Response to Editor (TC-2019-1)

Thank you for the handling of our manuscript. Below are private comments to you. We also include a response to A. Winstral. In addition, we include a 'track changes' and also a 'clean' version of our revision. We believe that we have handled all necessary revisions and that we have clearly demonstrated the improvement of our method. We hope to hear from you soon.

Comments to the Author:

Dear authors

Thanks for submitting the revised version of your manuscript. You have addressed all points in your replies raised by the reviewers. However, I believe you have failed to incorporate the arguments you bring forward to actually support your conclusions. I find it not sufficient to mention in the reply that you could have done this or that, or you would have even tried it, but it would not have changed the results.

In our first revision, we made numerous additions. Also, we tested several ways of building the regression model, and we found the results to be the same. So, perhaps there was a miscommunication. It was not that we could have tried a new approach. We actually did a new approach, but it did not make a difference. We state this explicitly in the revised paper.

I expect you to take the arguments by reviewer #2 more seriously and make the appropriate changes to the manuscript. I think it is not too difficult and you are actually close to a valuable contribution that includes a comprehensive, objective analysis with statistically supportable claims. If you are prepared to revise the manuscript accordingly I am happy to reconsider it for publication.

In the latest version you will find a side-by-side comparison of our model to three other widely used models. We apply all four models to three datasets:

- 1. The western North America snow pillow dataset (close to 2 million data points).
- 2. The complete western North America snow course / aerial marker data set (100,000+ data points).
- 3. The northeast USA collection of data sets (100,000+ measurements).

Our model has lower bias and RMSE in all cases, except for two very small northeast USA datasets (totaling about 1500 data points). We believe that this is a very convincing case that our approach is an improvement over existing methods.

Jürg Schweizer

Response to A. Winstral Review of TC-2019-1

Thank you for the recent review of our manuscript. We appreciate the investment of time that you have made in improving our analysis. Below, we provide point-by-point responses to the May 2019 review of our second draft. Reviewer comments are in black. Our responses are indented and in blue. All references to table/figure/line numbers refer to the 'clean' version of revision #2. One notable change is that we have revised our regression analysis to use 'winter precipitation' and 'winter temperature' rather than mean annual precipitation and mean February temperature. This reduced our RMSE values.

Though I firmly stated that the authors had not presented convincing evidence to support their claims, they chose to not implement and include any of my major suggestions for revisions to make the work more convincing. Instead they have largely chosen to reason away my suggestions. I don't wish to repeat my review nor get into a lengthy debate on the relevancy of my comments. Instead I'll just go with what the presented data say to me. The authors have derived a method for estimating snow densities that includes climatological variables, which provide a means of capturing spatial heterogeneity. They developed and tested this method using data from snow pillows and snow courses. By the authors own admissions (lines 46-50) these data all come from "relatively simple topography". Generally these are all located in flat, windsheltered locations. On the other hand the Sturm model, a well-regarded and oft-cited research piece, is based on similar data as well as data collected on manual traverses representing a range of topographic positions and snow deposition zones. The presented comparison with the Sturm model is conducted only at SNOTEL sites (i.e. flat, wind-sheltered). These same exact sites were used in both the calibration of the new model and for comparisons with the Sturm model. Results show that overall the new model performs better. However, if one were to eliminate taiga sites, which were not well represented in the Sturm data, the overall results are very similar (see table below).

We do not believe this to be an entirely correct statement. In Table 4 of the paper, we provide comparative results for 'all data' and also for the data broken out by snow class. In every row of this table, the results show that our model has a smaller bias and RMSE than Sturm's model.

Note also that, in the revision, we now compare our model to Sturm at all of the northeastern USA data (nearly all snow course, not snow pillow). Our model has lower bias and RMSE than Sturm for all of these data sources. We also now compare our model to Sturm at all (100,000+ measurements) NRCS snow course sites in western North America. These sites are independent from the model training data and use a different method (snow coring instead of snow pillow). Our model has lower bias and RMSE than Sturm for this independent data set.

Though the authors acknowledged that I raised an important point regarding their splitting of data in which all stations were included in both training and validation sets they state only that a station-dependent splitting method produced "extremely close" results to the original without actually presenting those results.

Yes, this was a good point, and we tested it out after your first review. The results were the same. It felt redundant to us to present numeric data (identical) for both of these cases in the revised manuscript. In our new revision, we now explicitly state (beginning of section 2.2) that we did our model building / validation both ways, and that the results were the same.

Given how similar the provided results are for non-taiga performance of the two models, the only conclusion I can draw from the presented data is that at sheltered, taiga sites the new model performs better. At other sheltered locations, the new model might be better or worse.

Table 4 shows that the current model has smaller biases and RMSEs for all snow classes, not just Taiga. For the non-taiga sites, our RMSE is usually ~20% smaller than Sturm. And, our biases are much smaller than the biases of Sturm.

Additionally, the new application of our model, side-by-side with Sturm for two independent data sets shows that our model consistently has lower RMSE and bias.

The new method is trained in the same conditions and sites as the validation was conducted whereas the Sturm method is based on a greater diversity of data from independent sites. Given this unbalanced methodology and the closeness of the results, I find the comparative assessments of model performance at sheltered, non-taiga sites to be uncertain.

See our above remarks. We believe the modifications we have made alleviate this point, which is similar to several above points.

Results averaged over all snow classes except taiga (taken from snow class percentages provided in Section 3.1 and results in Table 4) Sturm et al. Multi-variable two-equation R2 0.97 0.97 rmse (mm) 72.1 67.8 bias (mm) 1.76 -2.26

Regarding the usefulness and accuracy of the new methodology at sites other than typical SNOTEL stations for estimating densities nothing has been shown (e.g. the manuscript-referenced crowd-sourced and Lidar data that are gathered in a variety of topographic settings). No data is presented for anything other than flat, wind-sheltered locations therefore conclusions on model performance in any other conditions are not possible.

We showed in our original paper our model applied a great variety of data (snow course, mostly) from the northeastern USA. The northeastern US snow courses (NY and ME Snow Survey sites) are not typical SNOTEL stations and include both forested and open sites in both flat and topographically complex settings. At Hubbard Brook, the snow courses are forested areas about ¹/₄ hectare in size. Thompson Farm in Durham, NH, USA includes a forested site and open site. Sleeper's River in Vermont also includes forested and open field sites across a range of topographic classes.

In addition to this, we have now included all western North America snow course data (100,000+ measurements). These are completely different data from the SNOTEL snow pillow data.

So, we have great confidence in the ability of our model to perform in a wide variety of environments.

Yes, the maps look pretty and capture greater heterogeneity but how accurate are they? A theoretical argument can easily be made that the Sturm method – based on a more diverse set of data – would actually be better.

I would be remiss if I didn't further comment on one of my major suggested revisions that wasn't followed up on: direct comparisons to the Jonas et al. method. Rather than including direct comparisons to the Jonas method (based on over 11,000 observations and cited over 140 times) as suggested, the authors have chosen to make comparisons to the simple Pistocchi method that is solely a function of day-of-year (based on 206 observations and cited 5 times). According to the authors this was necessary because the Jonas method is dependent on month of year, elevation, and a geographic "offset" term. Certainly the former two variables are available to the authors. The presence of the offset term however leads the authors to conclude that the Jonas model cannot be applied to other regions while implying that Jonas et al. did not "construct" their model for such applications. Yet in referring to the importance of the offset term Jonas et al. state, "However, the minor importance of regional effects suggests that the model may also be applicable in other regions with similar snow climatologic conditions." In fact, if one averaged the regional offset term over all the data records in the Jonas application it comes to a mere 3 kg/m3. One could in fact, easily optimize the Jonas "offset" term to the data presented here in the calibration set. (It is my personal belief that any comprehensive analysis should include this). Yet even a straight-out-of-the-box Jonas application using the average offset or none at all would be insightful. If, in fact, the presented model performs better than the Jonas model at the tested sites then this would show that there are indeed regional constraints present in the Jonas model that must be accounted for. On its own, these insights on regionality for one of the most widely cited density parameterizations would be relevant. Of course, this would also lend greater credence to the model presented in this work as well. This entire analysis including optimization could probably be done in less than a day. Without optimizing the offset term, this is about 5 lines of code that could even be handled in a spreadsheet. I truly don't understand why this revision wasn't undertaken.

We now present results for the Jonas model applied to (1) the SNOTEL data, (2) the northeastern USA data, and (3) all NRCS snow course data. Please see sections 3.3, 3.4, and 3.5. The present model has lower bias and RMSE than Jonas for (1), for four out of 6 datasets in (2) and for (3). The two datasets for (2) where Jonas has lower RMSE and bias are the smallest datasets by 1-2 orders of magnitude.

Unfortunately, save for the inclusion of the Pistocchi model comparison, the authors have presented no new data. It is my opinion that the presented work still does not compellingly support the stated conclusions, particularly this one (lines 432-33), "The results presented in this

study show that the regression equation described by equations (5, 7-8) is an improvement (lower bias and RMSE) over other widely used bulk density equations."

The present model is now compared against three others (Sturm, Jonas, and Pistocchi) for many different datasets from different regions and different methodologies. The results objectively show that the present model has lower values for bias and RMSE.

The authors have the data available to make this a much more extensive and scientifically supportable work (e.g. significance tests would be a nice touch).

We are not 100% sure which specific tests you are asking for. We have provided metrics such as RMSE, R2, and bias. If you are referring to significance tests related to the linear regression analysis, the p values for each variable were 0, and we have now stated that in the manuscript. We also (this was discussed in the original paper and the discussion remains) indicate the use of adjusted R2 values in the construction of the model. This is important since one can always add more predictors and improve the R2. The adjusted R2 ensures that we are only adding in more predictors that produce enough of an improvement in R2 to justify the inclusion.

I think I have provided several constructive ideas on how to go about this. At the very least, if they weren't to follow up on these suggestions they need to objectively evaluate their results and in my opinion, substantially scale back their claims.

In summary, our model is compared to three others for three different datasets, representing a wide variety of methodologies (for measuring SWE) and physical locations.

- 1. Western North America snow pillow data
- 2. Western North America snow course data
- 3. Northeast USA data (mostly snow course, some snow pillow)

For all three of these datasets, our model had the smallest errors and biases.

Converting Snow Depth to Snow Water Equivalent Using 1 **Climatological Variables** 2

3

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- 18

19 Abstract. We present a simple method that allows snow depth measurements to be converted to snow water

20 equivalent (SWE) estimates. These estimates are useful to individuals interested in water resources, ecological

21 function, and avalanche forecasting. They can also be assimilated into models to help improve predictions of total

22 water volumes over large regions. The conversion of depth to SWE is particularly valuable since snow depth

23 measurements are far more numerous than costlier and more complex SWE measurements. Our model regresses

24 SWE against snow depth (h), day of water year (DOY) and climatological (30-year normal) values for winter

25 (December, January, February) precipitation (PPTWT) and the difference (TD) between mean temperature of the

26 warmest month and mean temperature of the coldest month, producing a power-law relationship. Relying on

27 climatological normals rather than weather data for a given year allows our model to be applied at measurement

28 sites lacking a weather station. Separate equations are obtained for the accumulation and the ablation phases of the

29 snowpack. The model is validated against a large database of snow pillow measurements and yields a bias in SWE

- 30 of less than 2 mm and a root-mean-squared-error (RMSE) in SWE of less than 60 mm. The model is additionally
- 31 validated against two completely independent sets of data; one from western North America, and one from the
- 32 northeast United States. Finally, the results are compared with three other models for bulk density that have varying
- 33 degrees of complexity and that were built in multiple geographic regions. The results show that the model described
- 34 in this paper has the best performance for the validation data sets.

