed grouse because it influences overwinter survival (Shipley et al., 2020). Understanding the effects of snow roosting habitat on ruffed grouse survival would require identification of candidate snow properties with the potential to mediate this relationship. Depth is a clear choice, as is persistence (i.e., the length of time an area remains snow-covered). However, more complicated measures, like snow softness or surface crusting (related to the capacity for grouse to bury themselves within the snowpack) or the thermal resistance (related to the insulative properties of the snowpack), may also impact roost site quality and associated grouse survival (Devers et al., 2007; Whitaker & Stauffer, 2003). Assessment of these properties would likely lead to a more nuanced and accurate understanding of the influence of snow roosting habitat characteristics on ruffed grouse fitness.

Moreover, the wildlife and snow professionals in this example may require unique, synthesized snow information describing value-added combinations of these properties, such as a variable that indicates the number of days when both depth and softness met or exceeded certain thresholds required for ideal winter roosting habitat. In collaboration with wildlife professionals, snow professionals could provide insight on how to create and represent these value-added covariates. For example, snow density could serve as an adequate index for snow softness, but the validity of this assumption depends on the processes controlling density evolution. Snow professionals can employ a comprehensive understanding of physical snowpack processes and properties to make this determination.

spatial, temporal, and informational specifications for the datasets describing those snow attributes. Because both wildlife and snow processes occur at various spatial and temporal scales, this requires a hierarchical systems approach (O'Neill et al., 1986; Urban et al., 1987), prioritizing consideration of scales and resolutions that will best address research and management objectives and most appropriately represent the snow properties of interest given the unique study region. Additionally, project resources, such as computational capacity, time, personnel, and funding, may affect some of these decisions. Correctly specifying dataset dimensions involves initial team discussion of data expectations, ensuring early transparency regarding the utility and limitations of available snow information resources. Snow data spanning the largest possible area, at the finest spatial and temporal scales, for the longest time period, and detailing the greatest number of snow variables, would likely strain project resources and add unnecessary complexity to analyses.

The spatial, temporal, and informational details of generalized, one-size-fits-all snow products are often poorly suited to address individual project needs. Therefore, we advocate tailoring snow data specifications to each unique wildlife–snow application. Operational snow data products (i.e., datasets created for meteorological and hydrological applications that are regularly produced and publicly available) often seem like a viable solution because they are readily accessible. In some cases, these may be appropriate, depending on the individual wildlife–snow application. However, fit-for-purpose snow information typically allows a far more precise evaluation of wildlife–snow relationships and maximizes the utility and efficiency of those data (Boelman et al., 2019).

## Defining dataset specifications

For each wildlife–snow research and management question, the specific wildlife processes of interest, and the hierarchical system scale at which those occur, play a driving role in determining the appropriate spatial and temporal scale at which to evaluate wildlife–snow interactions (O'Neill et al., 1986; Urban et al., 1987). Similarly, the distribution of physiographic features controlling snow conditions in the study area, the spatial and temporal scales over which snow properties of interest vary, and the spatial and temporal scales at which project-specific snow information is best represented will be unique for each application. Ultimately, the resolution of a snow dataset, therefore, balances the scale of snow property distribution and evolution with the scale at which that snow property is likely to influence ecology, and particularly the resolution at which that relationship may be captured by available wildlife data (e.g., frequency of GPS location fixes).

Landscape features, such as vegetation structure, and topographic slope, aspect, and elevation, can drive environmental conditions like wind speeds, air temperatures, and snowfall quantities (Broxton et al., 2014; Elder et al., 1991; Liston et al., 2002; Liston et al., 2007; Sturm & Wagner, 2010). These conditions impact the evolution of snow properties, such as depth, density, strength, stratigraphy, and ice layers (Elder et al., 1991; Elder et al., 1998; Sturm et al., 1995; Sturm & Liston, 2021). Generally, if the distribution of these snow-controlling features is relatively homogenous, a snow dataset of coarser spatial resolution may appropriately represent conditions; however, if extensive spatial heterogeneity exists, finer spatial resolution datasets may be required (Daly, 2006; Watson, Anderson, et al., 2006). Moreover, defining dataset requirements is often best achieved when snow professionals can visit the study area alongside wildlife professionals to gain a stronger understanding of the important processes occurring in the wildlife–snow system and initiate discussions of study design to collect and couple wildlife and snow observations (Figure 2). Step 2 is further illustrated in Box 2: Ruffed grouse example.

## Step 3: Build the necessary datasets

Once wildlife and snow professionals have identified the types of snow information needed and determined the spatial, temporal, and informational requirements, it is then necessary to determine if these project-specific data exist. If they do exist, access to the information could prove challenging (e.g., requiring a fee or certain account credentials to download), and it may be necessary to further process data for use in wildlife analyses. However, the required, relevant datasets often do not exist (Boelman et al., 2019; Rose et al., 2015). In this case, snow professionals can help to determine if the use of related, but different, ready-made information will be sufficient, or if field data collection, remote sensing snow information, snow modeling

### BOX 2 Ruffed grouse example

Dataset specifications depend on the scope of the research project. The main objective of the example ruffed grouse project is to create spatial and temporal maps of adequate extent and resolution to describe the snow habitat distribution and quality for several specific years for comparison with grouse survival data. This goal requires accounting for local, daily (or sub-daily) snow-evolution processes, like wind and solar radiation, that impact specific snow properties, such as depth and softness, at the microclimate scale. In contrast, if the goal was to estimate inter-annual variability and long-term trends (e.g., decadal) in snow habitat distribution and quality across a broad area to compare with general population trends, the snow dataset specifications would be defined to capture the year-to-year variation in more synoptic-scale winter snowfall, temperature, and wind regimes.

Definition of dataset specifications is also dependent upon the characteristics of the study region. It is relatively simple to conceptualize the snow depth and persistence properties in the ruffed grouse example; however, without snow science expertise, knowledge may be limited surrounding the physical snow processes, such as wind-produced deposition and erosion that, in turn, control more complicated attributes, including the softness and thermal resistance parameters. Determining the best spatial and temporal scales to represent these processes and properties is equally complex. As an example, on south-facing slopes (in the Northern Hemisphere), snow melting and refreezing can result in a hard surface crust, inhibiting burrowing by grouse (Devers et al., 2007). Because crusting of the surface is an important component of the coupled biotic and abiotic system for this project, wildlife and snow professionals likely need data at sufficient temporal resolution to resolve the diurnal cycle (e.g., 1- to 3-h time increment), accounting for the role of afternoon sun exposure in characterizing softness. This snow surface change, in turn, may impact the other identified, relevant properties (depth, persistence, and thermal resistance or insulating qualities). Representations of snow softness, either through density metrics or more detailed consideration of micro-scale properties like grain type and bonding, would require different levels of project resource investment and produce different returns in data quality and provided information. The desired snow variables, and the resources available to produce those data, should all be accounted for when collaboratively making decisions about how best to represent the relevant snow information across space and time for a given project.

tools, or a combination of all three (i.e., data–model fusion) is required to accomplish project goals.

