Snow Interception Modeling: Isolated Observations have led to Land Surface Models Lacking Appropriate Climate Sensitivities

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Abstract
When formulating a hydrologic model, scientists rely on parameterizations of multiple processes based on field data, but literature review suggests that more frequently people select parameterizations that were included in pre-existing models rather than re-evaluating the underlying field experiments. Problems arise when limited field data exist, when "trusted" approaches do not get reevaluated, and when processes fundamentally change in different environments. The physics and dynamics of snow interception by conifers, including both loading and unloading of snow, is just such a case. The most commonly used interception parameterization is based on data from four trees from one site, but field study results are not directly transferable between environments. The process varies dramatically between locations with relatively warmer versus colder winters. Here, we combine a comprehensive literature review with a model to demonstrate essential improvements to model representations of snow interception. We recommend that, as a first and essential step, all models include increased loading due to increased adhesion and cohesion when temperatures rise from -3 and 0°C. The commonly used parameters of a fixed maximum value for loading and an e-folding time for unloading are not supported by observations or physical understanding and are not necessary to reproduce observations. In addition to unloading based on physical processes, such as wind or

canopy warming, all models must represent melting of in-canopy snow so that it can be unloaded in liquid form. As a second step, we propose field experiments across climates and forest types to investigate: a) a representation of the force balance between adhesion and cohesion versus gravity for both interception efficiency and rates of unloading, b) wind effects during and between storms, and c) lubrication when snow melts. For greatest impact, this framework requires dedicated field measurements. These processes are essential for models to accurately represent the impacts of dynamically changing forest cover and snow cover on both global albedo and water supplies.

Keywords: forest, snow, modeling, interception, hydrology, albedo, vegetation, history

1. INTRODUCTION

Both forest cover and snow processes are changing globally at unprecedented rates (Adams et al., 2009; Allen, 2009; Bormann, Brown, Derksen, & Painter, 2018; Halofsky, Peterson, & Harvey, 2020). These changes, their interactions, and their impacts are critical components of any model of the terrestrial water balance and energy balance. Substantial research has demonstrated that modeling forest-snow interactions is complicated (Dickerson-Lange et al., 2017; Helbig et al., 2020; Rutter et al., 2009). However, global land surface model representations of canopy snow interception are currently based on a handful of observations from only two studies, as reviewed below. Employing a larger literature review and an interception model, we propose how to improve process representation of accumulation, ablation, and unloading of snow in the forest canopy. These improvements are critical for models that span multiple climates (e.g., global, mountain, and/or climate change applications), as many current parameterizations are not transferable in space or time.

Differences in snow accumulation under forests compared to the open are the dominant drivers of net changes in snow duration (Dickerson-Lange et al., 2017; Lundquist, Dickerson-Lange, Lutz, & Cristea, 2013), which means that interception processes must be modeled correctly in order to accurately simulate forest effects on snow under multiple weather regimes. Interception dynamics vary widely with forest structure and regional climate, as well as between individual storms (Carlyle-Moses & Gash, 2011; Lundquist et al., 2013; Moeser, Stähli, & Jonas, 2015). However, given historic difficulty in measuring interception (Friesen, Lundquist, & Van Stan, 2015), current measurements and understanding are limited to a few locations representing a minority of forest structures and climatic settings. Due to a lack of better information, parameterizations that have been validated in only one specific setting are being used in global models, while parameterizations from another setting can differ in even the sign of their response to temperature (Andreadis, Storck, & Lettenmaier, 2009; Clark et al., 2015; Hedstrom & Pomeroy, 1998). These differing parameterizations can lead to very different climate sensitivities in different models (Figure 1), most of which formulate some maximum interception capacity per unit of horizontal surface area of vegetation (Figure 1b). Hedstrom and Pomeroy (1998) formulated maximum snow interception per unit vegetation area decreasing with temperature, due to increased snow rebound and decreased tree-branch stiffness, while

Andreadis et al. (2009) described it increasing rapidly as temperatures warm above -3°C, due to increasing cohesiveness of snow at warmer temperatures (Figure 1b). While these two parameterizations match at low temperatures, a well-calibrated model subjected to warmer temperatures (e.g., for a climate sensitivity experiment) would show a very different hydrologic response: interception will vary by a factor of four depending on the model chosen with subsequent effects on snowpack and soil moisture. These two formulations are based on (Fig. 1d) branches clipped to a pole in the Rocky Mountains (Schmidt & Gluns, 1991) or (Figure 1e) two Douglas Firs on weighing lysimeters in the Oregon Cascades (Storck, 2000) and provide the basis for the majority of our models.

[Insert Figure 1]

Changes in land surface albedo are another important, yet poorly understood, feedback in global climate variability. Variability in land surface albedo between CMIP5 climate models can explain 40-50% of the spread in modeled warming over the northern hemisphere (Qu & Hall, 2014; Thackeray & Fletcher, 2016), and the albedo spread is due primarily to how models represent snow-vegetation interactions, with the largest disagreements near the boreal forest (Essery, 1998; Loranty, Berner, Goetz, Jin, & Randerson, 2014; Thackeray, Fletcher, & Derksen, 2014; Thackeray, Qu, & Hall, 2018). While some of these variations are due simply to structural representations of vegetation at climate model scales (Loranty et al., 2014), intercepted snow in the canopy affects albedo (Webster & Jonas, 2018), and model differences in how intercepted snow is removed from the canopy play an important role in the energy balance (Thackeray et al., 2014). Snow unloading (Figure 1c) also varies widely between models and may be a function of air temperature and wind speed (Roesch, Wild, Gilgen, & Ohmura, 2001) or a constant rate, leading to exponential decay of canopy snow (Hedstrom and Pomeroy, 1998).

Both albedo and snow stored under the canopy matter to society, and calculations of both are influenced strongly by how a model represents both the capacity of snow to accumulate in the canopy and the rate, timing, and mechanism(s) of how that snow is removed from the canopy. In addition to increasing albedo, the longer snow stays on the canopy, the longer there is time for canopy snow to sublimate, which can result in about 30% of the winter precipitation returning to the atmosphere (Sexstone et al., 2018), or additional melt from the canopy, resulting in liquid water that may not be stored in the underlying snowpack. Consequently, over most of the snow accumulation season in forested environments, canopy interception is the primary driver of spatial variability of snow on the ground. Total seasonal snow in the canopy can be increased by either increasing interception loading capacity, decreasing ablation, or decreasing unloading, requiring that these processes be examined together.

Here, we review the literature to explain the history and epistemology of snow interception modeling (Section 2), including the origin and evolution of algorithms in current models and the original observations on which they are based. We focus specifically on loading and unloading in the context of weather and climate, leaving issues of forest structure and sublimation as a subject for future work. We re-examine the observational literature in a global context to assess which process representations are most supported by field and laboratory data to provide recommendations and key hypotheses for testing. We employ a simple model of interception (Section 3) to illustrate how model representations lead to different climatic sensitivities, to establish priorities regarding essential observations for validation and needed model modifications to adequately represent responses to forest and climatic change (Section 4). Finally, we outline a path forward for both observationalists and modelers to ensure a more holistic approach to understanding and modeling combined forest-snow-climate change (Section 5).