35 1 Introduction

36 In many parts of the world, snow plays a leading-order role in the hydrological cycle (USACE, 1956; Mote et al.,

- 37 2018). Accurate information about the spatial and temporal distribution of snow water equivalent (SWE) is useful to
- 38 many stakeholders (water resource planners, avalanche forecasters, aquatic ecologists, etc.), but can be time
- 39 consuming and expensive to obtain.
- 40

41 Snow pillows (Beaumont, 1965) are a well-established tool for measuring SWE at fixed locations. Figure 1 provides 42 a conceptual sketch of the variation of SWE with time over a typical water year. A comparatively long accumulation 43 phase is followed by a short ablation phase. While simple in operation, snow pillows are relatively large in size and 44 they need to be installed prior to the onset of the season's snowfall. This limits their ability to be rapidly or 45 opportunistically deployed. Additionally, snow pillow installations tend to require vehicular access, limiting their 46 locations to relatively simple topography. Finally, snow pillow sites are not representative of the lowest or highest 47 elevation bands within mountainous regions (Molotch and Bales, 2005). In the western United States (USA), the 48 Natural Resources Conservation Service (NRCS) operates a large network of Snow Telemetry (SNOTEL) sites, 49 featuring snow pillows. The NRCS also operates the smaller Soil Climate Analysis Network (SCAN) which 50 provides the only, and very limited, snow pillow SWE measurements in the eastern USA.

51

52 SWE can also be measured manually, using a snow coring device that measures the weight of a known volume of 53 snow to determine snow density (Church, 1933). These measurements are often one-off measurements, or in the 54 case of 'snow courses' they are repeated weekly or monthly as a transect of measurements at a given location. The 55 simplicity and portability of coring devices expand the range over which measurements can be collected, but it can 56 be challenging to apply these methods to deep snowpacks due to the limited length of standard coring devices. Note 57 that there are numerous different styles of coring devices, including the Adirondack sampler and the Mt. Rose / 58 Federal sampler (Church and Marr, 1937). The NRCS operates a large network of snow course sites (USDA, 2011) 59 in the western United States.

60

61 There are a number of issues that affect the accuracy of both snow pillow and snow coring measurements. With

62 coring measurements, if the coring device is not carefully extracted, a portion of the core may fall out of the device.

63 Or, snow may become compressed in the coring device during insertion. These effects have led to varying

64 conclusions, with some studies (e.g., Sturm et al., 2010) showing a low SWE bias and other studies (e.g., Goodison,

65 1978) showing a high SWE bias. As noted by Johnson et al. (2015) a good rule of thumb is that coring devices are

66 accurate to around \pm 10%. Also, studies comparing different styles of snow samplers report statistically different

- 67 results, suggesting that SWE measurements are sensitive to the design of the specific coring device, such as the
- 68 presence of holes or slots, the device material, etc. (Beaumont and Work, 1963; Dixon and Boon, 2012). With snow
- 69 pillows, some studies (e.g., Goodison et al., 1981) note that ice bridging can lead to low biases in measured SWE,
- 70 with the snow surrounding the pillow partly supporting the snow over the pillow. Other studies (Johnson and Marks,
- 71 2004; Dressler et al., 2006; Johnson et al., 2015) note a more complex situation with SWE under-reported at times,

but over-reported at other times. Note that when snow pillow data are evaluated, they are most commonly compared
to coring measurements at the same location.

74

75 All methods of measuring SWE are challenged by the fact that SWE is a depth-integrated property of a snowpack. 76 This is why the snowpack must be weighed, in the case of a snow pillow, or a core must be extracted from the 77 surface to the ground. This measurement complexity makes it difficult to obtain SWE information with the spatial 78 and temporal resolution desired for watershed-scale studies. Other snowpack properties, such as the depth h, are 79 much easier to measure. For example, using a graduated device such as a meterstick or an avalanche probe to 80 measure the depth takes only seconds. Automating depth measurements at a fixed location can easily be done using 81 low-cost ultrasonic devices (Goodison et al., 1984; Ryan et al., 2008). High-spatial-resolution measurements of 82 snowpack depth are commonly made with Light Detection and Ranging (LIDAR). One example of this is the 83 Airborne Snow Observatory program (ASO; Painter et al., 2016). The comparatively high expense of airborne 84 LIDAR surveys typical limits measurements geographically (to a few basins) and temporally (weekly to monthly

- 85 interval).
- 86

Given the relative ease in obtaining depth measurements, it is common to use *h* as a proxy for SWE. Figure 1 shows a conceptual sketch of the variation of SWE with *h* over a typical water year. Noting the arrows on the curve, we see that SWE is multi-valued for each *h*. This is due to the fact that the snowpack increases in density throughout the water year, producing a hysteresis loop in the curve. A large body of literature exists on the topic of how to convert *h* to SWE. It is beyond the scope of this paper to provide a full review of these 'bulk density equations,' where the density is given by $ρ_b = SWE/h$. Instead, we refer readers to the useful comparative review by Avanzi et al. (2015).

Here, we prefer to discuss a limited number of previous studies that illustrate the spectrum of methodologies and

- 94 complexities that can be used to determine ρ_b or SWE.
- 95

96 Many studies express ρ_b as an increasing function (often linear) of *h*. In some cases (e.g., Lundberg et al., 2006) a

97 second equation is added where $\rho_{\rm b}$ attains a constant value when a threshold *h* is exceeded. A single linear equation

98 captures the process of densification of the snowpack during the accumulation phase, but performs poorly during the

99 ablation phase, where depths are decreasing but densities continue to increase or approach a constant value.

100 Other approaches choose to parameterize $\rho_{\rm b}$ in terms of time, rather than *h*. Pistocchi (2016) provides a single

101 equation while Mizukami and Perica (2008) provide two sets of equations, one set each for early and late season.

102 Each set contains four equations, each of which is applicable to a particular 'cluster' of stations. This clustering was

103 driven by observed densification characteristics and the resulting clusters are relatively spatially discontinuous.

104 Jonas et al. (2009) take the idea of region- (or cluster-) specific equations and extend it further to provide

105 coefficients that depend on time and elevation as well. They use a simple linear equation for ρ_b in terms of *h* and the

106 slope and intercept of the equation are given as monthly values, with three elevation bins for each month (36 pairs of

107 coefficients). There is an additional contribution to the intercept (or 'offset') which is region-specific (one of 7

108 regions).

110 These classifications, whether based on region, elevation, or season, are valuable since they acknowledge that all

- 111 snow is not equal. McKay and Findlay (1971) discuss the controls that climate and vegetation exert on snow density,
- and Sturm et al. (2010) address this directly by developing a snow density equation where the coefficients depend
- upon the 'snow class' (5 classes). Sturm et al. (1995) explain the decision tree, based on temperature, precipitation,
- 114 and wind speed, that leads to the classification. The temperature metric is the 'cooling degree month' calculated
- during winter months only. Similarly, only precipitation falling during winter months was used in the classification.
- 116 Finally, given the challenges in obtaining high quality, high-spatial-resolution wind information, vegetation
- 117 classification was used as a proxy. Using climatological values (rather than values for a given year), Sturm et al.
- 118 (1995) were able to develop a global map of snow classification.
- 119

120 There are many other formulations for snow density that increase in complexity and data requirements. Meloysund 121 et al. (2007) express $\rho_{\rm b}$ in terms of sub-daily measurements of relative humidity, wind characteristics, air pressure, 122 and rainfall, as well as h and estimates of solar exposure ('sun hours'). McCreight and Small (2014) use daily snow 123 depth measurements to develop their regression equation. They demonstrate improved performance over both Sturm 124 et al. (2010) and Jonas et al. (2009). However, a key difference between the McCreight and Small (2014) model and 125 the others listed above is that the former cannot be applied to a single snow depth measurement. Instead, it requires a 126 continuous time series of depth measurements at a fixed location. Further increases in complexity are found in 127 energy-balance snowpack models (SnowModel, Liston and Elder, 2006; VIC, Liang et al., 1994, DHSVM, 128 Wigmosta et al., 1994, others), many of which use multi-layer models to capture the vertical structure of the 129 snowpack. While the particular details vary, these models generally require high temporal-resolution time series of 130 many meteorological variables as input. 131 132 Despite the development of multi-layer energy-balance snow models, there is still a demonstrated need for bulk 133 density formulations and for vertically integrated data products like SWE. Pagano et al. (2009) review the 134 advantages and disadvantages of energy-balance models and statistical models and describe how the NRCS uses 135 SWE (from SNOTEL stations) and accumulated precipitation in their statistical models to make daily water supply

- 136 forecasts. If SWE information is desired at a location that does not have a SNOTEL station, and is not part of a
- 137 modeling effort, then bulk density equations and depth measurements are an excellent choice.
- 138
- 139 The present paper seeks to generalize the ideas of Mizukami and Perica (2008), Jonas et al. (2009), and Sturm et al.,
- 140 (2010). Specifically, our goal is to regress physical and environmental variables directly into the equations. In this
- 141 way, environmental variability is handled in a continuous fashion rather than in a discrete way (model coefficients
- 142 based on classes). The main motivation for this comes from evidence (e.g., Fig. 3 of Alford, 1967) that density can
- 143 vary significantly over short distances on a given day. Bulk density equations that rely solely on time completely
- 144 miss this variability and equations that have coarse (model coefficients varying over either vertical bins or horizontal
- 145 grids) spatial resolution may not fully capture it either.

146	
147	Our approach is most similar to Mizukami and Perica (2008), Jonas et al. (2009), and Sturm et al., (2010) in that a
148	minimum of information is needed for the calculations; we intentionally avoid approaches like Meloysund et al.
149	(2007) and McCreight and Small (2014). This is because our interests are in converting h measurements to SWE
150	estimates in areas lacking weather instrumentation. The following sections introduce the numerous data sets that
151	were used in this study, outline the regression model adopted, and assess the performance of the model.
152	2 Methods
153	
154	2.1 Data
155	
156	2.1.1 Snow Depth and Snow Water Equivalent
157	In this section, we list sources of 1970-present snow data utilized for this study (Table 1). With regards to snow
158	coring devices, we refer to them using the terminology preferred in the references describing the datasets.
159	
160	2.1.1.1 USA NRCS Snow Telemetry and Soil Climate Analysis Networks
161	SNOTEL (Serreze et al., 1999; Dressler et al., 2006) and SCAN (Schaefer et al. 2007) stations in the contiguous
162	United States (CONUS) and Alaska typically record sub-daily observations of h, SWE, and a variety of weather
163	variables (Figure 2a). The periods of record are variable, but the vast majority of stations have a period of record in
164	excess of 30 years. For this study, data from all SNOTEL sites in CONUS and Alaska and northeast USA SCAN
165	sites (Figure 2b) were obtained with the exception of sites whose period of record data were unavailable online.
166	Only stations with both SWE and <i>h</i> data were retained.
167	
168	2.1.1.2 Canada (British Columbia) Snow Survey Data
169	Goodison et al. (1987) note that Canada has no national digital archive of snow observations from the many
170	independent agencies that collect snow data and that snow data are instead managed provincially. The quantity and
171	availability of the data vary considerably among the provinces. The Water Management Branch of the British
172	Columbia (BC) Ministry of the Environment manages a comparatively dense network of Automated Snow Weather
173	Stations (ASWS) that measure SWE, h, accumulated precipitation, and other weather variables (Figure 2a). For this
174	study, data from all British Columbia ASWS sites were initially obtained. As with the NRCS stations, only ASWS
175	stations with both SWE and h data were retained.
176	
177	2.1.1.3 USA NRCS Snow Course / Aerial Marker Data
178	The snow survey program (USDA, 2008) dates to the 1930s and includes a large number of snow course and aerial
179	marker sites (Figure 2c) in western North America. While the measurement frequency is variable, it is most
180	commonly monthly. To generate a dataset for this study, data were extracted using the National Water and Climate

181 Center Report Generator 2.0. This allows filtering by time period, elevation band, and other elements. All sites with182 data between 1980-2018 were included (Figure 2c).