## Fundamentals of data–model fusion

Snow properties, and the processes that control their evolution, are ultimately based on the physical relationships between weather and climate conditions and the landscapes over which they operate (Liston et al., 2007; Liston & Hiemstra, 2011). Therefore, weather data, such as gridded atmospheric (re)analyses or meteorological station data, and knowledge of how weather controls physical snow processes, can be combined to produce most required snow datasets. The latest generation of numerical snow modeling tools does this by spatially and temporally distributing and evolving weather information over various land surfaces to simulate snow processes and properties. Further, these modeling tools can also incorporate field and remote sensing data to reproduce observations and create improved snow products using a data–model fusion approach. Previous studies (e.g., Boelman et al., 2019; Glass et al., 2021; Pedersen et al., 2021) have argued that a data–model fusion approach is increasingly necessary to produce the high-quality, fit-for-purpose data products at appropriate spatial and temporal resolutions required to answer the wide range of wildlife–snow research and management questions. Data–model fusion systems can produce more accurate and sophisticated spatiotemporal snow distributions and evolutions than are possible with ground-based, airborne, or satellite observational datasets, or models, alone (Boelman et al., 2019; Daly, 2006; Hedrick et al., 2015; Heilig et al., 2015; Stuefer et al., 2013).

## Creating new, wildlife-relevant variables

In addition to filling spatial and temporal gaps in snow observations, the inclusion of modeling tools allows wildlife and snow professionals to build new variables that are generally not measured in the field or remotely (e.g., from space). These can include complex synthesis variables, like strength, that combine numerous information sources to create data products with increased information and added value. While many of these wildlife-relevant variables can be measured, some are difficult to observe because such synthesis characteristics frequently depend on a large suite of snow properties. Additionally, it is challenging to measure these variables across broad spatial areas, or at the specific times when animals experience those snow conditions (e.g., during mid-winter episodic snowmelt; Pedersen et al., 2015). The collaborative development and application of project-specific, wildlife-relevant snow variables are required to answer wildlife–snow research and management questions most effectively (Boelman et al., 2019) and will lead to a stronger understanding of the mechanistic links between animals and snow properties (Glass et al., 2021; Loe et al., 2020; Pedersen et al., 2021). Step 3 is further illustrated in Box 3: Ruffed grouse example.

**BOX 3 Ruffed grouse example**

Assume wildlife and snow professionals have determined that they require snow depth, persistence, softness, and thermal resistance information to evaluate the influence of snow on ruffed grouse survival. First, it is worth determining if any publicly available, operational snow products are suitable to address the project questions; input from snow professionals can help in this determination and the identification of suitable datasets. For example, depth could be included using a ready-made modeling and data assimilation product, like the 1-km, daily National Oceanic and Atmospheric Administration (NOAA)/National Weather Service (NWS)/National Operational Hydrologic Remote Sensing Center (NOHRSC) Snow Data Assimilation System (SNODAS) snow depth datasets (Barrett, 2003; Carroll et al., 2001). Similarly, snow persistence information may be accessible with remote sensing datasets, like the 1-km, daily NOAA Interactive Multisensor Snow and Ice System snow-cover product (Ramsay, 1998; USNIC, 2008), or the 500-m, daily National Aeronautics and Space Administration (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) snow-cover product (Hall et al., 2002). Wildlife and snow professionals can work together to understand how these datasets are generated, their limitations, and their applicability for understanding ruffed grouse fitness. If snow professionals determine that density is an acceptable proxy for softness, they may recommend calculating it from the publicly available SNODAS depth and SWE information. For reference, snow density, $\rho_s$ (kg m$^{-3}$), can be calculated from depth and SWE using the following equation,

$$\rho_s = \rho_w \frac{SWE}{HS}, \quad (1)$$

where $\rho_w = 1000\ \mathrm{kg\ m^{-3}}$ is the water density, SWE (in meters) is the snow-water-equivalent depth, and HS (in meters) is the snow depth.

If density is not a suitable proxy for softness in the ruffed grouse application, it may be necessary to make field measurements of snow properties like stratigraphy, hardness, or collapse pressure, or even to evaluate snow grain properties like type, size, and grain-to-grain bonding qualities. In addition, depending on how the softness has been defined, it is likely that the associated stratigraphy, density, and grain properties can be used to define thermal resistance or insulating characteristics (Liston et al., 2002, Liston et al. 2020). These field observations could be used in conjunction with snow modeling tools to produce spatio-temporal distributions and evolutions of these properties that likely have greater utility for this application. In addition, the use of data–model fusion systems would facilitate the production of more relevant, value-added synthesis variables, such as the number of days that snow conditions met depth and softness thresholds indicative of ideal roosting habitat.

## Step 4: Implement quality control procedures

Across scientific disciplines, quality assurance and quality control (QA/QC) of datasets are critical steps after data collection or assembly and before using the data in any further analyses (Campbell et al., 2013). Quality assurance / quality control is important both for data collected as part of a given project and for data acquired from outside sources. Many standard procedures will be familiar to any researcher experienced in data collection, manipulation, or modeling. Snow-specific data checks and subsequent automated data validation using graphical, range, and exceedance methods (Liston & Elder, 2006b; Meek & Hatfield, 1994; Serreze et al., 1999) are best facilitated by collaboration with members of that discipline. Wildlife professionals can also provide important validation controls based on their unique, local knowledge of the study system, such as Traditional Ecological Knowledge (Huntington, 2000) or an awareness of additional, historical snow measurements that are not publicly available. Step 4 is further illustrated in Box 4: Ruffed grouse example.

## Step 5: Incorporate snow information in wildlife analyses

The final collaborative step is to incorporate snow information into analyses of wildlife–snow relationships. Depending on the unique wildlife–snow study, the way in which this occurs varies greatly. However, certain characteristics of snow datasets may complicate their implementation within wildlife models. For instance, spatial and temporal autocorrelation of snow properties may require attention prior to using snow datasets within ecological analyses. Failure to account for this potential issue risks violating the assumptions of statistical tests and may lead to erroneous conclusions about wildlife–snow processes.

**BOX 4 Ruffed grouse example**

If snow density was deemed a suitable proxy for softness in the ruffed grouse project, experienced snow professionals could provide feedback on reasonable density ranges. This knowledge would be useful whether density data were derived from publicly available snow data products (e.g., SNODAS), measured in the field across different snow types (e.g., new, faceted, and wind compacted), or collected using another method. For example, new snow densities at low temperatures are unlikely to exceed $150\ \mathrm{kg\ m^{-3}}$ under any circumstances except the presence of considerable wind, while the density of weak, dry, faceted snow is unlikely to exceed $250\ \mathrm{kg\ m^{-3}}$ (Dawson et al., 2017; Sturm et al., 2010). The review of density data by snow professionals in this application would provide useful initial data validation. Moreover, the familiarity of the team wildlife professionals with the example study system (e.g., their knowledge of additional snow field measurements in the area) would further assist in quality control.