2. HISTORY OF SNOW INTERCEPTION MODELING

2.1 Basic Formulations and Concepts

Most models take a similar form for the basics of interception. When snow falls from the sky, some fraction of it is intercepted by the forest canopy, up to some maximum amount that the given canopy can hold, while the remaining fraction falls to the ground below (Figure 1). The snow in the canopy may sublimate or fall beneath or adjacent to the canopy. The canopy snow may also melt, in which case it may evaporate, drip to the ground below, and/or lubricate the remaining canopy snow so that some mixture of melted and solid snow falls to the ground below. Key parameters involved in modeling these processes include interception efficiency, I_e (the fraction of snowfall intercepted at each timestep), the maximum interception, I_{max}, the sublimation rate, q_s, the melt rate of intercepted snow, M, and the unloading rate, U. In most models, these are some function of leaf area index, LAI, and/or fractional forest cover, which represent how much canopy cover is present. Some models explicitly represent the canopy energy balance and phase changes within it, while others parameterize conceptually how snow behaves within the canopy (Table 1). We focus here on interception efficiency, maximum interception, melt, and unloading, because these components have the most relevant empirical evidence, with sublimation and canopy structure left as subjects for future research.

[Insert Table 1]

2.2 Model Family Trees

While significant earlier work existed observing and quantifying snow interception (section c below), Hedstrom and Pomeroy (1998), hereafter referred to as HP98, were arguably the first to develop a coherent system of equations for modeling all of the processes involved and have influenced many models developed in subsequent years. Here we review their work in the context of the literature as a whole, also highlighting parallel developments and diverging ideas.

2.2.1 Interception

HP98 defined the interception rate as a function asymptotically approaching zero as total interception approaches I_{max},

$$\frac{dI_s}{dt} = \left(I_{max} - I_s\right)\left(1 - e^{-C_l P_s \Delta t / I_{max}}\right) / \Delta t \qquad (1)$$

where I_s is the intercepted snow per unit area, I_{max} is the maximum possible intercepted snow, P_s is snowfall, t is time, and C_l is the canopy leaf contact area per unit ground area. This function stemmed from prior work by (Satterlund & Haupt, 1967), who weighed a Douglas-fir and a western white pine sapling (each ~ 4 m high) during two storms in northern Idaho, showing an increase and then leveling off of intercepted snow amounts over the course of these storms. Satturlund and Haupt presented a conceptual understanding that interception rates start low (when there was no snow in the tree), increase as initial snowflakes bridge gaps between the needles, and then decrease again as falling ice crystals bounce off and as branches bend sufficiently for snow to fall off, essentially approaching the maximum interception capacity. This representation is referred to as a sigmoidal efficiency curve. Only the decrease in efficiency as I_s approaches I_{max} was preserved in HP98's formulation, making it an exponential, rather than sigmoidal, function. The maximum value was modeled as

$$I_{max} = \alpha\left(0.27 + \frac{46}{\rho_s}\right) LAI \qquad (2)$$

where LAI is the leaf area index, α is recommended to be 6.6 and 5.9 km m^{-2} for pine and spruce following (Schmidt & Gluns, 1991), and the fresh snow density in kg m^{-3} is estimated by

$$\rho_s = 67.92 + 51.25 e^{\frac{(T_{air})}{2.59}} , \qquad (3)$$

where T_{air} is air temperature (°C).

The numbers in equation 2 are based primarily on the two study sites in Schmidt and Gluns (1991): Fraser Experimental Forest, Colorado, USA, winter 1989, and Nelson, British Columbia, Canada, winter 1990. At both locations, approximately 30-cm long branches of different tree species (Engelmann spruce, subalpine fir, and lodgepole pine, Fig. 1d) were attached to a horizontal steel rod about 1 m above the snow surface. After each storm period, the snow was shaken off each branch and into a plastic bag, which was weighed. Total snowfall was estimated from what accumulated on an adjacent snow board. Schmidt and Gluns (1991) mentioned greater cohesive forces at temperatures between -3 and 0°C multiple times (discussed further below), but these comments were not translated into equations or functional forms in HP98's model development.

The fresh snow density numbers (equation 3) are based on storm total snow board measurements from the two sites in Schmidt and Gluns (1991, their Table 2), as well as from observations from the Central Sierra Snow Laboratory in California (USACE, 1956) (their plate 8-1, Fig. 4). Note that the observations were taken over storm-total time periods, which varied in duration but were generally 6-hours or longer, while the model equation is typically applied at hourly timesteps. Due to the complexity of processes witnessed, both studies report the relationship as likely highly uncertain, and subsequent studies have found air temperature to be a poor predictor of new snowfall density (Wayand, Clark, & Lundquist, 2017), their Fig. 7). These equations have gone on to be used in a number of land surface models (Table 1 and Fig. 2), including VISA (G. Y. Niu & Yang, 2004), Noah-MP (G.-Y. Niu et al., 2011), CLM (Lawrence et al., 2019), and CLASS (Bartlett, MacKay, & Verseghy, 2006; Bartlett & Verseghy, 2015).

The concept of a maximum interception load appears in all models (Table 1). The sigmoidal form (Satterlund & Haupt, 1967), of slow initial interception rates that increase with time, only reappears in a recent development of FSM (Moeser et al., 2015). Additionally, the influence of temperature and snow cohesion on interception, while dropped in HP98, reappeared in an independent line of snow model development (Figures 1b and 2), described in (Andreadis et al., 2009) and utilized in the VIC and DHSVM models. The basic interception model is based on two winters in the Oregon Cascades, where two full sized Douglas Firs were weighed on load cells (Storck 2000, Fig. 1d). Temperatures at this site hovered near 0°C all winter, but Storck (2000) noted that during one cold storm when temperatures were less than -5°C, the maximum interception decreased by a factor of 4. Andreadis et al. (2009) combined this observation with the results of (Kobayashi, 1987), who found that between -3 and 0°C, the cohesion of ice increases, leading to increased interception on boards. Thus, they modeled the maximum snow interception as increasing linearly between -3 and 0°C by a factor of 4.

To summarize, interception processes in almost all current land surface models can be traced back to the evolution of interception efficiency in two storms in Idaho, which helped inform equation (1) in HP98. The value of I_{max} in these models was determined by the behavior of branches attached to a steel rod, or by comparing a few events in Oregon combined with a study on boards, with the decision between the two approaches depending primarily on which specific research groups and other modeling papers a given model stemmed from (Figure 1 and Figure 2). While the originating studies all examined evergreen conifers in mountains, the two study areas had very different climates (maritime vs. continental), with different temperature regimes.

[Insert Figure 2]

2.2.2 Unloading

While maximum snow accumulation in interception models follows either HP98 or Storck 2000 (Figure 2), representations of unloading of canopy snow are more varied (Figure 3). Given their differing foci on relatively cold (HP98) and warm (Storck 2000) environments, HP98 described snow unloading from a tree as an exponential function of time, approaching zero over a few days, while Storck (2000) observed frequent unloading whenever temperatures rose above zero. Illustrated on the right side of Figure 3, (Storck, Lettenmaier, & Bolton, 2002) quantified the ratio of solid snow mass release to meltwater drip to be 0.4, and this formulation was incorporated by Essery et al. (2003) in JULES and by Andreadis et al. (2009) in VIC and DHSVM. Pomeroy's further development of the HP98 model added an additional term, based on work by (Gelfan, Pomeroy, & Kuchment, 2004), wherein all snow was unloaded from the canopy in solid form when ice-bulb temperatures remained above freezing for 3 hours in the presence of wind speed greater then 0.5 m s^{-1}, but not all models using the equations of HP98 added this modification (Fig. 3). A third line of reasoning originated with (Roesch, Wild, Gilgen, & Ohmura, 2001), who were trying to improve albedo representations over the boreal forest in the ECHAM4 GCM and disagreed with the premise of HP98 that intercepted snow would approach zero simply as a function of time. Drawing on four observational studies with general descriptions of how snow unloads at higher wind speeds and at temperatures greater than -3°C, they formulated unloading to be a fraction of the existing intercepted snow, with the fraction varying with the observed wind speed and canopy air temperature relative to threshold values. Liston and Elder (2006), in developing SnowModel, unloaded snow as a function of air temperatures greater than 0°C but did not include wind-related unloading. These functions were adopted by multiple land surface models in the years following (Fig. 3). Note that model decisions about whether to calculate canopy snowmelt (and subsequent meltwater drip) appear to be made independently of decisions about snow unloading (Fig. 3), with the exception of models deriving from Storck et al. (2002), which directly relate solid snow unloading with dripping melt water.