183

184 2.1.1.4 Northeast USA Data

185 In addition to the data from the SCAN sites, snow data for this project from the northeast US come from two 186 networks and three research sites (Figure 2b). The Maine Cooperative Snow Survey (MCSS, 2018) network 187 includes h and SWE data collected by the Maine Geological Survey, the United States Geological Survey, and 188 numerous private contributors and contractors. MCSS snow data are collected using the Standard Federal or 189 Adirondack snow sampling tubes typically on a weekly to bi-weekly schedule throughout the winter and spring, 190 1951-present. The New York Snow Survey network data were obtained from the National Oceanic and Atmospheric 191 Administration's Northeast Regional Climate Center at Cornell University (NYSS, 2018). Similar to the MCSS, 192 NYSS data are collected using Standard Federal or Adirondack snow sampling tubes on weekly to bi-weekly

- 193 schedules, 1938-present.
- 194

195 The Sleepers River, Vermont Research Watershed in Danville, Vermont (Shanley and Chalmers, 1999) is a USGS 196 site that includes 15 stations with long-term weekly records of h and SWE collected using Adirondack snow tubes. 197 Most of the periods of record are 1981-present, with a few stations going back to the 1960s. The sites include 198 topographically flat openings in conifer stands, old fields with shrub and grass, a hayfield, a pasture, and openings in 199 mixed softwood-hardwood forests. The Hubbard Brook Experiment Forest (Campbell et al., 2010) has collected 200 weekly snow observations at the Station 2 rain gauge site, 1959-present. Measurement protocol collects ten samples 201 2 m apart along a 20 m transect in a hardwood forest opening about 1/4 hectare in size. At each sample location along 202 the transect, h and SWE are measured using a Mt. Rose snow tube and the ten samples are averaged for each 203 transect. Finally, the Thompson Farm Research site includes a mixed hardwood forest site and an open pasture site 204 (Burakowski et al. 2013; Burakowski et al. 2015). Daily (from 2011-2018), at each site, a snow core is extracted 205 with an aluminum tube and weighed (tube + snow) using a digital hanging scale. The net weight of the snow is 206 combined with the depth and the tube diameter to determine ρ_b , similar to a Federal or Adirondack sampler.

207

208 2.1.1.5 Chugach Mountains (Alaska) Data

In the spring of 2018, we conducted three weeks of fieldwork in the Chugach mountains in coastal Alaska, near the city of Valdez (Figure 2d-e). We measured *h* using an avalanche probe at 71 sites along elevational transects during March, April, and May. The elevational transects ranged between 250 and 1100 m (net change along transect) and were accessible by ski and snowshoe travel. At each site, we measured *h* in 8 locations within the surrounding 10 m^2 , resulting in a total of 550+ snow depth measurements. These 71 sites were scattered across 8 regions in order to capture spatial gradients that exist in the Chugach mountains as the wetter, more-dense maritime snow near the coast gradually changes to drier, less dense snow on the interior side.

217 2.1.1.5 Data Pre-Processing

- 218 Figure 3 demonstrates that it is not uncommon for automated snow pillow measurements to become noisy or non-
- 219 physical, at times reporting large depths when there is no SWE reported. This is different from instances when
- 220 physically plausible, but very low densities might be reported; say in response to early season dry, light snowfalls. It
- 221 was therefore desirable to apply some objective, uniform procedure to each station's dataset in order to remove clear
- 222 outlier points, while minimizing the removal of valid data points. We recognize that there is no accepted
- standardized method for cleaning bivariate SWE-*h* data sets. While Serreze et al. (1999) offer a procedure for
- 224 SNOTEL data in their appendix, it is relevant only for precipitation and SWE values, not *h*. Given the strong
- 225 correlation between *h* and SWE, we instead choose to use common outlier detection techniques for bivariate data.
- 226

227 The Mahalanobis distance (MD; Maesschalck et al., 2000) quantifies how far a point lies from the mean of a

- 228 bivariate distribution. The distances are in terms of the number of standard deviations along the respective principal
- 229 component axes of the distribution. For highly correlated bivariate data, the MD can be qualitatively thought of as a
- 230 measure of how far a given point deviates from an ellipse enclosing the bulk of the data. One problem is that the MD
- is based on the statistical properties of the bivariate data (mean, covariance) and these properties can be adversely
- affected by outlier values. Therefore, it has been suggested (e.g., Leys et al., 2018) that a 'robust' MD (RMD) be
- calculated. The RMD is essentially the MD calculated based on statistical properties of the distribution unaffected
- by the outliers. This can be done using the Minimum Covariance Determinant (MCD) method as first introduced byRousseeuw (1984).
- 236

Once RMDs have been calculated for a bivariate data set, there is the question of how large an RMD must be in order for the data point to be considered an outlier. For bivariate normal data, the distribution of the square of the RMD is χ^2 (Gnanadesikan and Kettenring, 1972), with p (the dimension of the dataset) degrees of freedom. So, a rule for identifying outliers could be implemented by selecting as a threshold some arbitrary quantile (say 0.99) of χ_p^2 . For the current study, a threshold quantile of 0.999 was determined to be an appropriate compromise in terms of removing obviously outlier points, yet retaining physically plausible results.

243

244 A scatter plot of SWE vs. h for the SNOTEL dataset from CONUS and AK reveals many non-physical points, 245 mostly when a very large h is reported for a very low SWE (Figure 4a). Approximately 0.7% of the original data 246 points were removed in the pre-processing described above, creating a more physically plausible scatter plot (Figure 247 4b). Note that the outlier detection process was applied to each station individually. The distribution of 'day of year' 248 (DOY) values of removed data points was broad, with a mean of 160 and a standard deviation of 65. Note that the 249 DOY origin is 1 October. The same procedure was applied to the BC snow pillow, NRCS snow course, and 250 northeast USA data sets as well (not shown). Table 1 summarizes useful information about the numerous data sets 251 described above and indicates the final number of data points retained for each. We acknowledge that our process 252 inevitably removes some valid data points, but, as a small percentage of an already small 0.7% removal rate, we

253 judged this to be acceptable.

Table 1: Summary of information about the datasets used in this study. Datasets in bold font were used to construct the regression model. The numbers of stations and data points reflect the post-processed data.

Dataset Name	Dataset Type	Number	Number and	Precision (h / SWE)
		of retained	percentage of	
		stations	retained data	
			points	
NRCS SNOTEL	Snow pillow (SWE),	791	1,900,000	(0.5 in / 0.1 in)
	ultrasonic (h)		(99.3%)	
NRCS SCAN	Snow pillow (SWE),	5	7094	(0.5 in / 0.1 in)
	ultrasonic (<i>h</i>)		(97.8%)	
British Columbia Snow Survey	Snow pillow (SWE), ultrasonic (<i>h</i>)	31	61,000 (97.5%)	(1 cm / 1 mm)
NRCS Snow Survey	Federal sampler / Aerial	1085	116.000	(0.5 in / 0.1 in) for
NRC5 Show Survey	marker	1005	(99.6%)	manual sampler
	marker		()).0/0)	(2 in / n/a) for aerial
				marker
Maine Geological	Adirondack or Federal	431	28,000	(0.5 in / 0.5 in)
Survey	sampler (SWE and <i>h</i>)		(99.3%)	```´`
Hubbard Brook	Mount Rose sampler (SWE	1	704	(0.1 in / 0.1 in)
(Station 2), NH	and h)		(99.4%)	
Thompson Farm, NH	Snow core (SWE and <i>h</i>)	2	988	0.5 in / 0.5 in)
1	``````````````````````````````````````		(99.4%)	,
Sleepers River, VT	Adirondack sampler	14	7214	(0.5 in / 0.5 in)
-	-		(99.4%)	
New York Snow	Adirondack or Federal	523	44,614	(0.5 in / 0.5 in)
Survey	sampler (SWE and <i>h</i>)		(98.2%)	
Chugach Mountains,	Avalanche probe (h)	71	71	(1 cm)
AK			(100%)	

257

254

258 2.1.2 Climatological Variables

259 30-year climate normals at 1 km resolution for North America were obtained from the ClimateNA project (Wang et 260 al., 2016). This project provides grids for minimum, maximum, and mean temperature, and total precipitation for a 261 given month. These grids are based on the PRISM normals (Daly et al., 1994) and are available for the periods 262 1961-1990 and 1981-2010. For this study, the more recent climatology was used. The ClimateNA project also 263 provides a wide array of derived bioclimatic variables, such as precipitation as snow (PAS), frost-free-period (FFP), 264 mean annual relative humidity (RH) and others. Wang et al. (2012) summarize these additional variables and how 265 they are derived. Figure 5 shows gridded maps of winter (sum of December, January, February) precipitation 266 (PPTWT) and the temperature difference (TD) between the mean temperature of the warmest month and the mean 267 temperature of the coldest month. The latter variable (TD) is a measure of continentality. 268

269 2.2 Regression Model

270 In order to demonstrate the varying degrees of influence of explanatory variables, several regression models were

271 constructed. In each case, the model was built by randomly selecting 50% of the paired SWE-*h* measurements from

the aggregated CONUS, AK, and BC snow pillow datasets. The model was then validated by applying it to the

- 273 remaining 50% of the dataset and comparing the modeled SWE to the observed SWE for those points. We
- 274 constructed a second version of the regression models by randomly selecting 50% of the snow pillow stations and
- using all of the data from those stations. The model was then validated by applying it to the data from the remaining
- 276 50% of the stations. These two methods provided identical results, likely due to the very large sample size (N) of our
- dataset. In all cases, the p values from the linear regression were 0, again due to the large sample size. Additional
- validation was done with the northeast USA datasets (SCAN snow pillow and various snow coring datasets) and the
- 279 NRCS snow course dataset, which were completely left out of the model building process.
- 280

281 2.2.1 One-Equation Model

The simplest equation, and one that is supported by the strong correlation seen in the portions of Figure 3 when SWE is present, is one that expresses SWE as a function of *h*. A linear model is attractive in terms of simplicity, but this limits the snowpack to a constant density. An alternative is to express SWE as a power law, i.e.,

- 286 (1) $SWE = Ah^{a_1}$.
- 287

285

288 This equation can be log-transformed into

- 289
- 290 (2) $log_{10}(SWE) = log_{10}(A) + a_1 log_{10}(h)$
- 291

which immediately allows for simple linear regression methods to be applied. With both *h* and SWE expressed in units of mm, the obtained coefficients are $(A, a_1) = (0.146, 1.102)$. Information on the performance of the model will be deferred until the results section.

295

296 2.2.2 Two-Equation Model

Recall from Figures 1 and 4 that there is a hysteresis loop in the SWE-*h* relationship. During the accumulation phase, snow densities are relatively low. During the ablation phase, the densities are relatively high. So, the same snowpack depth is associated with two different SWEs, depending upon the time of year. The regression equation given above does not resolve this difference. This can be addressed by developing two separate regression equations, one for the accumulation (*acc*) and one for the ablation (*abl*) phase. This approach takes the form

302

303 (3) $SWE_{acc} = Ah^{a_1}; DOY < DOY^*$

304

305 (4) $SWE_{abl} = Bh^{b_1}; DOY \ge DOY^*$

306

307 where DOY is the number of days from the start of the water-year, and DOY^* is the critical or dividing day-of-water-308 year separating the two phases. Put another way, DOY^* is the day of peak SWE. Interannual variability results in a 309 range of DOY^* for a given site. Additionally, some sites, particularly the SCAN sites in the northeast USA,

- 310 demonstrate multi-peak SWE profiles in some years. To reduce model complexity, however, we investigated the use
- 311 of a simple climatological (long term average) value of *DOY*^{*} at each site. For each snow pillow station, the average
- 312 DOY* was computed over the period of record of that station. Analysis of all of the stations revealed that this
- 313 average *DOY*^{*} was relatively well correlated with the climatological mean April maximum temperature (the average
- of the daily maximums recorded in April; $R^2 = 0.7$). However, subsequent regression analysis demonstrated that the
- 315 SWE estimates were relatively insensitive to *DOY*^{*} and the best results were actually obtained when *DOY*^{*} was
- uniformly set to 180 for all stations. Again, with both SWE and *h* in units of mm, the regression coefficients turn out
- 317 to be $(A, a_1) = (0.150, 1.082)$ and $(B, b_1) = (0.239, 1.069)$.
- 318

319 As these two equations are discontinuous at DOY^* , they are blended smoothly together to produce the final two-320 equation model

321

322 (5)
$$SWE = SWE_{acc} \frac{1}{2} (1 - tanh[0.01\{DOY - DOY^*\}]) +$$

323
$$SWE_{abl} \frac{1}{2} (1 + tanh[0.01\{DOY - DOY^*\}])$$

324

The coefficient 0.01 in the tanh function controls the width of the blending window and was selected to minimizethe root mean square error of the model estimates.