Datasets collected across geographical space and over time frequently contain some degree of spatial or temporal dependence between subsequent samples (Legendre & Legendre, 2012), and snow data are no exception (Blöschl, 1999; Pomeroy & Gray, 1995). Autocorrelation of predictor variables, when unaccounted for in statistical models, introduces pseudoreplication to a modeling framework and inflates the probability of incorrectly detecting statistical significance (Type I error; Legendre & Legendre, 2012). However, the spatial and temporal scales at which snow properties are correlated (i.e., the correlation length) vary greatly depending on the property in question, other snow properties, and a wide range of climatological, meteorological, and geographical factors (Hannula et al., 2016). Wildlife professionals using a systematic sampling regime to incorporate snow covariates may therefore inadvertently sample at locations or times that are autocorrelated, if sample intervals coincide with the scale of autocorrelation. The inclusion of snow professionals when first developing field protocol can help eliminate these issues by factoring the spatial and temporal dependence of snow properties into sampling design (Figure 2). Additionally, after data collection is complete, it is often desirable to assess the degree of autocorrelation in observations. This can be achieved using methods (in the case of spatial autocorrelation) such as Moran's *I* mapping to evaluate correlation length (Dormann et al., 2007; Fortin, 2020), and if spatial dependence is detected, several statistical methods exist to address the issue, such as eigenvector mapping (Dormann et al., 2007). Comparable methods exist to diagnose and address issues of temporal dependence. Snow professionals can help minimize spatial and temporal dependence during the data collection process and can subsequently provide insights on how best to assess and mitigate this potential issue within the compiled datasets. Step 5 is further illustrated in Box 5: Ruffed grouse example.

## SNOW DATA FOR WILDLIFE APPLICATIONS

Snow datasets have traditionally been developed for use in physical science disciplines, such as hydrology, climatology, meteorology, and water resource management (Brown, 2000; Butt & Bilal, 2011; Dietz et al., 2012). Consequently, snow data frequently have inadequate spatial or temporal coverage and resolutions or irrelevant snow property information for many wildlife research, management, and monitoring applications (Boelman et al., 2019). This data deficiency may result in wildlife professionals using sub-optimal snow information, ignoring the snow component of ecosystems, or, in extreme cases, ignoring seasons of the year usually associated with snow (i.e., fall, winter, and spring; as described in Boelman et al., 2019; Loe et al., 2020). For example, one of the most common snow dataset variables, SWE, is likely less relevant than depth, for which it is sometimes substituted due to the frequent correlation between these two properties.

Snow data commonly incorporated into ecological applications are often ready-made, publicly available products, such as remote sensing datasets, including NASA/United States Geological Survey (USGS) Landsat (Wulder et al., 2019) and NASA MODIS snow-covered fraction (Hall et al., 2002), or point observations from operational snow observing stations, such as SWE measurements from Natural Resources Conservation Service (NRCS) Snow Telemetry (SNOTEL; Serreze et al., 1999) sites (Jackson et al., 2021; John et al., 2020; Middleton et al., 2013). While these agency products have utility for many wildlife applications, they are often used by default, when more tailored, wildlife-relevant snow information could provide a more nuanced understanding of wildlife–snow relationships.

In general, three types of snow information exist: (1) field observations, (2) remote sensing measurements,

**BOX 5 Ruffed grouse example**

To evaluate the potential effects of snow roosting habitat availability and quality on ruffed grouse survival, snow depth field measurements may be necessary. It is important that from an early stage, the sampling scheme consists of transects that extend beyond the correlation length of this variable. This likely involves initial sampling and testing to determine at what spatial and temporal scales snow properties such as depth are non-independent within the study area. In addition, it would likely be important to implement a stratified sampling scheme based on study area weather and landscape heterogeneity to measure this snow property within different snowy landscape (snowscape) habitats or sub-domains, ensuring adequate characterization of the variability in snow properties across the study area. Once field data collection is complete, tests of spatial and temporal dependence should be conducted. If autocorrelation of snow property data is likely to impact wildlife analyses, this issue should be accounted for with appropriate statistical methods.

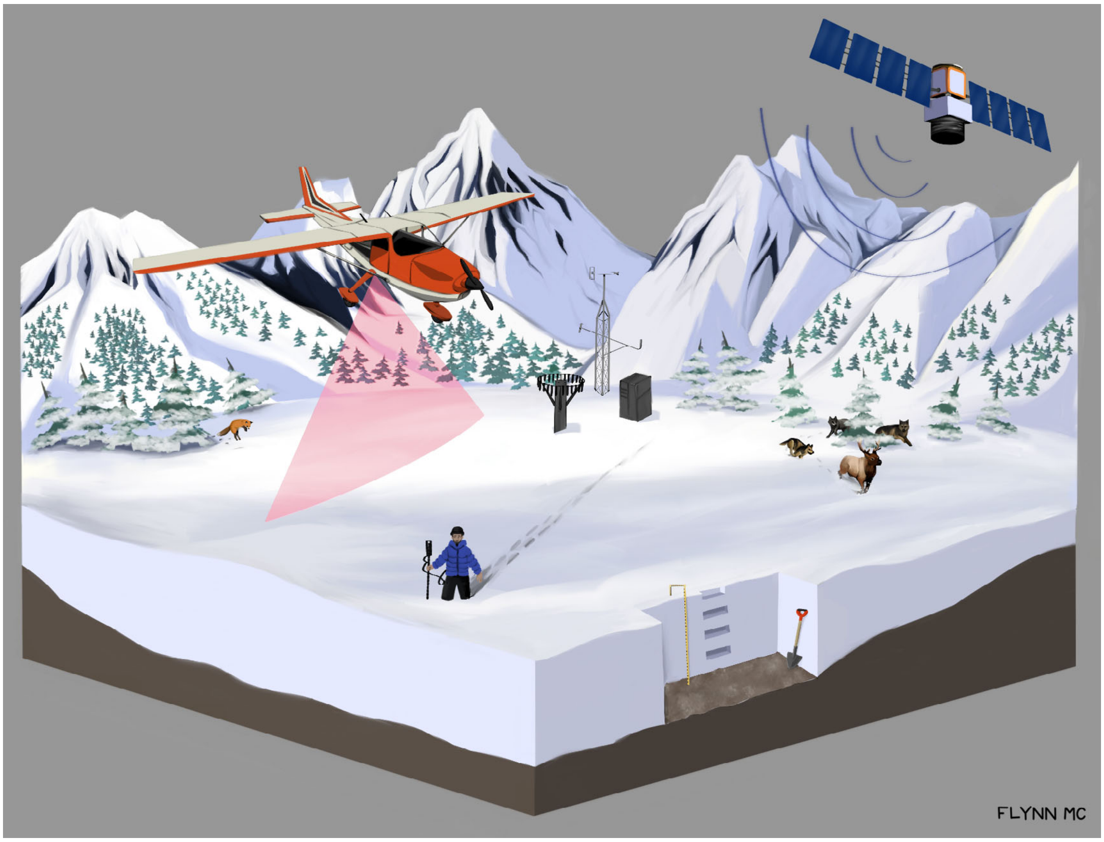


**FIGURE 3** Two types of snow information (ground-based measurements and remote sensing observations) that can be used to answer wildlife–snow interaction questions. Example ground-based measurements include point observations of snow properties made manually across the landscape (i.e., snow depth transect and snow pit) and snow data measured using an automated Natural Resources Conservation Service (NRCS) Snow Telemetry (SNOTEL) station. Example remote sensing observations include aerial lidar and satellite imagery. Graphic courtesy of Flynn Melendy-Collier

and (3) data–model fusion products (Figure 3). In what follows, we summarize these three main data types, with an emphasis on data–model fusion systems because of their flexibility and utility for diverse wildlife applications. While our examples of snow information focus on North America, they represent similar information found in other areas of the world. We compare four examples of data–model fusion systems that generally represent the range in complexity of such systems, and we detail the strengths and weaknesses of each of these showcased methods. For each type of snow information, we describe how wildlife and snow expertise can be integrated to maximize the utility, quality, and benefit of those types of data in collaborative wildlife–snow projects. We do this using an example GYE wildlife application (Boxes 6–8: GYE example).