[Insert Figure 3]

2.3 Recommendations Based on Published Observations

Measurements of canopy snow interception are difficult (see (Friesen et al., 2015) for a review of techniques), but many more direct measurements exist than appear to have been used in model development. Here, we review these observations to determine in which aspects they agree with current modeling practices for interception and unloading, and in which aspects they suggest fundamental changes are necessary.

2.3.1 Interception efficiency reaching 0 when total interception approaches a specific I_{max} is not supported from collective observational evidence.

(Satterlund & Haupt, 1967) originated the idea of sigmoidal interception efficiency with time, reaching a maximum interception value. This function was based on earlier work on the interception of liquid precipitation (Merriam, 1960). After hanging and weighing two 4 m high saplings (Douglas Fir and White Pine) for one month in Priest River, Idaho in a clearing sheltered from the wind, their data showed that after snow initially fell on the tree, the interception rate increased rapidly and then leveled off (Figure 4a). They described the leveling off as the capacity of the tree to retain snow.

[Insert Figure 4]

While most models include the idea that interception efficiency approaches zero as a maximum interception value is approached, no published dataset other than Satterlund and Haupt's examining conifers fits this form better than it would fit a constant interception efficiency (Figure 4). Often only one or a few data points that appear to indicate a maximum interception are used to justify the maximum. Data from both Switzerland and France (Helbig et al., 2020), their Figure 5, show near constant interception efficiency over a range of snowfall amounts. The exception is (Moeser et al., 2015), who showed an initially increasing and then decreasing interception efficiency over 9 storms in Switzerland. Observations from the Nothofagus forests of the Southern Andes (Huerta, Molotch, & McPhee, 2019) suggest that the models of both Hedstrom and Pomeroy (1998) and Moeser et al. (2016) consistently underestimated the largest interception events, which would indicate their decrease in interception efficiency was not supported.

Separately, observations in Japan show accumulated snow depth on boards of different widths flattens out only for the heaviest snowfall and not for cases of moderate snowfall (Shidei, 1952) (translation can be found on page 119, Fig. 7.21 in (Bunnell, McNay, & Shank, 1985)). Using spatial measurements in Hokkaido, Japan, (Lundberg, Nakai, Thunehed, & Halldin, 2004) found that the snowfall fraction intercepted and lost to sublimation varied strongly with forest sky view fraction but had no relationship with snowfall magnitude.

Throughout the literature, the raw data present a question: is a changing interception efficiency, or maximum interception capacity, supported over a constant value? The presence of a stable maximum interception amount, pervasive in our modeling, may not be the best fit for the data available (Fig. 4b-f). The discrepancy may be due, at least in part, to the difference between a canopy system (which often has multiple layers of branches, including those overlapping from adjacent trees) and an isolated hung sapling, or to the aggregation of multiple storms vs. a presentation from one specific storm sequence. It could be due to a belief that there ought to be a maximum carrying capacity, irrespective of whether there is evidence in the available data, or to the true carrying capacity being so large (e.g., the point where a tree breaks) that measuring it is impractical. Another explanation could be that the apparent maximum is reached when unloading rates equal interception rates, although this equilibrium would likely be quite variable between trees, storms, etc. A final consideration is how different functional forms of this equation affect model stability. We explore these questions further in Section 3.

2.3.2 Changing snow cohesion and adhesion with temperature is a well-documented and essential physical process to include.

The efficiency of snow interception is a function of adhesion and cohesion countered by elastic rebound. The cohesion between snow crystals increases between the temperatures of -3 and 0°C, and this increased cohesion increases snow interception (Bunnell et al., 1985). The angle of repose of a pile of snow crystals increases rapidly at temperatures above -3.5°C, approaching nearly vertical at temperatures near 0°C (Kuroiwa, 1967). Increased interception with warming temperatures has been observed on boards (Kobayashi, 1987; Pfister & Schneebeli, 1999; Shidei, 1952), when weighing trees (Shidei, 1952; Storck, 2000) and through comparing snow accumulation under trees and nearby clearings after storms (Dickerson-Lange et al., 2017; Roth & Nolin). Quasi-liquid layers are apparent on ice at temperatures slightly below 0°C (Sazaki, Zepeda, Nakatsubo, Yokomine, & Furukawa, 2012), and these facilitate increased growth rates of bonds between snow crystals. Any sequence of events leading to a thin film of water present on the trees or previously-intercepted snow before snow falls leads to the greatest adhesion and hence, the greatest interception efficiency (Bunnell et al., 1985; Shidei, 1952).

Schmidt and Gluns (1991) found that elastic rebound, i.e., bouncing, is greater for snow with higher specific gravity, but they also wrote, “Greater specific gravity is associated most often with warm storms, where cohesive forces reduce elastic rebound.” Similarly, (Filhol & Sturm, 2019) found that colder crystals bounced more, but that crystal type mattered as well as temperature. In general crystal type is also a function of air temperature (Libbrecht, 2019; Nakaya, 1954). At temperatures between -3 and 0°C, snow crystals generally form dendrites and plates, which adhere and form aggregates more readily than needles and columns, which form at temperatures between -10 and -3°C (Nakaya, 1954). Below -10°C, dendrites form again, but at these colder temperatures, cohesion is much less (Nakaya, 1954). The total range of solid precipitation types possible at temperatures near 0°C, from crystals to ice pellets to freezing rain, is diverse and complex (Stewart, Thériault, & Henson, 2015). Even HP98, whose functional form of I_{max} (Figure 1) indicates the opposite, noted, "There is a slight trend for greater interception efficiency at higher temperatures."

To summarize, all of our physical understanding and empirical evidence indicates that the air temperature during snowfall is a critical predicting variable of the efficiency at which snow is intercepted by the canopy. To a first order, some representation of increased interception efficiency with temperatures rising between -3 and 0°C, should be included in all land surface models. To further improve, some representation of the impact of temperatures prior to storm on the canopy (cold versus warm enough to have a thin film of liquid water), as well as the cloud physics and meteorology leading to the crystal type, should be included. However, using the concept of I_{max}, which in some models changes with temperature (Figure 1), may not be the best approach, as examined in Section 3.

2.3.3 Wind and warmer temperatures control the rate and timing of unloading snow and should be included in modeling.

Despite its use in many models, no observational data are presented in the literature that support snow unloading as predominantly an exponential decay function of time. This functional form may be used as a proxy for other processes but has no empirical or physical basis. Rather, the literature supports wind removing 33-100% of the snow load in cases of dry and cold snow without near-melt layers to bond it (Bunnell et al., 1985; Goodell, 1959; Hoover & Charles, 1967); in many cases, wind also limits the net amount of snow intercepted during colder storms, likely due to unloading happening simultaneously with interception. The effect of wind on decreasing interception is greater when branches (or boards, as tested) are at steeper angles (Shidei, 1952).