327

328 2.2.3 Two-Equation Model with Climate Parameters

A final model was constructed by incorporating climatological variables. Again, the emphasis in this study is on methods that can be implemented at locations lacking the time series of weather variables that might be available at a weather or SNOTEL station. Climatological normals are unable to account for interannual variability, but they do preserve the high spatial gradients in climate that can lead to spatial gradients in snowpack characteristics. Stepwise linear regression was used to determine which variables to include in the regression. The initial list of potential variables included was

- 335
- 336

(6) SWE = f(h, z, PPTWT, PAS, TWT, TD, DOY, RH)

337

338 where *z* is the elevation (m), *PPTWT* is the winter (sum of December, January, February) precipitation (mm), *PAS* is

mean annual precipitation as snow (mm), *TWT* is the winter (December, January, February) mean temperature ($^{\circ}C$),

340 *TD* is the difference between the mean temperature of the warmest month and the mean temperature of the coldest

- 341 month (°C), DOY is the day of water year, and RH is the relative humidity (%). In the stepwise regression,
- 342 explanatory variables were accepted only if they improved the adjusted R² value by 0.001. The result of the
- 343 regression yielded
- 344
- 345 (7) $SWE_{acc} = Ah^{a_1}PPTWT^{a_2}TD^{a_3}DOY^{a_4}; DOY < DOY^*$

340 347

(8) $SWE_{abl} = Bh^{b_1}PPTWT^{b_2}TD^{b_3}DOY^{b_4}; \quad DOY \ge DOY^*$

349 or, in log-transformed format,

350

348

351

(9)
$$log_{10}(SWE_{acc}) = log_{10}(A) + a_1 log_{10}(h) + a_2 log_{10}(PPTWT) + a_3 log_{10}(TD) + a_4 log_{10}(DOY); DOY < DOY^*$$

352 353

354 (10) $log_{10}(SWE_{abl}) = log_{10}(B) + b_1 log_{10}(h) + b_2 log_{10}(PPTWT) +$

355
$$b_3 log_{10}(TD) + b_4 log_{10}(DOY); \quad DOY \ge DOY^*$$

356

357 indicating that only snow depth, winter precipitation, temperature difference, and day of water year were relevant. 358 Manual tests of model construction with other variables included confirmed that Eqns. (7-8) yielded the best results. 359 These two SWE estimates for the individual (acc and abl) phases of the snowpack were then blended with Eqn. (5) 360 to produce a single equation for SWE spanning the entire water year. The obtained regression coefficients were 361 $(A, a_1, a_2, a_3, a_4) = (0.0533, 0.9480, 0.1701, -0.1314, 0.2922)$ and $(B, b_1, b_2, b_3, b_4) = (0.0481, 1.0395, 0.1701, -0.1314, 0.2922)$ 362 0.1699, -0.0461, 0.1804). The physical interpretation of these coefficients is straightforward. For example, both a_2 363 and b_2 are greater than zero. So, for two locations with equal h, DOY, and TD, the location with greater PPTWT will 364 have a greater SWE and therefore density. These locations are typically maritime climates with wetter, denser snow. 365 In contrast, both a_3 and b_3 are less than zero. Therefore, for two locations with equal h, DOY, and PPTWT, the 366 location with greater TD (a more continental climate) will have a lower density, which is again an expected result. 367 These trends are similar in concept to Sturm et al. (2010), whose discrete snow classes (based on climate classes) 368 indicate which snow will densify more rapidly. 369 **3 Results**

370 A comparison of the three regression models (one-equation model, Eq. (2); two-equation model, Eqs. (3-5); multi-

371 variable two-equation model, Eqs. (5, 7-8)) is provided in Figure 6. The left column shows scatter plots of modeled

372 SWE to observed SWE for the validation data set with the 1:1 line shown in black. The right column shows

distributions of the model residuals. The vertical lines in the right column show the mean error, or model bias.

374 Visually, it is clear that the one-equation model performs relatively poorly with a large negative bias. This large

375 negative bias is partially overcome by the two-equation model (middle row, Figure 6). The cloud of points is closer

to the 1:1 line and the vertical black line indicating the mean error is closer to zero. In the final row of Figure 6, we

377 see that the multi-variable two-equation model yields the best result by far. The residuals are now evenly distributed

378 with a small bias. Several metrics of performance for the three models, including R^2 (Pearson coefficient), bias, and

379 root-mean-square-error (RMSE), are provided in Table 2. Figure 7 shows the distribution of model residuals for the

380 multi-variable two-equation model as a function of DOY.

2	01	
Э	02	

rable 2. Summary of performance	metries for the th	ee regression mou	ens presented in bee
Model	\mathbb{R}^2	Bias (mm)	RMSE (mm)
One-equation	0.946	-19.5	102
Two-equation	0.962	-5.1	81
Multi-variable two-equation	0.978	-1.2	59

Table 2: Summary of performance metrics for the three regression models presented in Section 2.2.

384 It is useful to also consider the model errors in a non-dimensional way. Therefore, an RMSE was computed at each 385 station location and normalized by the winter precipitation (PPTWT) at that location. Figure 8 shows the probability 386 density function of these normalized errors. The average RMSE is approximately 15% of PPTWT with most values 387 falling into the range of 5-30%. The spatial distribution of these normalized errors is shown in Figure 9. For the 388 SNOTEL stations, it appears there is a slight regional trend, in terms of stations in continental climates (Rockies) 389 having larger relative errors than stations in maritime climates (Cascades). The British Columbia stations also show 390 higher relative errors.

391

392 3.1 Results for Snow Classes

393 A key objective of this study is to regress climatological information in a continuous rather than a discrete way. The 394 work by Sturm et al. (2010) therefore provides a valuable point of comparison. In that study, the authors developed 395 the following equation for density ρ_h

396

397 (11)
$$\rho_b = (\rho_{max} - \rho_0) \left[1 - e^{(-k_1 h - k_2 DOY)} \right]$$

398

399 where ρ_0 is the initial density, ρ_{max} is the maximum or 'final' density (end of water year), k₁ and k₂ are coefficients, 400 and DOY in this case begins on January 1. This means that their DOY for October 1 is -92. The coefficients vary 401 with snow class and the values determined by Sturm et al. (2010) are shown in Table 3.

 $+\rho_0$

402

403 Table 3: Model parameters by snow class for Sturm et al. (2010)

Table 5. Model parameters by snow class for Sturm et al. (2010).						
Snow Class	ρ_{max}	ρ_0	k1	k ₂		
Alpine	0.5975	0.2237	0.0012	0.0038		
Maritime	0.5979	0.2578	0.0010	0.0038		
Prairie	0.5941	0.2332	0.0016	0.0031		
Tundra	0.3630	0.2425	0.0029	0.0049		
Taiga	0.2170	0.2170	0.0000	0.0000		

404

405 To make a comparison, the snow class for each SNOTEL and British Columbia snow survey (Rows 1 and 3 of Table 406 1) site was determined using a 1-km snow class grid (Sturm et al., 2010). The aggregated dataset from these stations 407 was made up of 27% Alpine, 14% Maritime, 10% Prairie, 11% Tundra, and 38% Taiga data points. Equation (11) 408 was then used to estimate snow density (and then SWE) for every point in the validation dataset described in Section 409 2.2. Figure 10 compares the SWE estimates from the Sturm model and from the current multi-variable, two-equation 410 model (Equations 5, 7-8). The upper left panel of Figure 10 shows all of the data, and the remaining panels show the 411 results for each snow class. In all cases, the current model provides better estimates (narrow cloud of points; closer 412 to the 1:1 line). Plots of the residuals by snow class are provided in Figure 11, giving an indication of the bias of

- 413 each model for each snow class. Summaries of the model performance, broken out by snow class, are given in Table
- 414 4. The current model has smaller biases and RMSEs for each snow class.
- 415

416	Table 4: Comp	arison of model	performance by	Sturm et al.	(2010) a	and the current study.
-----	---------------	-----------------	----------------	--------------	----------	------------------------

Model	Sturm et al.	(2010)	-	Multi-variable two-equation model			
Snow Class	R ²	Bias (mm)	RMSE (mm)	\mathbb{R}^2	Bias (mm)	RMSE (mm)	
All Data	0.928	-29.2	111	0.978	-1.2	59	
Alpine	0.973	10.1	55	0.978	-2.7	48	
Maritime	0.968	-16.8	109	0.975	-7.8	95	
Prairie	0.967	18.7	56	0.971	-0.7	45	
Tundra	0.956	-10.5	82	0.974	-2.9	59	
Taiga	0.943	-80.0	151	0.978	2.6	54	

418 **3.2** Comparison to Pistocchi (2016)

419 In order to provide an additional comparison, the simple model of Pistocchi (2016) was also applied to the validation

420 dataset. His model calculates the bulk density as

421

422 (12) $\rho_b = \rho_0 + K(DOY + 61),$

423

424 where ρ_0 has a value of 200 kg m⁻³ and K has a value of 1 kg m⁻³. The *DOY* for this model has its origin at

425 November 1. Application of this model to the validation dataset yields a bias of 55 mm and an RMSE of 94 mm.

426 These results are comparable to the Sturm et al. (2010) model, with a larger bias but smaller RMSE.

427

428 3.3 Comparison to Jonas et al. (2009)

429 A final point of comparison can be provided by the model of Jonas et al. (2009). The full version of that model

430 contains region-specific offset parameters that are not relevant to North America, so the following partial version of

431 the model is used (their Eq. 4):

432

433 (13) $\rho_b = ah + b$,

434

435 where the parameters (a, b) vary with elevation and month, as given by Table 5. Note that coefficients are not given

436 for every month. Application of the Jonas et al. (2009) model to the snow pillow dataset yields a bias of -5 mm and

437 an RMSE of 69 mm. These results are not directly comparable to those of the current model (Table 2, row 3) since

438 the Jonas et al. (2009) model is unable to compute results for several months of the year. To make a direct

439 comparison to the current model, it is necessary to first remove those data points (about 5%). When this is done, the

440 current model yields a bias of -0.3 mm and an RMSE of 59 mm.

442 Table 5: Model coefficients (*a*, *b*) for the Jonas et al. (2009) model.

Month	<i>z</i> > 2000 <i>m</i>	2000 m > z > 1400 m	1400 <i>m</i> > <i>z</i>
January	(206, 52)	(208, 47)	(235, 31)

February	(217, 46)	(218, 52)	(279,9)
March	(272, 26)	(281, 31)	(333, 3)
April	(331,9)	(354, 15)	(347, 25)
May	(378, 21)	(409, 29)	(413, 19)
June	(452,8)	n/a	n/a
July	(470, 15)	n/a	n/a
August	n/a	n/a	n/a
September	n/a	n/a	n/a
October	n/a	n/a	n/a
November	(206, 47)	(183, 35)	(149, 37)
December	(203, 52)	(190, 47)	(201, 26)

444 3.4 Results for Northeast USA

445 The regression equations in this study were developed using a large collection of snow pillow sites in CONUS, AK,

446 and BC. The snow pillow sites are limited to locations west of approximately W 105° (Figure 2a). By design, the

447 data sets from the northeastern USA (Section 2.1.1.3) were left as an entirely independent validation set. These

448 northeastern sites are geographically distant from the training data sets, subject to a very different climate, largely

449 use different methods (snow coring, with the exception of the SCAN network) and are generally at much lower

450 elevations than the western sites, providing an interesting opportunity to test how robust the current model is.

451

452 Figure 12 graphically summarizes the datasets and the performance of the multi-variable two-equation model of the

453 current study. The RMSE values are comparable to those found for the western stations, but, given the

454 comparatively thinner snowpacks in the northeast, represent a larger relative error (Table 5). The bias of the model

is consistently positive, in contrast to the western stations where the bias was negligible. Note that Table 5 also

456 includes results from the application of the other three models discussed. Sturm et al. (2010) cannot be applied to

457 several of the datasets since their available 1 km snowclass dataset cuts off at -71.6° longitude. The current model

458 and the Jonas et al. (2009) model perform better than the other two models, with the current model generally

459 outperforming the Jonas et al. (2009) model. The two datasets where the Jonas et al. (2009) model has a slightly

460 better performance are the two smallest datasets (less than 1000 measurements; see Table 1).

- 461
- Table 5: Performance metrics for various models applied to the northeastern USA datasets. Bold font is used to highlight the model with the best performance for each dataset.