The GYE (Figure 4) represents an area of longstanding ecological interest because of its biodiversity, concentration of big game species and species of conservation concern, history of wildlife research and management, and inclusion of Yellowstone and Grand Teton National Parks (Huff & Varley, 1999; Keiter, 1991). Snow conditions in the GYE serve as an important driver of wildlife movement behaviors (Bruggeman et al., 2009; Rickbeil et al., 2019), survival (Ruth et al., 2011), and reproduction (Inman et al., 2007). Snow-mediated elk predation by wolves has been of particular interest to researchers and managers (Brodie et al., 2014; Gese & Grothe, 1995; Wilmers et al., 2020). Thus, there is a broad requirement for flexible, diverse snow information capable of representing the complex snow dynamics governing these ecological processes.

## Field measurements

Field measurement data typically represent snow processes and associated properties at a single point in space and time, or at regular time intervals (e.g., daily, weekly, monthly, or annually; Figure 3). While generally considered high quality and reliable, this information largely finds utility in validating and bolstering other sources of spatially and temporally distributed snow information. Used alone, these datasets may be adequate for studies occurring at very small spatial and temporal scales (e.g., studies of individual lemming tunnels, such as Poirier et al., 2019 or reindeer and caribou [*Rangifer tarandus*] cratering, such as Beumer et al., 2017), or in a highly homogenous landscape (e.g., flat mesa top or prairie), where few point observations are likely representative of the snow conditions over a larger area (Watson, Anderson, et al., 2006). However, point observations are inadequate for many wildlife applications because they do not provide snow information for other, nonmeasured areas or time periods. In addition, existing large-scale snow field campaigns (e.g., NASA snow campaigns) are designed to measure snow attributes like SWE and albedo (i.e., surface reflectivity) to fulfill hydrologic and climate-focused missions, and they are typically led by non-wildlife groups (Brucker et al., 2017; Elder et al., 2009; Yueh et al., 2009). While properties that may be important

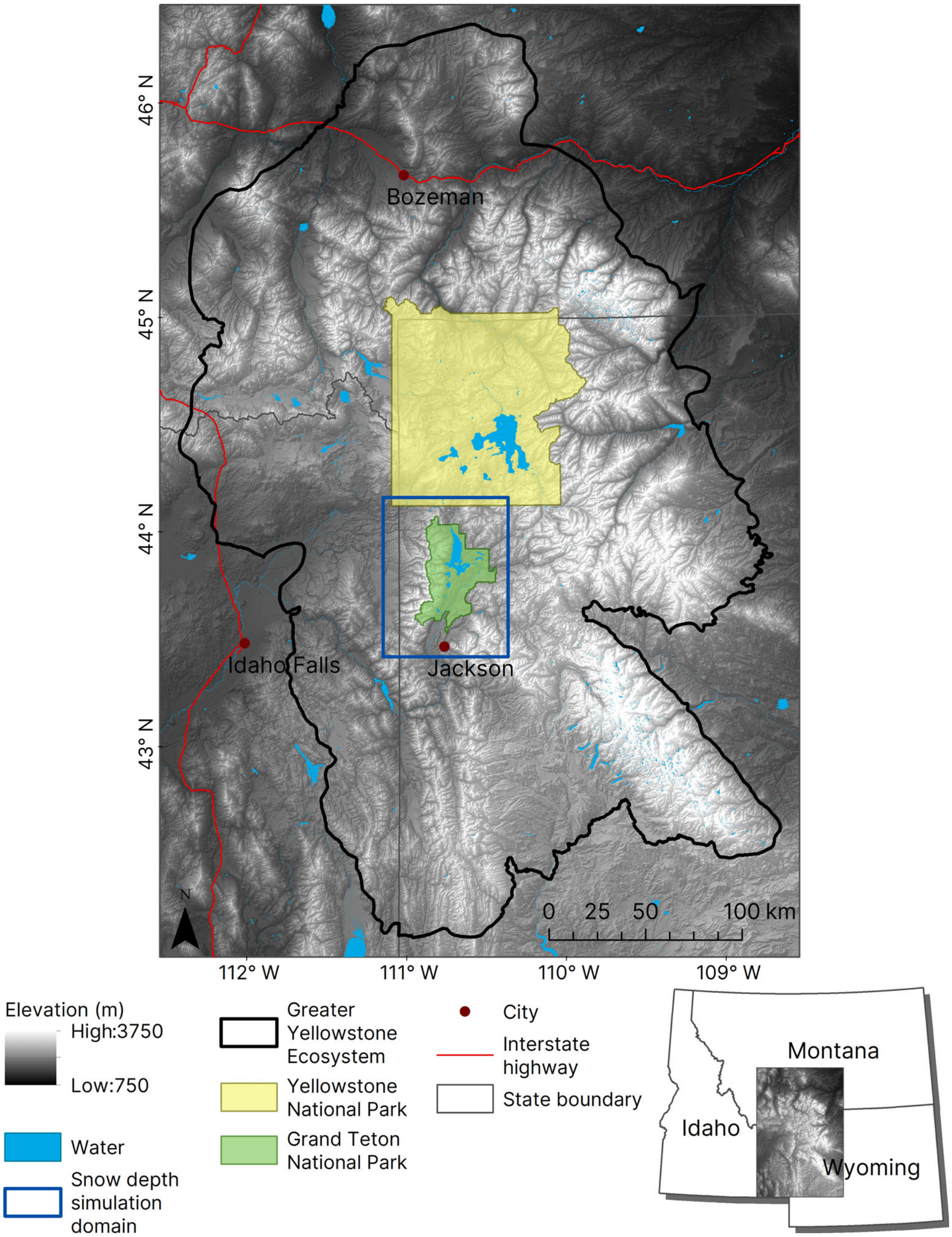


**FIGURE 4** Reference map for the Greater Yellowstone Ecosystem (GYE; black-bordered polygon) example wildlife–snow application. This map showcases the topographic variation in the area (as indicated by the black-to-white, low-to-high elevation gradient), the location of water features (light blue polygons), and the locations of the Grand Teton (green polygon) and Yellowstone (yellow polygon) National Parks. This map also provides context for the Figure 5 snow depth simulations covering a subset of the GYE (dark blue-bordered polygon). Other municipal features, including cities (red circles), interstate highways (red lines), and state boundaries (gray lines) are also included to provide further geographical context.

for wildlife, such as snow depth, are usually measured, the most wildlife-relevant snow variables are often not included in these publicly available, observational datasets. Moreover, wildlife professionals may not have the snow measurement expertise to implement their own snow field programs; obstacles faced in doing so include uncertainty regarding which snow properties to measure, the tools and techniques that should be used to measure them (and how to acquire such equipment), an appropriate sampling scheme, and the amount of effort required to properly characterize the relevant snow conditions in a given area for a specific application. Snow professionals can help design safe and effective field campaigns that do not over-extend project resources, while still adequately reflecting the snow processes and properties of interest. Such field measurement expertise is exemplified in Kinar and Pomeroy (2015), in which the techniques and equipment for making *in situ* snow measurements are thoroughly reviewed. The use of field measurements in collaborative wildlife–snow science is further explored in Box 6: GYE example.