Rainfall and temperatures warming above 0°C are also common causes of snow unloading. (Satterlund & Haupt, 1970) report that most frequently snow was "washed off of the trees by rain." While the correlation in timing of warm temperatures and unloading is frequently reported in the literature and is represented in the majority of models (Table 1 and Figure 3), many models do not calculate melt for intercepted snow in the canopy. Thus, many unload all snow in a solid form, even at warmer temperatures. Quantifying how much intercepted snow is unloaded as solid snow versus meltwater is difficult, and reports are often anecdotal. Satturlund and Haupt (1970) stated that only 5% of the intercepted snow became liquid meltwater drip, and (Kittredge, 1953) reported that meltwater drip was uncommon in the Sierra Nevada, California. (David H Miller, 1962), working in Oregon, reported that meltwater drip was "like a shower" and a constant nuisance to researchers. (David Hewitt Miller, 1966) postulated that the "the release of intercepted snow occurs after 20% of it has melted" based on examination of the timing and likely energy input to snow observed by studies weighing a tree in Japan (Shidei, 1952). Storck (2000) derived the conclusion that 40% of liquid meltwater drip falls as solid snow based on careful comparisons of adjacent lysimeter readings in the open and under the forest during two different 2-week periods in two Decembers when there was neither rain nor melting of ground snow. Storck (2000) advised that the consistency of a 40% ratio across only two carefully-chosen study periods was more of a hypothesis to be further tested than a conclusive value. Thus, while energy available for melt, e.g., warmer temperatures, is clearly associated with unloading, the form (solid or liquid) of that unloaded water is less clear. Unloaded solid snow adds mass to the underlying snowpack, while unloaded liquid water may either refreeze in the underlying snowpack or pass through the snow to contribute immediately to soil moisture and/or runoff.

3 METHODS: FORMULATING IMODEL

While immediate progress can be made by incorporating underutilized results from prior studies, further observational work is also needed. To prioritize this work, we need to know which parameters and processes have the largest impact on model output that matters to science and society. For global climate modeling, the albedo feedback is probably the most important, and so models need to be able to represent the timing of interception and snow unloading. From a hydrologic perspective, the greatest impact of canopy interception is how it influences net losses of snow from the system; that is, intercepted snow that changes phase to become water vapor and/or meltwater. Hydrologically, snow that is unloaded in solid form from the canopy is not significantly different from snow that was not intercepted in the first place. The duration snow stays in the canopy impacts the likelihood that intercepted snow will sublimate or melt.

Based on our findings in the literature in Section 2, we pose three main questions about modeling interception:

1) Is a constant interception rate better supported than a maximum interception capacity (I_{max})?
2) Is a temperature-dependent interception rate (either through a temperature-dependent I_{max} or a temperature dependent interception efficiency, I_e, without I_{max}) necessary?
3) How do choices of unloading formulas and parameterizations impact the answers to questions 1 and 2, and which unloading formulas are best supported by data?

While all existing models have a maximum interception parameter, the collective data supporting this is not clear (Section 2.c.i). Also, while interception efficiency physically should increase with temperature (Section 2.c.ii), incorporating this may not make a large difference in model performance, particularly if unloading depends on temperature. For example, Niu et al. (2011) illustrated Noah-MP simulations that match the dataset from Storck (2000) well, despite using formulations primarily derived from HP98 (Figure 2).

To answer these questions, we formulate the experimental interception model, iModel, which has two state variables: intercepted snow in the canopy (I_s) and snow under the canopy (SWE_u). The model is run in four configurations that test representations of canopy snow interception:

- Run 1: I_e constant, no I_{max}
- Run 2: $I_e \rightarrow 0$ as $I_s \rightarrow I_{max}$, and I_{max} is constant
- Run 3: $I_e \rightarrow 0$ as $I_s \rightarrow I_{max}$, and I_{max} is $f(T_{air})$
- Run 4: I_e is $f(T_{air})$, no I_{max}

Thus, runs 1 and 4 illustrate performance with no maximum interception capacity, compared to runs 2 and 3, which have I_{max}. Runs 3 and 4 illustrate the performance with interception as a function of air temperature, compared to runs 1 and 2, which have no temperature dependence on loading.

Sublimation rates are held constant so long as snow is present in the canopy. Unloading is modeled as a multiplier of snow in the canopy as a function of both temperature and wind speed, following the formulation of Roesch et al. (2001) and Niu et al. (2011), and/or as an exponential decay function, as in Hedstrom and Pomeroy (1998). Each has a multiplier coefficient (M_T, M_v, M_{td}) so that the process may be turned off or rates may be modified. Melting of snow in the canopy is modeled with a temperature-index formulation for air temperatures above 0°C. Thus, for runs 1 and 4,

$$\frac{dI_s}{dt}=I_e P_s - S - I_s\left(M_T \frac{T_{air}}{C_T} + M_v \frac{wind}{C_V} + M_{td} C_{td}\right) - M_{fac} T_{air} \quad (4)$$

and for runs 2 and 3,

$$\frac{dI_s}{dt}=\left[\left(I_{max}-I_S\right)\left(1-e^{-\left(\frac{P_S}{I_{max}}\right)}\right)\right]-S-I_s\left(M_T \frac{T_{air}}{C_T} + M_v \frac{wind}{C_V} + M_{td} C_{td}\right) - M_{fac} T_{air} \quad (5)$$

where I_e is interception efficiency, P_s is snowfall, I_{max} is the maximum interception capacity, S is sublimation rate, T_{air} is air temperature, *wind* is wind speed, C_T and C_V are coefficients for rates of unloading with temperature and wind, respectively. C_{td} is the rate of exponential-decay unloading, and M_{fac} is the melt factor for melt rate as a function of degrees C above 0°C. Snow below the canopy accumulates as a function of snowfall that is not intercepted plus unloaded solid snow from the canopy. Melt is not calculated for subcanopy snow. Liquid water falling from the canopy is presumed to pass through the subcanopy snowpack without contributing to subcanopy SWE. The model is initialized with zero snow and operates on an adaptive timestep, using the ode15s function in Matlab. Model code is included in the supplemental material.

Atmospheric forcing data are drawn from 1997-1998 observations at Umpqua, Oregon, described in Storck (2000). These include 2-hourly observations of precipitation, air temperature and wind, as well as weighing measurements of snow under the canopy, in the open, and in three trees. This location is chosen because of its high-quality observations and warm winter temperatures, to which we expect our model variations to be sensitive.

Model instances combine interception runs (described above) with parameter sets that span a range of representations of melting and unloading of canopy snow (Table 2). Model instances (run + parameter set) are compared to observations in two ways. First, magnitude and time evolution of model output timeseries are compared directly to observations of under-canopy snowpack and canopy snow. Second, the temperature sensitivities of the model instances are tested by repeating each model instance across a range of temperatures, by uniformly decreasing air temperature by 1 through 6°C. This range represents modeled snow evolution at colder sites experiencing the same sequence of weather events (e.g., as might be expected at nearby higher elevations). The modeled temperature sensitivity is compared to literature values.