	Multi-variable, two-equation model		Sturm et (2010)	t al.	Jonas et (2009)	t al. Pistocch (2015)		ıi
Dataset Name	Bias (mm)	RMSE (mm)	Bias (mm)	RMSE (mm)	Bias (mm)	RMSE (mm)	Bias (mm)	RMSE (mm)
	(IIIII)	(mm)	(mm)	(mm)	(mm)	(mm)	(mm)	(IIIIII)
Maine Geological Survey, ME	13.1	34.0	n/a	n/a	25.1	46.0	59.2	77.1
Hubbard Brook (Station 2), NH	21.8	66.6	34.2	76.9	19.4	65.4	52.0	90.8
Thompson Farm, NH	7.1	20.2	n/a	n/a	5.6	19.9	20.4	32.3
NRCS SCAN	-1.2	39.2	8.4	45.0	-2.8	40.6	23.4	56.9
Sleepers River, VT	14.4	28.2	36.5	48.9	20.4	33.5	55.8	67.1
New York Snow Survey	14.8	31.2	21.0	49.3	16.3	33.0	41.3	56.1

465 3.5 Results for NRCS Snow Course / Aerial Marker Data

466 The NRCS snow course and aerial marker data were also left out of the model building process so they provide an

- 467 additional and completely independent comparison of the various models considered. Recall that these data come
- 468 from snow course (coring measurements) and aerial surveys, which are different measurement methods than the
- 469 snow pillows which provided the data for construction of the current regression model. Table 6 shows the results
- 470 and demonstrates that the current model has the best performance.
- 471
- Table 6: Performance metrics for various models applied to the NRCS snow course and aerial marker dataset. Boldfont is used to highlight the model with the best performance.

	Multi-variable, two- equation model		Sturm et (2010)	al.	Jonas et al. (2009)		Pistocchi (2015)	
Dataset Name	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
	(mm)	(mm)	(mm)	(mm)	(mm)	(mm)	(mm)	(mm)
NRCS Snow Course / Aerial	0	59	-24	123	24	72	71	99
Marker								

474 4 Discussion

475 The results presented in this study show that the regression equation described by equations (5, 7-8) is an

476 improvement (lower bias and RMSE) over other widely used bulk density equations. The key advantage is that the

477 current method regresses in relevant parameters directly, rather than using discrete bins (for snow class, elevation,

478 month of year, etc.), each with its own set of model coefficients. The comparison (Figs. 10-11; Table 4) to the model

479 of Sturm et al. (2010) reveals a peculiar behavior of that model for the Taiga snow class, with a large negative bias

480 in the Sturm estimates. Inspection of the coefficients provided for that class (Table 3) shows that the model simply

481 predicts that $\rho_b = \rho_{max} = 0.217$ for all conditions.

482

483 When our multi-variable two-equation model, developed solely from western North American data, is applied to 484 northeast USA locations, it produces SWE estimates with smaller RSME values and larger biases than the western 485 stations. When comparing the SWE-h scatter plots of the SNOTEL data (Figure 4b) to those of the east coast data 486 sets (left column; Figure 12), it is clear that the northeast data generally have more scatter. This is confirmed by 487 computing the correlation coefficients between SWE and h for each dataset. It is unclear if this disparity in 488 correlation is related to measurement methodology or is instead a 'signal to noise' issue. Comparing Figures 4 and 489 12 shows the considerable difference in snowpack depth between the western and northeastern data sets. When the 490 western dataset is filtered to include only measurement pairs where h < 1.5 m, the correlation coefficient is reduced 491 to a value consistent with the northeast datasets. This suggests that the performance of the current (or other) 492 regression model is not as good at shallow snowpack depths. This is also suggested upon examination of the time 493 series of observed $\rho_b = SWE/h$ for a given season at a snow pillow site. Very early in the season, when the depths 494 are small, the density curve has a lot of variability. Later in the season, when depths are greater, the density curve 495 becomes much smoother. Very late in the season, when depths are low again, the density curve becomes highly 496 variable again. 497

498 Measurement precision and accuracy affect the construction and use of a regression model. Upon inspection of the 499 snow pillow data, it was observed that the precision of the depth measurements was approximately 25 mm and that 500 of the SWE measurements was approximately 2.5 mm. To test the sensitivity of the model coefficients to the 501 measurement precision, the depth values in the training dataset were randomly perturbed by +/- 25 mm and the SWE 502 values were randomly perturbed by +/- 2.5 mm and the regression coefficients were recomputed. This process was 503 repeated numerous times and the mean values of the perturbed coefficients were obtained. These adjusted 504 coefficients were then used to recompute the SWE values for the validation data set and the bias and RMSE were 505 found to be -10.5 mm and 72.7 mm. This represents a roughly 10% increase in RMSE, but a considerable increase in 506 bias magnitude (see Table 4 for the original values). This sensitivity of the regression analysis to measurement 507 precision underscores the need to have high-precision measurements for the training data set. Regarding accuracy, 508 random and systematic errors in the paired SWE - h data used to construct the regression model will lead to 509 uncertainties in SWE values predicted by the model. As noted in the introduction, snow pillow errors in SWE 510 estimates do not follow a simple pattern. Additionally, they are complicated by the fact that the errors are often 511 computed by comparing snow pillow data to coring data, which itself is subject to error. Lacking quantitative 512 information on the distribution of snow pillow errors, we are unable to quantify the uncertainty in the SWE

513 estimates.

514

515 Another important consideration has to do with the uncertainty of depth measurements that the model is applied to. 516 For context, one application of this study is to crowd-sourced, opportunistic snow depth measurements from 517 programs like the Community Snow Observations (CSO; Hill et al., 2018) project. In the CSO program, 518 backcountry recreational users submit depth measurements, typically taken with an avalanche probe, using a 519 smartphone in the field. The measurements are then converted to SWE estimates which are assimilated into 520 snowpack models. These depth measurements are 'any time, any place' in contrast to repeated measurements from 521 the same location, like snow pillows or snow courses. Most avalanche probes have cm-scale graduated markings, so 522 measurement precision is not a major issue. A larger problem is the considerable variability in snowpack depth that 523 can exist over short (meter scale) distances. The variability of the Chugach avalanche probe measurements was 524 assessed by taking the standard deviation of 8 h measurements per site. The average of this standard deviation over 525 the sites was 22 cm and the average coefficient of variation (standard deviation normalized by the mean) over the 526 sites was 15%. This variability is a function of the surface roughness of the underlying terrain, and also a function of 527 wind redistribution of snow. Propagating this uncertainty through the regression equations yields a slightly higher 528 (16%) uncertainty in the SWE estimates. CSO participants can do three things to ensure that their recorded depth 529 measurements are as representative as possible. First, avoid measurements in areas of significant wind scour or 530 deposition. Second, avoid measurements in terrain likely to have significant surface roughness (rocks, fallen logs, 531 etc.). Third, take several measurements and average them. 532

Expansion of CSO measurements in areas lacking SWE measurements can increase our understanding of the
 extreme spatial variability in snow distribution and the inherent uncertainties associated with modeling SWE in

- 535 these regions. It could also prove useful for estimating watershed-scale SWE in regions like the northeastern USA,
- 536 which is currently limited to five automated SCAN sites with historical SWE measurements for only the past two
- 537 decades. Additionally, historical snow depth measurements are more widely available in the Global Historical
- 538 Climatology Network (GHCN-Daily; Menne et al. 2012), with several records extending back to the late 1800s.
- 539 While many of the GHCN stations are confined to lower elevations with shallower snow depths, the broader
- 540 network of quality-controlled snow depth data paired with daily GHCN temperature and precipitation measurements
- 541 could potentially be used to reconstruct SWE in the eastern US given additional model development and refinement.

542 **5** Conclusions

- 543 We have developed a new, easy to use method for converting snow depth measurements to snow water equivalent
- 544 estimates. The key difference between our approach and previous approaches is that we directly regress in
- 545 climatological variables in a continuous fashion, rather than a discrete one. Given the abundance of freely available
- 546 climatological norms, a depth measurement tagged with coordinates (latitude and longitude) and a time stamp is
- 547 easily and immediately converted into SWE.
- 548

549 We developed this model with data from paired SWE-h measurements from the western United States and British

- 550 Columbia. The model was tested against entirely independent data (primarily snow course; some snow pillow) from
- 551 the northeastern United States and was found to perform well, albeit with larger biases and root-mean-squared-
- 552 errors. The model was tested against other well-known regression equations and was found to perform better. The
- 553 model was also tested against a large dataset of independent snow course and aerial marker measurements from
- 554 western North America. For this second independent test, the current model outperformed the other models
- 555 considered.
- 556

557 This model is not a replacement for more sophisticated snow models that evolve the snowpack based on high 558

- frequency (e.g., daily or sub-daily) weather data inputs. The intended purpose of this model is to constrain SWE 559
- estimates in circumstances where snow depth is known, but weather variables are not, a common issue in sparsely
- 560 instrumented areas in North America.

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565 7 Data Access

- 566 Numerous online datasets were used for this project and were obtained from the following locations:
- 567 1. NRCS Snow Telemetry: https://www.wcc.nrcs.usda.gov/snow/SNOTEL-wedata.html
- 568 NRCS Soil Climate Analysis Network: https://www.wcc.nrcs.usda.gov/scan/ 2.

569	3.	British Columbia Automated Snow Weather Stations:
570		https://www2.gov.bc.ca/gov/content/environment/air-land-water/water/water-science-data/water-data-
571		tools/snow-survey-data/automated-snow-weather-station-data
572	4.	Maine Cooperative Snow Survey: <u>https://mgs-maine.opendata.arcgis.com/datasets/maine-snow-survey-data</u>
573	5.	New York Snow Survey: http://www.nrcc.cornell.edu/regional/snowsurvey/snowsurvey.html
574	6.	Sleepers River Research Watershed. Snow data not available online; request data from contact at:
575		https://nh.water.usgs.gov/project/sleepers/index.htm
576	7.	Hubbard Brook Experimental Forest: https://hubbardbrook.org/d/hubbard-brook-data-catalog
577	8.	Climatological Data: https://adaptwest.databasin.org/pages/adaptwest-climatena
578 579	9.	NRCS Snow Course / Aerial Marker Data: <u>https://wcc.sc.egov.usda.gov/reportGenerator/</u>
580		
581	A Matla	b function for calculating SWE based on the results is this paper has been made publicly available at Github
582	(https://	github.com/communitysnowobs/snowdensity).
583		

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752 terrain, Water Resour. Res., 30, 1665-1679, https://doi.org/10.1029/94WR00436, 1994

- Figure 1: Conceptual sketch of the evolution of snow water equivalent (SWE) over the course of a water year (black line). Also shown is the evolution of SWE with snowpack depth over a water year (red line). Note the hysteresis loop due to the densification of the snowpack. 754 755



Figure 2: Distribution of measurement locations used in this study. (a) Western USA and Canada snow pillow

locations, with colors indicating station elevation in meters. (b) Northeast USA snow pillow and snow course locations, with stations colored according to data source. (c) Western North America snow course and aerial marker

locations, with colors indicating station elevation in meters. (d, e) Measurement sites in the Chugach Mountains, southcentral Alaska.







- Figure 4: Scatter plot of SWE vs. *h* for the complete SNOTEL dataset before (a) and after (b) removing data points, following the method described in Section 2.1.1.5. Symbols are colored by 'day of water year' (*DOY*; October 1 is
- 769 770 771 772
- the origin).



- Figure 5: Gridded maps of winter (December, January, February) precipitation (PPTWT) and temperature difference
- 775 776 (TD) between mean of warmest month and mean of coldest month) for North America. Maps are for the 1981-2010
- climatological period.





782 Figure 6: Two-dimensional histograms (heat maps; left column) of modeled vs. observed SWE and probability

density functions (right column) of the residuals for three simple models applied to the CONUS, AK, and BC snow pillow data. Warmer colors in the heat maps indicate greater density. The vertical lines in the right column indicate

the location of the mean residual, or bias. Top row (a-b): One-equation model (Section 2.2.1). Middle row (c-d):

786 Two-equation model (Section 2.2.2). Bottom row (e-f): Multi-variable two-equation model (Section 2.2.3).





Figure 7: Heat map of SWE residuals as a function of *DOY*.

Figure 8: Probability density function of snow pillow station root-mean-square error (RMSE) normalized by station
 winter precipitation (*PPTWT*).


Figure 9: Spatial distribution of snow pillow station root-mean-square error (RMSE) normalized by station winter
 precipitation (PPTWT).



Figure 10: Comparison of the multi-variable, two-equation model of the current study with the model of Sturm et al. (2010). The subpanels show modeled SWE vs. observed SWE for all of the data binned together, as well as for the data broken out by the snow classes identified by Sturm et al. (1995). The gray symbols show the Sturm result and the transparent heat maps (warmer colors indicate greater density) show the current result. The models are being applied to the validation data set (50% of the aggregated snow pillow data for CONUS, AK, and BC).