## Remote sensing products

Remote sensing snow datasets are created from remotely captured imagery collected with ground-based, airborne, or satellite platforms (Figure 3). Data acquisition can range from simple methods, such as camera trap photographs of snow stakes or landscapes throughout the winter season (Boelman et al., 2017; Sirén et al., 2018), to piloted or unpiloted aerial Light Detection and Ranging (lidar) imagery (Fernandes et al., 2018), and to satellite-based products (Dietz et al., 2012; Pan et al., 2020). Remotely sensed data generally provide greater coverage in space and time than on-the-ground observations, and they typically do not require field visits to make measurements. However, these products are often available only at relatively coarse spatial scales and temporal resolutions (e.g., 1-km spatial resolution or 8-day, repeat observation intervals; Rose et al., 2015); these limitations are particularly true for the previous generation of satellites, but meters-scale snow products are becoming increasingly common. Unfortunately, finer resolution snow products are generally produced from multi-spectral satellite sensors that are only able to map snow properties such as presence/absence or snow-covered fraction (Aalstad et al., 2020; Cannistra et al., 2021), which may require post-processing or be unfeasible to translate into more wildlife-relevant snow information (Boelman et al., 2019; Bokhorst et al., 2016). Moreover, satellite snow products are frequently riddled with artifacts from complications, such as cloud or canopy cover, that interfere with useful image acquisition and limit their utility for estimating snowpack properties (Dietz et al., 2012; Stillinger et al., 2019). Other remote sensing datasets, such as snow depth derived from lidar aerial surveys, often carry additional constraints, such as cost, the need to fly pre- and post-snow accumulation, and limited spatial and temporal coverage. Through communication with wildlife professionals, snow professionals can aid

**BOX 6 GYE example**

Researchers in the GYE studying snow season elk predation by wolves would likely be interested in answering two specific wildlife–snow questions: (1) What are the snow conditions at sites where wolves have killed elk (hereafter referred to as kill sites)? and (2) How do snow conditions at these sites compare with the general "character" of the study area's snowscape?

Assume that wildlife and snow professionals collaboratively determine strength and depth to be the most likely candidate snow properties to mediate wolf predation on elk. If relying on snow field measurements (either alone or for incorporation into a data–model fusion system), the first of these wildlife–snow questions would require wildlife and snow professionals to design time-efficient field protocols to evaluate snow conditions at kill sites. Efforts would likely include measuring snow depth in the vicinity of the kill site, digging a simple snow pit (Figures 2 and 3) to estimate the relative strength of snowpack layers using, for example, a hand-hardness test (Greene et al., 2016), and making measurements of predator and prey tracks including track length, width, and sinking depth (i.e., penetration depth from the snow surface; following Telfer & Kelsall, 1979). Both the snow pit and animal track measurement efforts would provide information about the snow that may facilitate evaluation of its potential role in the outcome of predator–prey interactions (Murray & Boutin, 1991; Nelson & Mech, 1986). This assumes that the snow conditions at the time of measurement represent those during the predator–prey encounter, which may or may not be valid. These protocols avoid excessive time investment in evaluating extraneous snow properties.

The second research question requires wildlife–snow teams to design a snowscape-scale sampling study. To properly characterize snow conditions across the study area, wildlife and snow professionals could collaboratively design a sampling scheme to assess relevant snow property distributions and capture important variation in distinct snowscape habitats or sub-domains. These sub-domains might include heavily forested areas with steep slopes; relatively flat, grass- and shrub-covered valleys with moderate wind speeds; and windy, high-mountain, short vegetation, alpine areas (Watson, Anderson, et al., 2006). Sampling sites should be randomly selected within each of these snowscape habitats, implementing a stratified random sampling scheme, with sampling locations constrained by requirements of safety and access. To capture peak snow-accumulation season conditions before snowmelt occurs (Sexstone et al., 2021), while also preventing any impingement on kill site assessments during the height of the fall and winter field season, snow measurements in the GYE could be made later in the winter. Snow conditions during other times of the winter season could also be evaluated using remote sensing data or data–model fusion simulations that incorporate these peak snow-accumulation season measurements. Sampling protocols to address this snowscape-scale research question, and to accurately characterize the study area's general snow properties, could include digging more detailed snow pits than previously described for addressing the first wildlife–snow question. These could serve to evaluate snow stratigraphy, hand-hardness of each layer, and density. Snow depths could be measured along several transects at each snowscape sampling site because depth can be one of the most spatially variable snow properties (Elder et al., 1991; Pomeroy & Gray, 1995; Sturm et al., 2010). This example field protocol design represents a collaborative effort meant to adequately address both of the aforementioned, multi-scale predator–prey-snow questions, while also accounting for study priorities, time and other resource limitations, and personnel safety.

in making collaborative decisions about how to access or collect remote sensing snow data; which products may be the most appropriate given the spatial, temporal, and informational requirements of each unique wildlife application; and how these datasets can be processed to meet project-specific requirements. The use of remote sensing products in collaborative wildlife–snow science is further explored in Box 7: GYE example.

## Data–model fusion systems

In addition to on-the-ground snow measurements and remotely sensed snow products, modeling tools can be used to estimate snow processes and properties at desired resolutions where and when observational and operationally produced snow information does not exist (Figure 5). Such modeling tools can bypass the spatial and temporal

**BOX 7 GYE example**

Remotely sensed snow data may enable researchers to better balance the goal of assessing general, study area snowscape conditions (the second example GYE research question) with ensuring personnel safety and logistical efficiency. To this end, the research team may wish to identify other snow data collection methods that would allow remote monitoring for a longer time, such as a network of trail cameras and snow stakes to assess changes in depth throughout the fall, winter, and spring (Cosgrove et al., 2021; Sirén et al., 2018). This solution could eliminate human travel in avalanche-prone areas and allow for additional data collection. Snow professionals could provide guidance on where to place camera and snow stake monitors to be most representative of the general snowscape evolution and to best complement a safe, end-of-season intensive snow measurement campaign (Elder et al., 1991, 1998; Kattelmann et al., 1988). In addition, snow professionals may have data processing algorithms and scripts that could assist with the subsequent image processing (Currier, 2016; Currier et al., 2017) and potentially the later incorporation of the data into a data–model fusion system (Liston et al., 2020; Liston & Hiemstra, 2008). There may also be operational, satellite-derived remote sensing products that could be useful in assessing snowscape characteristics, such as active microwave products that could be used to identify the timing of surface melt, rain-on-snow, and refreeze events that potentially contribute to ice layers within the snowpack (Bartsch et al., 2010).