[Insert Table 2]

Model parameters for canopy snowmelt and unloading are derived from the literature (Table 2). Experiments are performed with faster (A1) and slower (A2) rates of temperature- and wind-based unloading, as well as with exponential-decay unloading (A3), using the mean parameter value defined in HP98 and Mahat and Tarboton (2013). Given the prevalence of models that do not allow snow in the canopy to melt, we also perform sensitivity tests where we repeat the A1 and A3 experiments with melting (Mrate) set to 0. As a further sensitivity test, we double the sublimation rate in one experiment with A1 parameters and no melt (Table 2). In addition to visual inspection, the bias and mean absolute error (MAE) of model simulation compared to the observations is calculated.

4 IMODEL RESULTS

4.1 Comparisons to timeseries of observational data

Many model configurations were able to reasonably match the total snow accumulating under the canopy (Figure 5), but the goodness-of-fit (Table 3) depended on both the loading and unloading schemes chosen. Based on average bias and mean absolute error over the season, A1-R3 and A1-R4, both with relatively fast unloading parameters and temperature-dependent loading schemes, perform the best (Table 3). If we consider only the end of the accumulation season in mid-March (as might be done with a spring snow survey), the best fits are still A1-R3 and A1-R4, followed closely by A3NM-R3 (Figure 5), which unloads via exponential decay and allows no melt, even though the season-mean errors are higher for this run, suggesting that a single snow survey is not sufficient to determine the best modeling set-up.

[Insert Table 3]

The exponential decay unloading (A3) and particularly the exponential decay with no melt (A3NM) simulations showed a much smoother timeseries of snow accumulation than observed (Figure 5b), suggesting that snow unloading to the forest floor is not smooth in time, but rather punctuated by events. Because the exponential decay unloading left snow in the canopy longer, more sublimation from the canopy occurred, resulting in less SWE accumulating on the forest floor. The exponential decay with no melt simulations (A3NM) better matched the total mass balance under the canopy, but with a much poorer time-series evolution, due to the absence of melt loss being balanced by the excess of sublimation loss. The simulations without temperature-dependent loading (R1 and R2, blue colors) matched the observations better in the month of December, but then most overestimated below-canopy SWE by mid-January. The December storms were overall cooler than those occurring in January and February (Fig. 6c).

[Insert Figure 5]

Parameter sets A1 and A2, with faster and slower, respectively, rates of temperature- and wind-based unloading, had similar season-long error statistics compared to intercepted snow in the canopy (Table 3 and Figure 6a). The best fit to the magnitude and timing of observed interception (Figure 6a) varied between storms. Given the warm temperatures over the observation period (Figure 6c), the temperature-dependent loading runs (R3 and R4, warm colors) consistently resulted in greater interception magnitudes than the R1 and R2 runs (cool colors), with this difference being larger than the unloading rate changes between the A1 and A2 parameter sets. The best fitting simulation varied between individual storms, suggesting either that the physical differences between the storms were not accurately represented in the span of model runs or that the model differences were smaller than measurement errors.

[Insert Figure 6]

Changing to an exponential unloading scheme (A3) and not allowing canopy snow to melt (A3NM) resulted in much larger differences in modeled interception (Figure 6b). None of these simulations looked reasonable when compared to the interception timeseries (Figure 6b). The slower and non-event-triggered unloading left snow in the canopy longer, leading to larger accumulated differences in accumulation between the R1-R4 interception schemes. When implementing these slow unloading schemes, it is relatively more important to have less loading (R1 and R2, blue colors) and an I_{max} parameter (R2 and R3) to avoid much greater than observed snow in the canopy. Simulation A3R2 had the best interception timeseries match, although A3R1 better matched both snow under the tree and intercepted snow (Table 3).

These results suggest that, overall, the choices of using I_{max} vs. not and of having interception efficiency a function of temperature are not critical for matching observations at one site over one year. Adjustments to unloading schemes (exponential, A3, vs. temperature- and wind-based, A1 and A2) have a larger effect (Figure 6) than adjusting rates of unloading within one scheme (A1 vs A2). The results also indicate that direct measurements of snow loading the canopy, as in Fig. 6, and not just observations of snow below the canopy, as in Fig. 5, are required to distinguish between the more and less realistic loading and unloading configurations. Even with both of these types of observations, we can only clearly rule out exponential unloading (A3) and no melt parameter sets (A3NM).

4.2 Model sensitivity to temperature change

Umpqua, Oregon is barely cold enough to have snow accumulation, and so warming temperatures at this site resulted in simulations with no snow. Therefore, temperature-sensitivity experiments were conducted for cooling temperatures. While warming experiments are more conventional, this experiment reveals much about climate sensitivity (Figure 7). All of the runs with allowed canopy melt simulated a greater fraction of snow below the canopy at colder temperatures than warmer temperatures (Fig. 7a), due to the increased frequency of snow melting in the canopy under warmer conditions. Similarly, all runs that allowed melt simulated longer snow duration in the canopy at colder temperatures (Fig. 7b). Runs with no melt showed the least variation, with the two A1-no-melt model instances (not graphed, but with close to 0.65 fraction of snow below the canopy at all temperatures) showing no variation with temperature at all.

[Insert Figure 7]

The variations between simulations were much larger at warmer temperatures than at cooler temperatures. This indicates that observations at warmer snow sites are more able to distinguish differences between multiple model configurations, whereas comparisons to colder snow sites would not be as useful.

Across any set of unloading parameters, the runs with temperature dependent loading, Runs 3 and 4 (orange and red symbols in Fig. 7), showed the greatest change with temperature and best matched the observed temperature-dependent change of 50% decrease in the under-forest:open peak snow accumulation for a 3°C average winter temperature increase across multiple sites (Dickerson-Lange et al. 2017, their Fig. 3). These changes were greatest when the unloading rate was slow, provided melt occurred (A3). Simulations A2-R3 and A2-R4 both matched the observed fraction of snow below the canopy compared to the open (40%, Fig. 7) in addition to matching well the timeseries evolution of snow in the canopy (Fig. 6). They both had about 40% variation in relative fraction of snow under the canopy over the range of 0 to -6°C (Fig. 7). This value closely matches the observed 40% decrease in this ratio (which they termed canopy interception efficiency) between cold and warm storms which differed by ~6°C (Roth and Nolin 2019, their Fig. 4). These results suggest that temperature-dependent loading is important, but that this could be accomplished with either I_{max} or an interception efficiency formulation.

4.3 Model sensitivity to canopy snowmelt

Many model configurations (Fig. 3, orange-colored cells) do not allow canopy snow to melt. When we ran simulations with A1 unloading but with *Mrate* set to 0 (i.e., no snowmelt, A1NM in Table 2), the timeseries of intercepted snow looked similar, indicating the timing of snow unloading was correct, but too much snow accumulated underneath the forest canopy (Table 3). Also, the impact of temperature change on the fraction of snow beneath the canopy compared to the open disappeared. We experimented with doubling the sublimation rate, keeping all other factors the same (A1NM2S, Table 2). This resulted in a better match to the observed snow under the canopy but a worse match to the timeseries of snow in the tree, which disappeared too soon (Table 3). Because sublimation in iModel is fixed and not formulated as a function of temperature, this change did not affect the temperature-sensitivity of snow beneath the canopy.

Turning melt off in parameter set A3NM, with a slower unloading rate, also led to very unrealistic results (Fig. 6 and 7). An unrealistic amount of snow accumulated in the canopy (Fig. 6b), leading to very high fractions of time with snow in the tree (Fig. 7b). The sensitivity of these simulations to temperature change was also subdued (Fig. 7), with unrealistic changes for snow duration in the canopy for Runs 3 and 4, where increasing temperatures led to greater rates of interception, which then did not melt and unloaded very slowly. To summarize, with tuning of other parameters, a model with no canopy snow melt could match the seasonal observations of snow under the canopy and in the open but could not match the timeseries evolution of both observations of snow in the canopy and snow under the canopy. The model with no canopy snowmelt also could not represent the known climate sensitivity of fractional snow accumulation under the canopy or to snow duration in the canopy.