808 Figure 11: Comparison of the multi-variable, two-equation model of the current study with the model of Sturm et al.

809 (2010). The subpanels show probability density functions of the residuals of the model fits for all of the data binned 810 together, as well as for the data broken out by the snow classes identified by Sturm et al. (1995). The gray lines

show the Sturm result and the colored lines show the current result. The vertical lines show the mean error, or the

model bias, for both the Sturm and the current result. The models are being applied to the validation data set (50% of

813 the aggregated snow pillow data for CONUS, AK, and BC).

814



816 Figure 12: Results from application of the multi-variable, two-equation model to numerous east coast datasets. The

817 left column shows the SWE-*h* data for each dataset. Note that the black symbols are points removed by the outlier

818 detection procedure discussed in section 2.1.1.4. The remaining symbols are colored by DOY. The middle panel 819

plots heat maps of the model estimates of SWE against the observations of SWE with the 1:1 line included. Warmer 820 colors indicate higher densities. The right panel shows probability density functions of the model residuals, with the

821 vertical line indicating the mean error, or bias. Individual rows correspond to individual data sets and are labeled.





830 Figure 13: Results from application of the multi-variable, two-equation model to the NRCS snow course / aerial

marker dataset. The left column shows the SWE-*h* data for each dataset. Note that the black symbols are points

removed by the outlier detection procedure discussed in section 2.1.1.5. The remaining symbols are colored by

DOY. The middle panel plots heat maps of the model estimates of SWE against the observations of SWE with the 1:1 line included. Warmer colors indicate higher densities. The right panel shows probability the density function

1:1 line included. Warmer colors indicate higher densities. The right panel shows probability the density function ofthe model residuals, with the vertical line indicating the mean error, or bias.

835 836



Converting Snow Depth to Snow Water Equivalent Using 1 **Climatological Variables** 2

3

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19 Abstract. We present a simple method that allows snow depth measurements to be converted to snow water

- 20 equivalent (SWE) estimates. These estimates are useful to individuals interested in water resources, ecological
- 21 function, and avalanche forecasting. They can also be assimilated into models to help improve predictions of total
- water volumes over large regions. The conversion of depth to SWE is particularly valuable since snow depth 22
- 23 measurements are far more numerous than costlier and more complex SWE measurements. Our model regresses
- 24 SWE against snow depth (h), day of water year (DOY) and climatological (30-year normal) values for winter

25 (December, January, February) precipitation (PPTWT) and the difference (TD) between mean temperature of the

- 26 warmest month and mean temperature of the coldest month, producing a power-law relationship. Relying on
- 27 climatological normals rather than weather data for a given year allows our model to be applied at measurement
- 28 sites lacking a weather station. Separate equations are obtained for the accumulation and the ablation phases of the
- 29 snowpack, The model is validated against a large database of snow pillow measurements and yields a bias in SWE
- 30 of less than 2 mm and a root-mean-squared-error (RMSE) in SWE of less than 60 mm. The model is additionally
- 31 validated against two completely independent sets of data; one from western North America, and one from the
- 32 northeast United States. Finally, the results are compared with three other models for bulk density that have varying
- 33 degrees of complexity and that were built in multiple geographic regions. The results show that the model described
- 34 in this paper has the best performance for the validation data sets.

Formatted: Font: Italic Deleted: mean annual Formatted: Font: Italic Deleted: MAP Formatted: Font: Italic **Deleted:** mean February temperature $(\bar{T}_{F_{mean}})$, Deleted: , which introduces 'day of water year' (DOY) as an additional variable Deleted: 0.5 Deleted: approximately 65 Deleted: When the errors are investigated on a station-bystation basis, the average RMSE is about 5% of the MAP at each station.

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46 1 Introduction

- 47 In many parts of the world, snow plays a leading-order role in the hydrological cycle (USACE, 1956; Mote et al.,
- 48 2018). Accurate information about the spatial and temporal distribution of snow water equivalent (SWE) is useful to
- 49 many stakeholders (water resource planners, avalanche forecasters, aquatic ecologists, etc.), but can be time
- 50 consuming and expensive to obtain.
- 51

52 Snow pillows (Beaumont, 1965) are a well-established tool for measuring SWE at fixed locations. Figure 1 provides 53 a conceptual sketch of the variation of SWE with time over a typical water year. A comparatively long accumulation 54 phase is followed by a short ablation phase. While simple in operation, snow pillows are relatively large in size and 55 they need to be installed prior to the onset of the season's snowfall. This limits their ability to be rapidly or 56 opportunistically deployed. Additionally, snow pillow installations tend to require vehicular access, limiting their 57 locations to relatively simple topography. Finally, snow pillow sites are not representative of the lowest or highest 58 elevation bands within mountainous regions (Molotch and Bales, 2005). In the western United States (USA), the 59 Natural Resources Conservation Service (NRCS) operates a large network of Snow Telemetry (SNOTEL) sites, 60 featuring snow pillows. The NRCS also operates the smaller Soil Climate Analysis Network (SCAN) which 61 provides the only, and very limited, snow pillow SWE measurements in the eastern USA. 62 63 SWE can also be measured manually, using a snow coring device that measures the weight of a known volume of 64 snow to determine snow density (Church, 1933). These measurements are often one-off measurements, or in the 65 case of 'snow courses' they are repeated weekly or monthly as a transect of measurements at a given location. The 66 simplicity and portability of coring devices expand the range over which measurements can be collected, but it can 67 be challenging to apply these methods to deep snowpacks due to the limited length of standard coring devices. Note 68 that there are numerous different styles of coring devices, including the Adirondack sampler and the Mt. Rose /

Federal sampler (Church and Marr, 1937). <u>The NRCS operates a large network of snow course sites (USDA, 2011)</u>
in the western United States.

72 There are a number of issues that affect the accuracy of both snow pillow and snow coring measurements. With 73 coring measurements, if the coring device is not carefully extracted, a portion of the core may fall out of the device. 74 Or, snow may become compressed in the coring device during insertion. These effects have led to varying 75 conclusions, with some studies (e.g., Sturm et al., 2010) showing a low SWE bias and other studies (e.g., Goodison, 76 1978) showing a high SWE bias. As noted by Johnson et al. (2015) a good rule of thumb is that coring devices are 77 accurate to around \pm 10%. Also, studies comparing different styles of snow samplers report statistically different 78 results, suggesting that SWE measurements are sensitive to the design of the specific coring device, such as the 79 presence of holes or slots, the device material, etc. (Beaumont and Work, 1963; Dixon and Boon, 2012). With snow 80 pillows, some studies (e.g., Goodison et al., 1981) note that ice bridging can lead to low biases in measured SWE, 81 with the snow surrounding the pillow partly supporting the snow over the pillow. Other studies (Johnson and Marks, 82 2004; Dressler et al., 2006; Johnson et al., 2015) note a more complex situation with SWE under-reported at times,

83 but over-reported at other times. Note that when snow pillow data are evaluated, they are most commonly compared 84 to coring measurements at the same location. 85 86 All methods of measuring SWE are challenged by the fact that SWE is a depth-integrated property of a snowpack. 87 This is why the snowpack must be weighed, in the case of a snow pillow, or a core must be extracted from the 88 surface to the ground. This measurement complexity makes it difficult to obtain SWE information with the spatial 89 and temporal resolution desired for watershed-scale studies. Other snowpack properties, such as the depth h, are 90 much easier to measure. For example, using a graduated device such as a meterstick or an avalanche probe to 91 measure the depth takes only seconds. Automating depth measurements at a fixed location can easily be done using 92 low-cost ultrasonic devices (Goodison et al., 1984; Ryan et al., 2008). High-spatial-resolution measurements of 93 snowpack depth are commonly made with Light Detection and Ranging (LIDAR). One example of this is the 94 Airborne Snow Observatory program (ASO; Painter et al., 2016). The comparatively high expense of airborne 95 LIDAR surveys typical limits measurements geographically (to a few basins) and temporally (weekly to monthly 96 interval). 97 98 Given the relative ease in obtaining depth measurements, it is common to use h as a proxy for SWE. Figure 1 shows 99 a conceptual sketch of the variation of SWE with h over a typical water year. Noting the arrows on the curve, we see 100 that SWE is multi-valued for each h. This is due to the fact that the snowpack increases in density throughout the 101 water year, producing a hysteresis loop in the curve. A large body of literature exists on the topic of how to convert 102 h to SWE. It is beyond the scope of this paper to provide a full review of these 'bulk density equations,' where the 103 density is given by $\rho_{\rm b} = \text{SWE}/h$. Instead, we refer readers to the useful comparative review by Avanzi et al. (2015). 104 Here, we prefer to discuss a limited number of previous studies that illustrate the spectrum of methodologies and complexities that can be used to determine ρ_h or SWE. 105 106 107 Many studies express ρ_b as an increasing function (often linear) of *h*. In some cases (e.g., Lundberg et al., 2006) a 108 second equation is added where $\rho_{\rm b}$ attains a constant value when a threshold h is exceeded. A single linear equation 109 captures the process of densification of the snowpack during the accumulation phase, but performs poorly during the 110 ablation phase, where depths are decreasing but densities continue to increase or approach a constant value. 111 Other approaches choose to parameterize $\rho_{\rm h}$ in terms of time, rather than h. Pistocchi (2016) provides a single 112 equation while Mizukami and Perica (2008) provide two sets of equations, one set each for early and late season. 113 Each set contains four equations, each of which is applicable to a particular 'cluster' of stations. This clustering was 114 driven by observed densification characteristics and the resulting clusters are relatively spatially discontinuous. 115 Jonas et al. (2009) take the idea of region- (or cluster-) specific equations and extend it further to provide 116 coefficients that depend on time and elevation as well. They use a simple linear equation for $\rho_{\rm h}$ in terms of h and the 117 slope and intercept of the equation are given as monthly values, with three elevation bins for each month (36 pairs of 118

118 coefficients). There is an additional contribution to the intercept (or 'offset') which is region-specific (one of 7 119 regions). 121 These classifications, whether based on region, elevation, or season, are valuable since they acknowledge that all 122 snow is not equal. McKay and Findlay (1971) discuss the controls that climate and vegetation exert on snow density, 123 and Sturm et al. (2010) address this directly by developing a snow density equation where the coefficients depend 124 upon the 'snow class' (5 classes). Sturm et al. (1995) explain the decision tree, based on temperature, precipitation, 125 and wind speed, that leads to the classification. The temperature metric is the 'cooling degree month' calculated 126 during winter months only. Similarly, only precipitation falling during winter months was used in the classification. 127 Finally, given the challenges in obtaining high quality, high-spatial-resolution wind information, vegetation 128 classification was used as a proxy. Using climatological values (rather than values for a given year), Sturm et al. 129 (1995) were able to develop a global map of snow classification. 130 131 There are many other formulations for snow density that increase in complexity and data requirements. Meloysund 132 et al. (2007) express $\rho_{\rm b}$ in terms of sub-daily measurements of relative humidity, wind characteristics, air pressure, 133 and rainfall, as well as h and estimates of solar exposure ('sun hours'). McCreight and Small (2014) use daily snow 134 depth measurements to develop their regression equation. They demonstrate improved performance over both Sturm 135 et al. (2010) and Jonas et al. (2009). However, a key difference between the McCreight and Small (2014) model and 136 the others listed above is that the former cannot be applied to a single snow depth measurement. Instead, it requires a 137 continuous time series of depth measurements at a fixed location. Further increases in complexity are found in energy-balance snowpack models (SnowModel, Liston and Elder, 2006; VIC, Liang et al., 1994, DHSVM, 138 139 Wigmosta et al., 1994, others), many of which use multi-layer models to capture the vertical structure of the 140 snowpack. While the particular details vary, these models generally require high temporal-resolution time series of 141 many meteorological variables as input. 142 143 Despite the development of multi-layer energy-balance snow models, there is still a demonstrated need for bulk 144 density formulations and for vertically integrated data products like SWE. Pagano et al. (2009) review the 145 advantages and disadvantages of energy-balance models and statistical models and describe how the NRCS uses 146 SWE (from SNOTEL stations) and accumulated precipitation in their statistical models to make daily water supply

- 147 forecasts. If SWE information is desired at a location that does not have a SNOTEL station, and is not part of a
- 148 modeling effort, then bulk density equations and depth measurements are an excellent choice.
- 149

- 150 The present paper seeks to generalize the ideas of Mizukami and Perica (2008), Jonas et al. (2009), and Sturm et al.,
- 151 (2010). Specifically, our goal is to regress physical and environmental variables directly into the equations. In this
- 152 way, environmental variability is handled in a continuous fashion rather than in a discrete way (model coefficients
- based on classes). The main motivation for this comes from evidence (e.g., Fig. 3 of Alford, 1967) that density can
- vary significantly over short distances on a given day. Bulk density equations that rely solely on time completely
- 155 miss this variability and equations that have coarse (model coefficients varying over either vertical bins or horizontal
- 156 grids) spatial resolution may not fully capture it either.