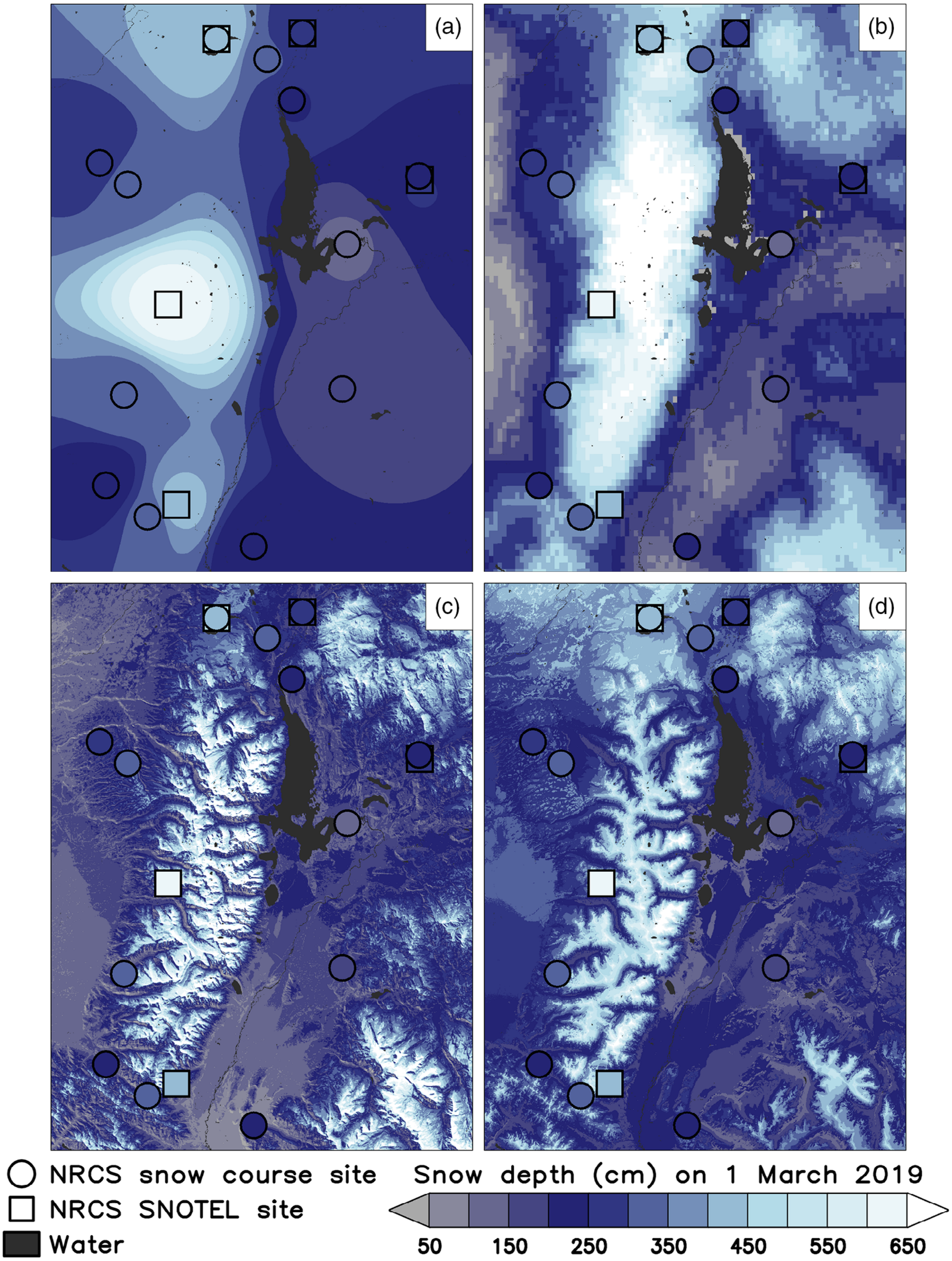


**FIGURE 5** Snow depth distributions produced using the four data–model fusion systems we describe: (a) inverse distance weighted interpolation, (b) Snow Data Assimilation System (SNODAS) products, (c) Yellowstone Snow Model, and (d) SnowModel. Snow depth is shown for a 65-km × 82-km area within the Greater Yellowstone Ecosystem over Jackson, Wyoming, USA on 1 March 2019. Natural Resources Conservation Service (NRCS) Snow Telemetry (SNOTEL; filled squares) and NRCS snow course (filled circles) snow-water equivalent measurements ($n = 18$) were utilized in conjunction with the average NRCS snow density value on this date for this area (277 kg m$^{-3}$) to generate snow depth distributions using each system. Panels (a), (c), and (d) represent snow depth at a 30-m spatial resolution, while panel (b) is on a 1-km grid (i.e., the spatial resolution of the SNODAS snow depth product). Land cover classified as water is represented on each plot by dark gray polygons. Further geographical context for this simulation domain is provided in Figure 4.

limitations of field measurements and remote sensing data but can suffer from simplistic, incomplete, or unrealistic representation of the physics controlling snow processes and properties across the landscape. Watson, Newman, et al. (2006) and Liston et al. (2007) provide summaries of many snow models and snow modeling approaches, though these reviews are non-exhaustive. As advocated in Boelman et al. (2019), we assert that the best path forward is to integrate field or remote sensing datasets with modeling tools in a data–model fusion approach to maximize the benefit of each individual input and produce more informative, realistic, and tailored snow products.

We describe four examples of modeling tools with data–model fusion capabilities. Each of these tools has been applied in wildlife applications, and they are generally representative of the available range of complexity in such assimilation systems. These four data–model fusion systems vary in how difficult they are to implement, and in the quality and utility of their data products; they can all be used to estimate and distribute snow properties of interest over space and through time. First, we present a simple inverse distance weighted spatial interpolation (Bartier & Keller, 1996; Erxleben et al., 2002; Shepard, 1968). Second, we detail a publicly available data assimilation product, SNODAS (Barrett, 2003; Carroll et al., 2001). Third, we summarize the Yellowstone Snow Model (YSM) that has been broadly applied for wildlife applications within the GYE (Figure 4; Wockner et al., 2002). Fourth, we describe SnowModel, a system that incorporates high-resolution meteorological, surface energy budget, blowing snow, and snowpack evolution sub-models to provide estimates and predictions of spatially and temporally distributed snow information (Liston et al., 2020; Liston & Elder, 2006a).

We apply each of these four example data–model fusion systems to a GYE domain covering Grand Teton National Park and the surrounding area (Figures 4 and 5). This domain was chosen to highlight how available snow observations of SWE and density (obtained from NRCS SNOTEL and snow course sites) can be assimilated within a data–model fusion framework to provide more wildlife-relevant snow information. In this example, we display snow depth calculated from these SWE and density properties, facilitating a visual comparison of the snow depth distribution produced using each of these four simulation systems. The use of data–model fusion systems in collaborative wildlife–snow science is further explored in Box 8: GYE example.