5 DISCUSSION

5.1 Sensitivities Identified by iModel and What They Indicate for Experimental Design

Our literature review and model experiments reveal that snow interception models have far more tunable parameters than there are measurements available to constrain them. In other words, very different combinations of choices of how processes of loading and unloading are represented can simulate snow under the canopy equally well. However, much fewer combinations are robust when we also compare to weighing measurements of snow in the canopy and to sensitivity to temperature change. In particular, only model formulations that included physically-based triggers for unloading (e.g., temperature and wind) could represent the observed time-series evolution, and only models that represented snow melting in the canopy and greater interception rates at warmer temperatures were able to represent the degree of climate sensitivity that has been observed. Given that most models are intended to simulate snow responses to changes in weather and climate, appropriately representing this sensitivity is essential.

These results indicate that to make further progress, concerted efforts must be made to simultaneously measure the mass balance in the canopy, beneath the canopy, and in the open near the canopy, across a range of weather and climate conditions. Historically, all of the most useful field studies for modeling included weighing trees, either through lysimeters (Shidei 1952; Storck 2000) or hanging a tree (Hedstrom and Pomeroy 1998). It is highly desirable to develop technologies that could quantify this for stands of trees rather than individual cut trees. Friesen et al. (2015) describe some techniques, but most are difficult to implement and/or still under development.

Our model results also demonstrate that model capability varies a lot between storms, even those with similar mean temperatures (Figure 6), and that different sequences of weather events lead to large interception variations. This suggests that field measurements should be maintained for multiple years in addition to at multiple locations to provide test data for modeling a wide variety of storm and inter-storm sequences.

5.2 Why changing I_e has a greater effect than changing I_{max} as a function of temperature

[Insert Figure 8]

As configured in most models, even if maximum interception varies as a function of temperature, interception efficiency will always be close to 1 at times when little snow in the tree (Figure 8). This is counter-intuitive to observations that (a) interception efficiency increases after initial snow bridges branches and provides a "sticky" substrate for subsequent snow and (b) that temperatures before and during a specific storm are important. In simulations with either rapid unloading, or frequent snow melting and unloading events, wherein snow in the canopy is often near 0, interception amounts were less sensitive to storm temperatures when an I_{max}=f(T_{air}) formulation (Run 3) was used. Setting I_e=f(T_{air}), as in Run 4, did not have this limitation.

5.3 Order of operations, model stability and time-stepping schemes

Often unloading happens during interception events, particularly in colder storms with high winds. While loading and unloading are two separate processes, data often contain both, and models may solve an ODE with adaptive timesteps and near-simultaneous adjustments of both loading and unloading, as we have here, or may have a set order of operations, such that unloading may only be allowed after an interception event. With this in mind, our concept that interception efficiency decreases over time might simply be an effect of simultaneous unloading. There is also a chance that within-storm unloading is accounted for twice in the model: first, by way of an erroneously reduced interception efficiency, and again by way of the unloading function. Thus, it is impossible to consider interception loading schemes, particularly those that approach a maximum capacity, without also considering unloading and the model's numerical configuration. Numerical details are seldom reported in papers and are beyond the scope of this work. However, we encourage anyone working on interception model development to pay particular attention to the coding of the processes.

5.4 Dripping water: Does it lead to denser subcanopy snow or a loss of hydrologic water storage

As formulated, iModel does not add liquid melt water to the snow below the canopy, and thus, whether a model simulates melt or simply unloads solid snow impacts the subcanopy SWE. Meltwater from the canopy has been observed refreezing in the snowpack (Teich et al., 2019), their Fig. 12, in some environments, so by not allowing meltwater drip to add to subcanopy SWE, iModel may be overestimating the hydrologic impact of melting canopy SWE. However, observations of snow stratigraphy and density in adjacent forest-covered and open areas show that while snow composition and the range of observed snow density under forests is clearly more variable than in an adjacent opening (Teich et al., 2019), under-canopy snow is not consistently more or less dense (Broxton, van Leeuwen, & Biederman, 2019), see their supplemental material. Therefore, the fate of melting canopy snow and under-forest snow evolution warrants further study.

5.5 Other factors that are likely very important, including sublimation

In arid climates, sublimation of snow from the canopy is more important than melt. The variation in how models simulate sublimation is much greater than loading and unloading formulations described here and is also even less grounded in observations. Turbulence and sublimation are notoriously hard to measure, especially over stable boundary layers (i.e., snow) and over complex (i.e., forested) surface variability. Note that we could also increase the modeled temperature-dependent variation in subcanopy:open SWE ratios by parameterizing sublimation as increasing with temperature. We chose not to do this because a) sublimation is a complicated factor of atmospheric moisture content and wind speed in addition to temperature, and b) the humidity at Umpqua, Oregon was quite high, resulting in little estimated winter-season sublimation from a range of formulas. While a full discussion of sublimation is beyond the scope of the work here, we emphasize that sublimation remains a very important research challenge.

We have also neglected the impact of canopy structure. Canopy elements with more solar exposure will lose intercepted snow first (either from sublimation or melting), and canopy elements with more wind exposure may either intercept more snow (e.g., preferential deposition of snowfall along downwind canopy edges or fog harvesting in riming conditions) or lose snow more rapidly (from wind unloading). While recent work has advanced understanding of the radiation balance in forest canopies ((Jonas, Webster, Mazzotti, & Malle, 2020; Malle, Rutter, Mazzotti, & Jonas, 2019; Mazzotti, Essery, Moeser, & Jonas, 2020; Mazzotti, Essery, Webster, Malle, & Jonas, 2020; C. D. Moeser, Broxton, Harpold, & Robertson, 2020; Musselman, Margulis, & Molotch, 2013; Musselman, Pomeroy, & Link, 2015; Seyednasrollah & Kumar, 2019; Webster & Jonas, 2018; Webster, Mazzotti, Essery, & Jonas, 2020; Webster, Rutter, &

Jonas, 2017), to date, this has focused more on the forest floor and less on the snow in the canopy itself.

5.6 Considerations for future work: We need more data

Given the history and the current state of the science, where should we focus our attention? First, with the exception of a few studies (e.g., Storck 2000), direct observations of snow interception have not been impressive in the years since the work in Japan in the 1950s and 60s. More locations and forest types should be targeted for careful, detailed lysimeter and tree weighing work, accompanied by accurate atmospheric data to run and test land surface models of snow evolution. These observations will require monetary and time contributions from the entire community and should be set up in a variety of winter climates that span the -10 to +2°C T_{mean} range for multiple winters to span a wide variety of weather sequences.