157		
158	Our approach is most similar to Mizukami and Perica (2008), Jonas et al. (2009), and Sturm et al., (2010) in that a	
159	minimum of information is needed for the calculations; we intentionally avoid approaches like Meloysund et al.	
160	(2007) and McCreight and Small (2014). This is because our interests are in converting h measurements to SWE	
161	estimates in areas lacking weather instrumentation. The following sections introduce the numerous data sets that	
162	were used in this study, outline the regression model adopted, and assess the performance of the model.	
163	2 Methods	
164		
165	2.1 Data	
166		
167	2.1.1 Snow Depth and Snow Water Equivalent	
168	In this section, we list sources of 1970-present snow data utilized for this study (Table 1). With regards to snow	
169	coring devices, we refer to them using the terminology preferred in the references describing the datasets.	
170		
171	2.1.1.1 USA NRCS Snow Telemetry and Soil Climate Analysis Networks	
172	SNOTEL (Serreze et al., 1999; Dressler et al., 2006) and SCAN (Schaefer et al. 2007) stations in the contiguous	
173	United States (CONUS) and Alaska typically record sub-daily observations of h, SWE, and a variety of weather	
174	variables (Figure 2a). The periods of record are variable, but the vast majority of stations have a period of record in	Deleted: -b
175	excess of 30 years. For this study, data from all SNOTEL sites in CONUS and Alaska and northeast USA SCAN	
176	sites (Figure 2b) were obtained with the exception of sites whose period of record data were unavailable online.	
177	Only stations with both SWE and <i>h</i> data were retained.	
178		
179	2.1.1.2 Canada (British Columbia) Snow Survey Data	
180	Goodison et al. (1987) note that Canada has no national digital archive of snow observations from the many	
181	independent agencies that collect snow data and that snow data are instead managed provincially. The quantity and	
182	availability of the data vary considerably among the provinces. The Water Management Branch of the British	
183	Columbia (BC) Ministry of the Environment manages a comparatively dense network of Automated Snow Weather	
184	Stations (ASWS) that measure SWE, h, accumulated precipitation, and other weather variables (Figure 2a). For this	
185	study, data from all British Columbia ASWS sites were initially obtained. As with the NRCS stations, only ASWS	
186	stations with both SWE and h data were retained.	
187		
188	2.1.1.3 USA NRCS Snow Course / Aerial Marker Data	Formatted: Font: Bold
189	The snow survey program (USDA, 2008) dates to the 1930s and includes a large number of snow course and aerial	
190	marker sites (Figure 2c) in western North America. While the measurement frequency is variable, it is most	

191 commonly monthly. To generate a dataset for this study, data were extracted using the National Water and Climate

193	Center Report Generator 2.0. This allows filtering by time period, elevation band, and other elements. All sites with	
194	data between 1980-2018 were included (Figure 2c).	
195		
196	2.1.1.4 Northeast USA Data	Deleted: 3
197	In addition to the data from the SCAN sites, snow data for this project from the northeast US come from two	
198	networks and three research sites (Figure 2b). The Maine Cooperative Snow Survey (MCSS, 2018) network	
199	includes h and SWE data collected by the Maine Geological Survey, the United States Geological Survey, and	
200	numerous private contributors and contractors. MCSS snow data are collected using the Standard Federal or	
201	Adirondack snow sampling tubes typically on a weekly to bi-weekly schedule throughout the winter and spring,	
202	1951-present. The New York Snow Survey network data were obtained from the National Oceanic and Atmospheric	
203	Administration's Northeast Regional Climate Center at Cornell University (NYSS, 2018). Similar to the MCSS,	
204	NYSS data are collected using Standard Federal or Adirondack snow sampling tubes on weekly to bi-weekly	
205	schedules, 1938-present.	
206		
207	The Sleepers River, Vermont Research Watershed in Danville, Vermont (Shanley and Chalmers, 1999) is a USGS	
208	site that includes 15 stations with long-term weekly records of h and SWE collected using Adirondack snow tubes.	
209	Most of the periods of record are 1981-present, with a few stations going back to the 1960s. The sites include	
210	topographically flat openings in conifer stands, old fields with shrub and grass, a hayfield, a pasture, and openings in	
211	mixed softwood-hardwood forests. The Hubbard Brook Experiment Forest (Campbell et al., 2010) has collected	
212	weekly snow observations at the Station 2 rain gauge site, 1959-present. Measurement protocol collects ten samples	
213	2 m apart along a 20 m transect in a hardwood forest opening about 1/4 hectare in size. At each sample location along	
214	the transect, h and SWE are measured using a Mt. Rose snow tube and the ten samples are averaged for each	
215	transect. Finally, the Thompson Farm Research site includes a mixed hardwood forest site and an open pasture site	
216	(Burakowski et al. 2013; Burakowski et al. 2015). Daily (from 2011-2018), at each site, a snow core is extracted	
217	with an aluminum tube and weighed (tube + snow) using a digital hanging scale. The net weight of the snow is	
218	combined with the depth and the tube diameter to determine ρ_b , similar to a Federal or Adirondack sampler.	
219		
220	2.1.1.5 Chugach Mountains (Alaska) Data	Deleted: 4
221	In the spring of 2018, we conducted three weeks of fieldwork in the Chugach mountains in coastal Alaska, near the	
222	city of Valdez (Figure 2d-e). We measured h using an avalanche probe at 71 sites along elevational transects during	Deleted: c-d
223	March, April, and May. The elevational transects ranged between 250 and 1100 m (net change along transect) and	
224	were accessible by ski and snowshoe travel. At each site, we measured h in 8 locations within the surrounding 10	
225	m ² , resulting in a total of 550+ snow depth measurements. These 71 sites were scattered across 8 regions in order to	
226	capture spatial gradients that exist in the Chugach mountains as the wetter, more-dense maritime snow near the coast	
227	gradually changes to drier, less dense snow on the interior side.	
228		

232 2.1.1.5 Data Pre-Processing 233 Figure 3 demonstrates that it is not uncommon for automated snow pillow measurements to become noisy or non-Deleted: depth 234 physical, at times reporting large depths when there is no SWE reported. This is different from instances when 235 physically plausible, but very low densities might be reported; say in response to early season dry, light snowfalls. It 236 was therefore desirable to apply some objective, uniform procedure to each station's dataset in order to remove clear 237 outlier points, while minimizing the removal of valid data points. We recognize that there is no accepted 238 standardized method for cleaning bivariate SWE-h data sets. While Serreze et al. (1999) offer a procedure for 239 SNOTEL data in their appendix, it is relevant only for precipitation and SWE values, not h. Given the strong 240 correlation between h and SWE, we instead choose to use common outlier detection techniques for bivariate data. 241 242 The Mahalanobis distance (MD; Maesschalck et al., 2000) quantifies how far a point lies from the mean of a 243 bivariate distribution. The distances are in terms of the number of standard deviations along the respective principal 244 component axes of the distribution. For highly correlated bivariate data, the MD can be qualitatively thought of as a 245 measure of how far a given point deviates from an ellipse enclosing the bulk of the data. One problem is that the MD 246 is based on the statistical properties of the bivariate data (mean, covariance) and these properties can be adversely 247 affected by outlier values. Therefore, it has been suggested (e.g., Leys et al., 2018) that a 'robust' MD (RMD) be 248 calculated. The RMD is essentially the MD calculated based on statistical properties of the distribution unaffected 249 by the outliers. This can be done using the Minimum Covariance Determinant (MCD) method as first introduced by 250 Rousseeuw (1984). 251 252 Once RMDs have been calculated for a bivariate data set, there is the question of how large an RMD must be in 253 order for the data point to be considered an outlier. For bivariate normal data, the distribution of the square of the 254 RMD is χ^2 (Gnanadesikan and Kettenring, 1972), with p (the dimension of the dataset) degrees of freedom. So, a 255 rule for identifying outliers could be implemented by selecting as a threshold some arbitrary quantile (say 0.99) of 256 χ_p^2 . For the current study, a threshold quantile of 0.999 was determined to be an appropriate compromise in terms of 257 removing obviously outlier points, yet retaining physically plausible results. 258 259 A scatter plot of SWE vs. h for the SNOTEL dataset from CONUS and AK reveals many non-physical points, Deleted: source 260 mostly when a very large h is reported for a very low SWE (Figure 4a). Approximately 0.7% of the original data 261 points were removed in the pre-processing described above, creating a more physically plausible scatter plot (Figure 262 4b). Note that the outlier detection process was applied to each station individually. The distribution of 'day of year' 263 (DOY) values of removed data points was broad, with a mean of 160 and a standard deviation of 65. Note that the 264 DOY origin is 1 October. The same procedure was applied to the BC snow pillow, NRCS snow course, and Deleted: 265 northeast USA data sets as well (not shown). Table 1 summarizes useful information about the numerous data sets 266 described above and indicates the final number of data points retained for each. We acknowledge that our process 267 inevitably removes some valid data points, but, as a small percentage of an already small 0.7% removal rate, we 268 judged this to be acceptable.

Table 1: Summary of information about the datasets used in this study. Datasets in bold font were used to construct the regression model. The numbers of stations and data points reflect the post-processed data

273 274

Dataset Name	Dataset Type	Number	Number and	Precision (h / SWE)
		of retained	percentage of	
		stations	retained data	
			points	
NRCS SNOTEL	Snow pillow (SWE),	791	1,900,000	(0.5 in / 0.1 in)
	ultrasonic (<i>h</i>)		(99.3%)	
NRCS SCAN	Snow pillow (SWE),	5	7094	(0.5 in / 0.1 in)
	ultrasonic (h)		(97.8%)	
British Columbia	Snow pillow (SWE),	31	61,000	(1 cm / 1 mm)
Snow Survey	ultrasonic (h)		(97.5%)	
NRCS Snow Survey	Federal sampler / Aerial	1085	116,000	(0.5 in / 0.1 in) for
	marker		<u>(99.6%)</u>	manual sampler
				(2 in / n/a) for aerial
				marker
Maine Geological	Adirondack or Federal	431	28,000	(0.5 in / 0.5 in)
Survey	sampler (SWE and h)		(99.3%)	
Hubbard Brook	Mount Rose sampler (SWE	1	704	(0.1 in / 0.1 in)
(Station 2), NH	and h)		(99.4%)	
Thompson Farm, NH	Snow core (SWE and <i>h</i>)	2	988	0.5 in / 0.5 in)
· · · · · · ·			(99.4%)	,
Sleepers River, VT	Adirondack sampler	14	7214	(0.5 in / 0.5 in)
	· · · · · · · · ·		(99.4%)	(
New York Snow	Adirondack or Federal	523	44,614	(0.5 in / 0.5 in)
Survey	sampler (SWE and h)		(98.2%)	````
Chugach Mountains,	Avalanche probe (<i>h</i>)	71	71	(1 cm)
AK			(100%)	

275

276 2.1.2 Climatological Variables

277	30-year climate normals at <u>1 km</u> , resolution for <u>North America</u> , were obtained from the <u>ClimateNA project (Wang et</u>
278	al., 2016). This project provides grids for minimum, maximum, and mean temperature, and total precipitation for a
279	given month. These grids are based on the PRISM normals (Daly et al., 1994) and are available for the periods
280	1961-1990 and 1981-2010. For this study, the more recent climatology was used. The ClimateNA project also
281	provides a wide array of derived bioclimatic variables, such as precipitation as snow (PAS), frost-free-period (FFP),
282	mean annual relative humidity (RH) and others. Wang et al. (2012) summarize these additional variables and how
283	they are derived. Figure 5 shows gridded maps of winter (sum of December, January, February) precipitation
284	(<u>PPTWT</u>) and the temperature difference (TD) between the mean temperature of the warmest month and the mean /
285	temperature of the coldest month. The latter variable (<i>TD</i>) is a measure of continentality.
286	•/
287	2.2 Regression Model
288	In order to demonstrate the varying degrees of influence of explanatory variables, several regression models were