## Inverse distance weighted interpolation

A simple way to produce snow property distribution maps is to spatially interpolate field observations (Figure 5a) of depth, SWE, or other snow variables of interest (Gilbert et al., 2017; Shipley et al., 2020). A widely used interpolation scheme is the inverse distance weighting (IDW) method (Bartier & Keller, 1996; Erxleben et al., 2002; Shepard, 1968). Inverse distance weighting assumes that spatial autocorrelation exists, and variables close to each other are more similar than those farther apart. To predict variable values at an unmeasured location, IDW uses the measured values surrounding that prediction location, and the closest measurements have a greater influence on the predicted values than more distant measurements. The weighting function that defines the relative influence of each measured value in the predicted values at unmeasured locations is inversely related to the distances between the measurement location and the unmeasured location.

The general IDW formula for a two-dimensional domain in the $x$–$y$ plane is:

$$v_{x,y} = \sum_{i=1}^{n} v_i d_{x,y,i}^{-p} \Big/ \sum_{i=1}^{n} d_{x,y,i}^{-p}, \tag{2}$$

where $v_{x,y}$ is the estimated variable at position $x$, $y$; $v_i$ is the $i$th known variable; $n$ is the number of known variables; $d_{x,y,i}$ is the distance between $v_{x,y}$ and $v_i$; and $p$ is a power exponent defined by the user. The term $d^{-p}$ defines the inverse distance weights in the IDW method, and the exponent $p$ controls the rate at which the weights decrease with increasing distance from the observation points. A low $p$ value indicates that more observations contribute to the predicted value, regardless of their distance, and produces a relatively smooth modeled surface. A high $p$ value indicates that only nearby observations influence the predicted value at the unmeasured location, and thus, produces a more spatially variable modeled surface.

To create the snow depth distributions depicted in Figure 5a, SNOTEL snow densities, $\rho_s$ (in kilograms per

**BOX 8 GYE example**

In this GYE predator–prey-snow application, it would be possible to achieve a deeper understanding of the role of snow in wolf–elk predation events if field measurements and remotely sensed depth data could be combined with modeling tools. Data–model fusion methods, such as those detailed in the following sub-sections, would allow the generation of spatially and temporally explicit snow information, maximizing the utility of field and camera trap datasets (Boxes 6 and 7: GYE example) and supplying higher quality, more detailed information for use in subsequent space- and time-varying analyses (Figure 5).

cubic meter), were used to convert SWE values to HS (in meters) using the following form of Equation (3):

$$HS = \frac{\rho_w}{\rho_s} SWE. \quad (3)$$

*Strengths and weaknesses*

The IDW method is simple to understand and implement. It also requires minimal investment of time and computing power, and it can be applied to a variety of snow observation variables. However, regardless of the *p* value used, the IDW method often produces unrealistic, concentric circles around each observed value. In addition, this method can create excessively smooth, oversimplified surfaces that fail to accurately represent spatial heterogeneity occurring at scales smaller than the sampling resolution (Figure 5a). This may be particularly problematic in highly heterogenous snow environments.

## Snow Data Assimilation System

Other commonly used sources for spatially distributed snow information for wildlife applications are NOAA/NWS/NOHRSC SNODAS products (Barrett, 2003; Carroll et al., 2001). The SNODAS products integrate data from satellite and airborne platforms, ground stations, and model-produced snow variables. The NOHRSC satellite remote sensing program uses NOAA Geostationary Operational Environmental Satellite (GOES) and Advanced Very High-Resolution Radiometer (AVHRR) imagery to produce daily maps of snow- and cloud-cover areal extent over the conterminous United States. In addition, the program utilizes data from the Airborne Gamma Radiation Snow Survey Program, which collects near real-time SWE measurements over a network of 1900 aircraft flight lines covering portions of 29 states (Carroll et al., 2001). These flights measure the amount of gamma radiation attenuated by the snow cover by comparing the results to data collected from the same flight lines under snow-free conditions and then convert those values to SWE. Ground-based depth and SWE data from NRCS SNOTEL sites and other observing networks are also used by SNODAS. Each day, NOHRSC obtains data from approximately 5000 NWS cooperative observers, 1100 automated SWE sensors, 1600 snow courses (i.e., snow measurement sites and transects), and 800 snow spotters (i.e., NWS citizen-science observers) across the United States and Canada (Carroll et al., 2001). Snow Data Assimilation System combines these satellite, airborne, and ground-based datasets and merges them with their weather analyses and modeled snow datasets to produce SWE and snow depth maps that are made publicly available. This operational system is run over the conterminous United States using a 1-h time step, and snow variable outputs are provided at 1-km spatial resolution and daily temporal resolution (Figure 5b).

*Strengths and weaknesses*

The SNODAS data products provide several wildlife-relevant snow variables (e.g., depth and density) over a relatively long period of record that will likely continue well into the future. Moreover, the snow information is generally high quality, and the daily temporal scale is adequate for many wildlife applications. Despite these advantages, the 1-km spatial scale of the data limits their applicability for many wildlife research and management projects (Brennan et al., 2013), and the provided snow information often still does not contain the most wildlife-relevant variables (e.g., snow structure and strength; Boelman et al., 2019).

## Yellowstone Snow Model

The latest version of the Natural Resources and Ecology Laboratory (NREL) Yellowstone Snow Model (YSM) is described in detail by Wockner et al. (2002). This spatially distributed snowpack model has been used extensively over the GYE area (Figure 4) for wildlife–snow studies (Barnowe-Meyer et al., 2010; Kauffman et al., 2007; Mao et al., 2005; Uboni et al., 2015). Yellowstone Snow Model simulates SWE distributions using SWE data from NRCS SNOTEL sites and other meteorological stations in the simulation domain (such as National Park Service-owned and operated stations). Yellowstone Snow Model creates SWE maps by initially distributing SWE observations across the GYE using IDW interpolation. The station observations and station elevations are then used to calculate SWE changes with elevation (i.e., SWE lapse rates). Next, a background topographic map is used to adjust the interpolated SWE distribution for elevations between SWE observations (Coughenour, 1992). This elevation-adjusted SWE distribution is then further modified for the effects of slope, aspect, and land cover type following Farnes et al. (1999). Farnes et al. (1999) used field observations from the GYE to quantify how topographic slope and aspect and forest canopy structure affected SWE on the ground. The empirical adjustment factors from this work are used in YSM to account for processes that are not explicitly represented in the model, like forest canopy interception of snowfall or enhanced solar radiation on south-facing slopes. To create a SWE distribution, YSM requires the following inputs covering the spatial domain, at the desired spatial resolution, and over the time period of interest: (1) digital elevation (topographic) data from which slope and aspect are calculated, (2) land cover data to define the forest canopy distribution, and (3) SWE observation data (SWE value with collection date and location).

*Strengths and weaknesses*

Compared to many other simple data–model fusion systems like IDW interpolation, YSM represents a more sophisticated option because it incorporates empirical, physical process representations that produce more realistic simulations of SWE conditions (Figure 5c). The empirical SWE adjustments are parameterized using the results of local, and current climate regime, field studies. It is also flexible in terms of spatial and temporal resolutions, and domains. Therefore, this model is quite suitable for wildlife applications within the GYE and potentially other ecologically similar areas, assuming the climate presented in the simulation of interest is similar to that when the empirical parameterizations were developed (i.e., 1999), and the vegetation-related adjustments (therefore the vegetation itself) are transferable to the new simulation domain. This system also accounts for locally unique processes in the GYE, such as snow conditions at geothermal hotspots, which are ignored in most other data–model fusion systems.