Next, researchers should capitalize on easier-to-obtain measurements that can be acquired more broadly to test how model parameters from heavily-instrumented sites transfer across domains. Time-lapse photography and space-borne imagery are both recent developments that allow us to observe, visually, how canopies intercept snow in space and time. Additionally, lidar technology has changed both how we view the forest (White et al., 2016) and the snow beside and beneath it (Deems, Painter, & Finnegan, 2013). Canopy structure can be explicitly resolved in three-dimensions, and snow depth can be mapped at 1-m spatial resolution with cm-vertical accuracy. Efforts should be made to optimally combine less-expensive visual data with information learned from lidar data to explore how to extend relevant canopy features to regions where lidar may not be available. For example, if canopy edge (Currier & Lundquist, 2018) and distance-to-edge (Mazzotti et al., 2019) characteristics are the best predictors of interception, we should explore how well a georeferenced photograph from above can map these. Bunnell et al. (1985) advise that "crown measurements taken in the absence of snow load may be markedly different from the shape of the crown when carrying snow," and the degree of variation will differ between species and with age in the same variety. Thus, such aerial or space-borne photographs should target different degrees of loading to develop model look-up tables of ground footprints as a function of intercepted snow for different conifer species.

Finally, land surface modelers and forest-snow hydrologists should collaborate with people working in neighboring disciplines. Working with atmospheric scientists in the context of coupled models could improve understanding of how different hydrometeor species and evolution (e.g., graupel or rime or different snow crystals) adhere to trees, as well as provide better constraints on sublimation. Working with water and forest managers and those specializing in forest structure and health to understand how forests change should elucidate the parameters most important to accurately represent snow interception. These are essential not only to accurately model hydrologic response following a bark beetle kill or forest fire, or to projected changes in climate, but also to help design management actions to support both forest and watershed health. For example, Bunnell et al. (1985) suggest that silviculture practices designed simply to increase the crown-height:base ratio to produce steeply sloping sides would reduce snow interception, and this may be most useful in windy environments.

6 CONCLUSIONS

Current global land surface representations of snow interception by forest canopies are based on a handful of observations from two locations. However, despite the similar observational basis, models vary in whether canopy loading capacity or efficiency increases with temperature, in whether or not they model canopy snow melt, and in how they represent unloading. These differences lead to very different climate sensitivities regarding how snow in forested regions is simulated with changes in temperatures.

Literature review reveals ample observational evidence that snow cohesion increases as temperatures approach the melting point, leading to greater interception efficiency. Model simulations show that while any of the existing snow loading parameterizations can match a season of intercepted snow data, only those with interception efficiency varying as a function of temperature were able to match the degree of climate sensitivity reported in the literature. The greatest spread in model simulations occurred during the warmest simulations, suggesting that observations at sites with relatively warmer snow are likely to be more valuable in evaluating model performance, particularly as it relates to ability to simulate the impacts of climate change on snow.

Model simulations also showed that while models with exponential unloading could match the net snow accumulation under the canopy, they did not match the timeseries evolution of snow in the canopy and below in a warm-snow environment. Furthermore, simulations without canopy snow melt showed the least climate sensitivity and were unable to match observations of both snow in the canopy and snow beneath the canopy. This suggests the simultaneous observations of snow mass in the canopy and beneath the canopy are required to determine the ideal model configuration and parameter set.

Collectively, our analysis suggests strongly, that, at a minimum, all model representations of snow interception should include the following:

- a temperature-based representation of increased cohesion as snow approaches the melting point, which increases the canopy interception efficiency and/or capacity
- model snow melt in the canopy
- a physical basis for snow unloading (e.g., temperature and wind dependence).

Without these process representations, modeled climate change impacts in forested-snow regions will be wrong. Only model representations including both changing loading capacities with temperature (see Section 3) and snow melt could recreate the temperature dependencies observed in nature (Fig. 7). Only model representations with unloading timing related to temperature could match timeseries of snow intercepted in the canopy (Fig. 6). Of the models reviewed here, the modular framework of SUMMA (Clark et al. 2015a and b) allows choosing all of these options together, but the user must set this configuration. VIC and DHSVM (Andreadis et al. 2009) include temperature-dependent loading, canopy snow melt, and unloading associated with canopy melt. VIC and DHSVM models do not include wind-dependent unloading, but as tested here, the temperature-related timing of unloading is more important both in matching the Umpqua, Oregon data and in representing climate sensitivity. Noah-MP (Niu et al. 2011) includes snow melt and physically-based unloading, but does not include temperature-dependent loading. Therefore, most models used for short- or long-term prediction over snow and forested terrain should update based on the results shown here.

The choice of modeling changes in interception efficiency (I_e) directly or in maximum interception efficiency (I_{max}, with I_e a function of I_{max}) led to differences in simulated snow, but these differences were smaller than most other changes tested. Therefore, we recommend not using I_{max} because it is an unnecessary model complication and is not supported in the literature (Figure 4), but if it is already built into a model, it is less important to update than the recommendations above.

In summary, we strongly recommend including snow physics that are known to occur as temperatures increase, namely canopy snowmelt and increased cohesion of snow above -3°C.

We also recommend not pursuing model functional forms that include exponential-decay based unloading or a maximum interception value. Rather, more physically-based model choices (such as temperature and wind dependent melt, and interception efficiency varying with temperature) should be pursued in the context of careful and coordinated field measurements. We recommend that the climate and hydrological sciences communities come together to support high-quality detailed observations of snow accumulation in, below, and adjacent to forest canopies, combined with high-quality energy balance observations, across multiple years and multiple locations, to provide the basis for further improving how we model this dynamic interface.

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TABLES

Table 1: *Canopy interception representations in commonly-used hydrologic land surface models, as well as a selection of snow models*

Note: For each process, ✓=yes, included, and blank indicates not included. Model citations are as follows: CRHM (Pomeroy et al. 2008; Ellis et al. 2010); VISA (Niu and Yang 2004); CLASS (Bartlett et al. 2006; Bartlett and Verseghy 2015); UEB (Mahat & Tarboton, 2014); VIC & DHSVM (Andreadis et al. 2009); SUMMA (Clark et al. 2015ab); Noah-MP (Niu et al. 2011; Barlage et al. 2015; G.-Y. Niu et al., 2011); JULES (Best et al. 2011; Essery et al. 2003a ; Essery, Pomeroy, Parviainen, & Storck, 2003); CLM (CLM 5.0 technical note; CLM4.0, Lawrence et al. 2011; Lawrence et al., 2019); SnowModel (Liston & Elder, 2006) ; FSM (Moeser et al., 2015; D. Moeser, Mazzotti, Helbig, & Jonas, 2016) ; AMUNDSEN (U. Strasser, Bernhardt, Weber, Liston, & Mauser, 2007; Ulrich Strasser, Warscher, & Liston, 2011).

	CRHM	VISA	CLASS	UEB	VIC/ DHSVM	SUMMA	Noah-MP	JULES	CLM	Snow Model	Moeser/FSM	AMUNDSEN
Tracks canopy snow temperature	✓				✓	✓						
Models melt of intercepted snow		✓		✓	✓	✓	✓	✓				✓
Interception efficiency asymptotes to 0 as I → I_{max} (exponential	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓

function)												
Interception efficiency asymptotes to 0 as I → I_{max} (sigmoidal function)											✓	
I_{max} function of density as defined by temperature	✓	✓	✓	✓		✓	✓					
I_{max} increases with temperature above -3°C					✓	✓						
Unloading exponential function of time	✓			✓		✓						
Unloading at temperatures at or above 0°C:	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
Full unloading	✓											
Partial unloading $f(T_{air})$ near or above 0°C		✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
**unloaded as all solid	✓	✓	✓			✓*			✓	✓	✓	✓
** unloaded as mix (solid & liquid)					✓	✓		✓				
Unloading as a function of wind speed		✓	✓			✓*	✓		✓			

** VIC, DHSVM, and JULES unload snow at 40% of the canopy snowmelt rate; Others unload independently of melt rate (or without allowing melt to occur)

*only in SUMMA 3.0 and later (https://github.com/NCAR/summa), not in the original; Note that SUMMA is a modular model framework and could be set up with or without these parameters.

Table 2. iModel Parameter Settings, including variations for Melt and Unloading

For runs labeled R1 to R4: R1, I_e=Iemin. For R2, I_{max}=Imaxmin. For R3, I_{max}=Imaxmin + Imaxscale(T_{air}(T_{air} -3)+3)/3. For R4, I_e=Iemin+Iescale*(T_{air}(T_{air} -3)+3)/3. Rain falling at temperatures below the RScutoff is assumed to be snowfall, with all rainfall above. Sources for parameter values: (a) Fig. 4d, Storck et al. (2000); (b) Andreadis et al. (2009); (c) (Martin et al., 2013), see their Table 1 for maximum measured intercepted snow in different climates; (d) (Raleigh & Lundquist, 2012) ; (e) (Lundberg & Halldin, 2001); (f) (Jessica D. Lundquist et al., 2008); (g) (Roesch et al., 2001); (h) (Mahat & Tarboton, 2014).*

Name	**Units**	**A1**	**A1NM**	**A1NM2S**	**A2**	**A3**	**A3NM**
Iemin	mm	0.6 [(a)]					
Iescale	mm °C^{-1}	0.4 [(b)]					
Imaxmin	mm	20 [(c)]					
Imaxscale	mm °C^{-1}	65 [(c)]					
Mrate	mm °C^{-1} hr^{-1}	4/24 [(d)]	0	0	4/24	4/24	0
Subrate	mm hr^{-1}	4/24 [(e)]	4/24	2*4/24	4/24	4/24	4/24
RScutoff	°C	1.6 [(f)]					
C_T	s^{-1}	1.87×10^5 [(g)]					
M_T	-	0.5	0.5	0.5	0.25	0	0
C_v	s^{-1}	1.56×10^5 [(g)]					
M_v	-	0.5	0.5	0.5	0.25	0	0
C_{td}	s^{-1}	1.2861×10^{-6} [(h)]					
M_{td}	-	0	0	0	0	1	1

Table 3. *Bias (B) and mean absolute error (MAE), over 18 November 1997 to 7 April 1998, presented as B/MAE at each table location, for comparison to measured snow under the canopy (top values) and measured snow in the canopy (bottom values) for each model combination of parameters (see Table 2) and runs. The best parameter set for each of the four runs is in bold. Times of zero snow within the evaluation period are included in the calculations. All units are mm.*

B/MAE (mm)	**A1**	**A1NM**	**A1NM2S**	**A2**	**A3**	**A3NM**
R1	34.5/35.0 -1.1/1.4	61.3/61.7 -0.9/1.3	43.5/43.9 -1.1/1.5	18.1/19.4 -0.8/1.3	**-6.8/8.2** **-0.0/1.4**	20.2/22.5 +3.1/3.5
R2	11.0/15.0 -0.8/1.3	48.9/49.7 -0.5/1.3	21.5/24.4 -0.9/1.4	**-6.9/10.9** **-0.5/1.1**	-29.2/29.2 +0.1/1.1	13.4/18.9 +1.7/2.0
R3	**0.2/9.6** **-0.4/1.2**	43.0/43.9 +0.0/1.3	10.1/15.5 -0.4/1.4	-23.2/23.2 +0.3/1.3	-59.1/59.1 +1.9/2.4	-4.6/12.5 +6.0/6.0
R4	**0.6/9.1** **-0.4/1.3**	43.9/44.7 +0.1/1.4	11.6/16.5 -0.4/1.5	-24.4/24.4 +0.5/1.5	-69.8/69.8 +3.1/3.6	-14.6/16.5 +9.8/9.9

FIGURE LEGENDS

Figure 1. (a) Illustration of canopy processes and parameters in land surface models: trees intercept snow with a fractional efficiency (I_e) up to a maximum value (I_{max}), and the remaining snowfall passes through the canopy. Snow in the canopy (I_s) may sublimate, melt, or unload. (b) Loading may or may not be parameterized as a function dependent on Imax, and loading capacity may or may not increase with temperature. (c) Unloading may be a function of air temperature (T_{air}) and wind or may be a constant rate proportional to intercepted snow, where C_T, C_V, and C_{td} represent different constants in the literature. (d) Branches clipped to a pole in the Rocky Mountains (Schmidt & Gluns, 1991). (e) Douglas Firs in weighing lysimeters in the Oregon Cascades (Storck, 2000).

Figure 2. Flow path of model development between the Hedstrom and Pomeroy vs. Andreadis I_{max} formulations shown in Fig. 1. Models listed in green boxes employ the solid red line in Fig. 1b (and formulas 2 & 3), while models listed in the blue boxes employ the black dashed line in Fig. 1b to model maximum interception as a function of temperature.

Figure 3. History of model development for snow unloading. Arrows indicate flow of information through paper citations, while blue colors represent models that calculate snowmelt, which is then lost from the canopy through melt water drip, and orange colors indicate models that do not calculate canopy snowmelt. White boxes are observational studies and not models.

Figure 4. (a) from Satturlund and Haupt (1967)'s Fig. 2, curves for two saplings for one storm event; (b) from Schmidt and Gluns (1991)'s Fig. 4, note large scatter of points around drawn curves as well as notation of a point off the top of the plotting range; (c) from Hedstrom and Pomeroy 1998's Fig. 6, note that modeled (filled squares) level off but that measured (diamonds) diverge from the model at high values; (d) from Storck 2000's Fig. 5.4, note single point taken as I_{max}, which does not diverge much from a linear fit; (e) from Watanabe and Ozeki 1964, as translated in Bunnell et al. 1985, their Fig 7.31; (f) from Roth and Nolin 2019's Fig. 5, note lack of any data suggesting a leveling off at I_{max}.

Figure 5. Timeseries of (a,b) modeled and observed snow accumulation on the ground under the canopy for water year 1997-1998 and (c,d) differences between model and observed. Model instance numbers refer to parameters (Table 2) + interception configurations (runs, described above). Line-styles (solid, dashed, etc.) vary with the parameter set (with a,c showing simulations with temperature and wind-based unloading and b,d showing simulations with exponential unloading), while colors vary with the interception configurations, with warmer colors representing interception schemes with greater interception amounts at warmer temperatures.

Figure 6. Intercepted snow for 1997-1998 (subset of time-period shown in Fig. 5), where A1-A3 refer to variations in parameter sets that control canopy snowmelt and unloading as in Table 2, and R1-R4 refer to loading schemes as in Section 3. Black lines show intercepted snow from three different species of trees cut and weighed on lysimeters. Note that the black lines in (a) and (b) are identical but shown with different y-axis ranges for clarity in presentation of the model output. (c) Measured air temperature at the site.

Figure 7. Temperature change sensitivity for year 1997-98 of all of the model configurations shown in Fig. 6 with regards to (a) the fraction of seasonal-total snow accumulating under the canopy compared to the open and (b) the fraction of time when snow is present in the canopy. Note: All simulations were performed with whole number temperature offsets; however, symbols are plotted with slight offsets from the whole number to better distinguish between different simulations. For reference, the observed 1997-98 fraction (at 0 temperature change) was 0.4, which is best matched by A2-R3 and A2-R4 in (a).

Figure 8. How (a) cumulative interception and (b) interception efficiency varies with cumulative snow intercepted in the tree when using the function in HP98 and many other models.