Although there are many advantages to using YSM for wildlife–snow applications, there are also inherent shortcomings. First, the most recent YSM code is only available by contacting the system authors. While this presents an additional challenge to wildlife professionals interested in using this data–model fusion system, it also ensures that system authors are aware of studies employing their model and provides an important opportunity for collaboration. Second, this system only provides SWE information, which is mostly useful as a rough proxy for other, more wildlife-relevant snow properties, such as winter severity. However, more valuable snow information, like snow depth, can be calculated using the YSM SWE distribution in concert with spatially distributed snow density information (Figure 5c). A third YSM restriction is that SWE distributions can only be generated by using spatially and temporally distributed observational SWE data, which is not always available or possible to collect. Lastly, because the effects of slope, aspect, and forest canopy structure incorporated into the model are based on the Farnes et al. (1999) GYE field observations, additional work is required to apply this system to other areas or times.

## SnowModel

SnowModel is a spatially distributed, physically based snow evolution data–model fusion system designed for application in all landscapes, climates, and conditions where snow occurs (Liston et al., 2020; Liston & Elder, 2006a). It is an aggregation of three sub-models that each resolve different environmental processes related to snow: EnBal (Liston, 1995; Liston et al., 1999) calculates surface energy exchanges and snowmelt; SnowPack-ML (Liston & Hall, 1995; Liston & Mernild, 2012) is a multi-layer snowpack model that simulates depth, density, SWE, and the evolution of other snow properties; and SnowTran-3D (Liston et al., 2007; Liston & Sturm, 1998) accounts for blowing snow. SnowModel is designed to run on grid increments of 1 m to 25 km and on temporal increments of 1 h to 1 day. Simulated processes include the time evolution of rain and snow precipitation, snow redistribution and erosion by wind, interception of snow by vegetative cover, and snowmelt.

Coupled to SnowModel is a meteorological distribution model called MicroMet (Liston & Elder, 2006b). MicroMet provides the high-resolution, gridded atmospheric information required by SnowModel. To do this, MicroMet is driven by publicly available or field-experiment-specific weather stations or gridded atmospheric datasets (typically from reanalyses). Also coupled to SnowModel is SnowAssim (Liston & Hiemstra, 2008). SnowAssim is designed to assimilate ground-based and remotely sensed snow observations within SnowModel. MicroMet and SnowAssim are integral components of SnowModel's data–model fusion system; MicroMet adds value to meteorological data by spatial downscaling and temporal interpolation, and SnowAssim incorporates snow-related observations.

To create snow property distributions, SnowModel requires the following inputs covering the spatial domain, at the desired spatial resolution, and over the time period of interest: (1) digital elevation (topographic) data, (2) land cover classification data, and (3) meteorological data (specifically air temperature, precipitation, relative humidity, wind speed, and wind direction). If the SnowAssim sub-model is also run, then any available snow property observations (e.g., SWE, depth, density, snow-onset date, or snow-free date) can be used to further refine the SnowModel outputs (Figure 5d).

*Strengths and weaknesses*

The SnowModel data–model fusion system has many benefits when compared with other data–model fusion systems. SnowModel simulations using SnowAssim display considerably more realistic spatial heterogeneity and temporal evolution than those provided by models or observations alone (Boelman et al., 2019; Liston et al., 2007; Liston et al., 2008; Pedersen et al., 2015; Pedersen et al., 2018; Pedersen et al., 2021; Stuefer et al., 2013). The synthesis, or fusion, of both modeled and observed datasets allows production of spatially and temporally continuous data distributions that match the observations where and when they occur. In addition, implicit in this data–model fusion approach is that the resulting snow property distributions are also realistic during time periods before and after the observations, and at locations between the observations. An additional benefit is that MicroMet, SnowModel, and SnowAssim have been designed to be flexible in terms of spatial and temporal domains, spatial and temporal resolutions, and snow property variables of interest. Therefore, they can be applied worldwide for any time and place and can produce tailored, project-specific data products. SnowModel also allows for the creation of targeted, value-added, synthesis variables relevant to specific wildlife–snow applications.

While there are advantages to SnowModel's flexibility, its complexity also carries disadvantages. As is the case with the YSM data–model fusion system, SnowModel code is only available by contacting the system author. Again, this adds additional steps to the process of employing this system in wildlife–snow studies, but communication with the system author is also likely to result in simulations that better address the wildlife research and management objectives. Moreover, SnowModel requires a far greater investment of time to understand and operate its data–model fusion programs. Lastly, computational requirements, both in terms of memory and data storage, are considerably greater than other snow-related data–model fusion systems. SnowModel simulations can produce large amounts of data, and novel approaches and methods to process and analyze such datasets are often required. Successful SnowModel applications have typically included direct collaborations with experienced SnowModel users and developers, particularly when a project requires the creation of new, synthesis variables for a specific application.

## A VISION FOR FUTURE WILDLIFE–SNOW SCIENCE

Answering today's most pressing wildlife–snow questions is challenging due to the difficulty of finding and applying appropriate snow information, and this obstacle has historically impeded a nuanced understanding of species and ecosystems influenced by snow. We argue that advancing our study of wildlife–snow interactions requires meaningful collaboration between wildlife and snow professionals. Through such collaborations, wildlife-relevant snow data, represented at appropriate spatial and temporal scales, can be collected, produced, and applied to conduct effective, high-quality research. Snowscape conditions continue to change worldwide, often becoming less predictable and more extreme, and it is, therefore, increasingly necessary for wildlife professionals to study wildlife–snow interactions and monitor change in those relationships through time (Berger et al., 2018; Berteaux et al., 2017; Boelman et al., 2019; Callaghan et al., 2011; Pedersen et al., 2020). To ensure success in this endeavor, and to genuinely integrate these two sciences, wildlife and snow professionals must partner in the development and execution of wildlife–snow projects. Finally, professionals from both fields must work together to communicate and disseminate research results accurately and clearly, given the terminology differences that exist between these two disciplines.

Here, we have provided a five-step procedure to facilitate this collaborative process with the goal of improving understanding of wildlife–snow relationships across research, management, and long-term monitoring applications. Additionally, we have described some key data sources that can be used when following this interdisciplinary approach, placing particular emphasis on data–model fusion systems. These systems offer greater flexibility and scope than snow data observations that are limited in space and time; spatially distributed, temporally evolving datasets are required to evaluate most wildlife–snow interactions. Data–model fusion systems greatly expand the data resources available to research and management teams, and thus, the reliance on less biologically meaningful snow information at inappropriate spatial and temporal resolutions is no longer necessary. Our intention is for this publication to guide wildlife and snow professionals seeking answers to complex wildlife–snow questions and to foster more integrative projects incorporating tailored, wildlife-relevant snow information.

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### CONFLICT OF INTEREST

The authors declare no conflict of interest.

### ORCID

*Adele K. Reinking* https://orcid.org/0000-0002-9082-4315

*Stine Højlund Pedersen* https://orcid.org/0000-0003-0078-8873
*Thomas W. Glass* https://orcid.org/0000-0001-7494-4918
*Brendan A. Oates* https://orcid.org/0000-0003-2815-9518
*Niels M. Schmidt* https://orcid.org/0000-0002-4166-6218

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