- 289 constructed. In each case, the model was built by randomly selecting 50% of the paired SWE-h measurements from
- 290 the aggregated CONUS, AK, and BC snow pillow datasets. The model was then validated by applying it to the

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Deleted: PRISM website (Daly et al., 1994). PRISM normals for British Columbia (BC), Canada, were obtained from the ClimateBC project (Wang et al., 2012), also for the 1981-2010 period. Finally, PRISM normals for Alaska (AK) were obtained from the Integrated Resource Management Applications (IRMA) Portal run by the National Park Service. The AK normals are for the 1971-2000 period and have a slightly coarser resolution (approximately 1.5 km). Figure 5 shows gridded maps of mean annual precipitation (*MAP*) and mean February Temperature (\overline{T}_F) for these three climate products, plotted together. Other temperature products (max and min temperatures; other months) were obtained as well, but are not shown.¶

308 remaining 50% of the dataset and comparing the modeled SWE to the observed SWE for those points. We 309 constructed a second version of the regression models by randomly selecting 50% of the snow pillow stations and 310 using all of the data from those stations. The model was then validated by applying it to the data from the remaining 311 50% of the stations. These two methods provided identical results, likely due to the very large sample size (N) of our 312 dataset. In all cases, the p values from the linear regression were 0, again due to the large sample size. Additional 313 validation was done with the northeast USA datasets (SCAN snow pillow and various snow coring datasets) and the 314 NRCS snow course dataset, which were completely left out of the model building process. 315 316 2.2.1 One-Equation Model 317 The simplest equation, and one that is supported by the strong correlation seen in the portions of Figure 3 when 318 SWE is present, is one that expresses SWE as a function of h. A linear model is attractive in terms of simplicity, but 319 this limits the snowpack to a constant density. An alternative is to express SWE as a power law, i.e., 320 321 $SWE = Ah^{a_1}.$ (1)322 323 This equation can be log-transformed into 324 325 (2) $log_{10}(SWE) = log_{10}(A) + a_1 log_{10}(h)$ 326 327 which immediately allows for simple linear regression methods to be applied. With both h and SWE expressed in 328 units of mm, the obtained coefficients are $(A, a_1) = (0.146, 1.102)$. Information on the performance of the model 329 will be deferred until the results section. 330 331 2.2.2 Two-Equation Model 332 Recall from Figures 1 and 4 that there is a hysteresis loop in the SWE-h relationship. During the accumulation 333 phase, snow densities are relatively low. During the ablation phase, the densities are relatively high. So, the same 334 snowpack depth is associated with two different SWEs, depending upon the time of year. The regression equation 335 given above does not resolve this difference. This can be addressed by developing two separate regression 336 equations, one for the accumulation (acc) and one for the ablation (abl) phase. This approach takes the form 337 338 $SWE_{acc} = Ah^{a_1}; \quad DOY < DOY^*$ (3) 339 340 (4) $SWE_{abl} = Bh^{b_1}; \quad DOY \ge DOY^*$ 341 342 where DOY is the number of days from the start of the water-year, and DOY is the critical or dividing day-of-water-Deleted: (October 1 is the origin), 343 year separating the two phases. Put another way, DOY^* is the day of peak SWE. Interannual variability results in a 344 range of DOY* for a given site. Additionally, some sites, particularly the SCAN sites in the northeast USA,

346	demonstrate multi-peak SWE profiles in some years. To reduce model complexity, however, we investigated the use								
347	of a simple climatological (long term average) value of <i>DOY</i> <u>at each site</u> . For each snow pillow station, the average								
348	DOY* was computed over the period of record of that station. Analysis of all of the stations revealed that this								
349 350	average <i>DOY</i> [*] was relatively well correlated with the climatological mean April maximum temperature (the average								
350 351	of the daily maximums recorded in April; $R^2 = 0.7$). However, subsequent regression analysis demonstrated that the SWE estimates were relatively insensitive to <i>DOY</i> [*] and the best results were actually obtained when <i>DOY</i> [*] was								
352	uniformly set to 180 for all stations. Again, with both SWE and h in units of mm, the regression coefficients turn out								
353	to be $(A, a_1) = (0.150, 1.082)$ and $(B, b_1) = (0.239, 1.069)$.								
354									
355	As these two equations are discontinuous at <i>DOY</i> [*] , they are blended smoothly together to produce the final two-								
356	equation model								
357									
358	(5) $SWE = SWE_{acc} \frac{1}{2} (1 - tanh[0.01\{DOY - DOY^*\}]) +$								
359	$SWE_{abl}\frac{1}{2}(1 + tanh[0.01\{DOY - DOY^*\}])$								
360									
361	The coefficient 0.01 in the tanh function controls the width of the blending window and was selected to minimize								
362	the root mean square error of the model estimates.								
363									
364	2.2.3 Two-Equation Model with Climate Parameters								
365	A final model was constructed by incorporating climatological variables. Again, the emphasis in this study is on	D							
366	methods that can be implemented at locations lacking the time series of weather variables that might be available at								
367	a weather or SNOTEL station. Climatological normals are unable to account for interannual variability, but they do								
368	preserve the high spatial gradients in climate that can lead to spatial gradients in snowpack characteristics. Stepwise	D							
369	linear regression was used to determine which variables to include in the regression. The initial list of potential	D							
370	variables included was	D							
371		F							
372	(6) $SWE = f(h, z_{\P}PPTWT, PAS, TWT, TD, DOY, RH_{\P})$	F							
373		D							
374	where z is the elevation (m), <u>PPTWT is the winter (sum of December, January, February) precipitation (mm), PAS is</u>	D							
375	mean annual precipitation as snow (mm), TWT is the winter (December, January, February) mean temperature (°C),	(Fe							
376	TD is the difference between the mean temperature of the warmest month and the mean temperature of the coldest	(Fe							
377	month (°C), DOY is the day of water year, and RH is the relative humidity (%). In the stepwise regression,	- Fo							
378	explanatory variables were accepted only if they improved the adjusted R ² value by 0.001. The result of the	Fe D							
379	regression yielded	D							
380		m							
381									
501	(7) $SWE_{acc} = Ah^{a_1}PPTWT^{a_2}TD^{a_3}DOY^{a_4}; DOY < DOY^*$	(J. of							

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) (Deleted: , <i>MAP</i> is the mean annual precipitation (mm)
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Y	Deleted: represent the mean of minimum, mean, and maximum daily values for the months January through April

maximum daily values for the months January through April (J, F, M, A). For example, $\overline{T}_{J_{min}}$ is the climatological normal of the average of the daily minimum temperatures observed in January.

395 $SWE_{abl} = Bh^{b_1}PPTWT^{b_2}TD^{b_3}DOY^{b_4}; \quad DOY \ge DOY^*$ (8) 396 397 or, in log-transformed format, 398 399 $log_{10}(SWE_{acc}) = log_{10}(A) + a_1 log_{10}(h) + a_2 log_{10}(PPTWT) + a_2 log_{1$ (9) 400 $a_3 log_{10}(TD) + a_4 log_{10}(DOY); DOY < DOY^*$ 401 402 (10) $log_{10}(SWE_{abl}) = log_{10}(B) + b_1 log_{10}(h) + b_2 log_{10}(PPTWT) +$ 403 $b_3 log_{10}(TD) + b_4 log_{10}(DOY); \quad DOY \ge DOY^*$ 404 405 indicating that only snow depth, winter precipitation, temperature difference, and day of water year were relevant. 406 Manual tests of model construction with other variables included confirmed that Eqns. (7-8) yielded the best results. 407 These two SWE estimates for the individual (acc and abl) phases of the snowpack were then blended with Eqn. (5) 408 to produce a single equation for SWE spanning the entire water year. The obtained regression coefficients were 409 $(A, a_1, a_2, a_3, a_4) = (0.0533, 0.9480, 0.1701, -0.1314, 0.2922)$ and $(B, b_1, b_2, b_3, b_4) = (0.0481, 1.0395, 0.9480, 0.1701, -0.1314, 0.2922)$ 410 $0.1699_{y} - 0.0461, 0.1804_{y}$. The physical interpretation of these coefficients is straightforward. For example, both a_{2} 411 and b₂ are greater than zero. So, for two locations with equal h. DOY, and TD, the location with greater PPTWT will 412 have a greater SWE and therefore density. These locations are typically maritime climates with wetter, denser snow. 413 In contrast, both a_3 and b_3 are less than zero. Therefore, for two locations with equal h, DOY, and PPTWT, the 414 location with greater TD (a more continental climate) will have a lower density, which is again an expected result. 415 These trends are similar in concept to Sturm et al. (2010), whose discrete snow classes (based on climate classes) 416 indicate which snow will densify more rapidly. 417 **3 Results** 418 A comparison of the three regression models (one-equation model, Eq. (2); two-equation model, Eqs. (3-5); multi-419 variable two-equation model, Eqs. (5, 7-8)) is provided in Figure 6. The left column shows scatter plots of modeled 420 SWE to observed SWE for the validation data set with the 1:1 line shown in black. The right column shows 421 distributions of the model residuals. The vertical lines in the right column show the mean error, or model bias. 422 Visually, it is clear that the one-equation model performs relatively poorly with a large negative bias. This large 423 negative bias is partially overcome by the two-equation model (middle row, Figure 6). The cloud of points is closer 424 to the 1:1 line and the vertical black line indicating the mean error is closer to zero. In the final row of Figure 6, we 425 see that the multi-variable two-equation model yields the best result by far. The residuals are now evenly distributed 426 with a small bias. Several metrics of performance for the three models, including R² (Pearson coefficient), bias, and 427 root-mean-square-error (RMSE), are provided in Table 2. Figure 7 shows the distribution of model residuals for the 428 multi-variable two-equation model as a function of DOY.

429

394

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	lodel		R ²	Bias (mm)	RMSE (mm)							
	One-equation		0.946	-19.5	102	_						
	wo-equation		0.962	-5.1	81	_		_				
M	/ulti-variable tw	o-equation	0.97 <mark>8</mark>	- <u>1.2</u>	<u>59</u>				eleted: 2			
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	s useful to also	leted: 67										
stat	tion location and	d normalized by	the winter preci	ipitation (PPTWT)	at that location. Figu	ure 8 shows the	probability	De	eleted: mean annual maximum SWE (SWEm			
den	nsity function of	these normalize	ed errors. The av	verage RMSE is ap	proximately 15% of	f <i>PPTWT</i> with	most values	Fo	rmatted: Font: Italic			
fall	ling into the ran	ge of 5- <u>30</u> %. Th	e spatial distrib	ution of these norm	nalized errors is show	wn in Figure 9.	For the	De	leted: 1			
SN	OTEL stations,	it appears there	is a slight regio	nal trend, in terms	of stations in contine	ental climates (Rockies)	De	eleted: SWE _{max} ,			
hav	ving larger relati	ve errors than st	tations in mariti	me climates (Casca	ades). The British Co	olumbia station	s also show	De	leted: 25			
	ther relative erro							De	leted: northern			
шgi		13.						De	eleted: smaller			
3.1	Results for Sn	ow Classes										
A k	key objective of	this study is to r	regress climatol	ogical information	in a continuous rath	er than a discre	te way. The					
wor	ork by Sturm et a	l. (2010) therefor	ore provides a va	aluable point of co	mparison. In that stu	udy, the authors	developed					
the	e following equa	tion for density	ρ_b									
		the following equation for density ρ_b										
	$() \alpha = (\alpha)$	(-2)[1-2]	$(-k_1h-k_2DOY)$] \perp	2								
(11)	1) $\rho_b = (\rho_m)$	$ax - \rho_0) \big[1 - e^{\zeta} \big]$	$\left[-k_1h-k_2DOY\right] +$	$ ho_0$								
(11)												
(11)					(end of water year),	k_1 and k_2 are co	pefficients,					
(11) whe	here ρ_0 is the init	ial density, ρ_{max}	is the maximum	n or 'final' density	(end of water year), / for October 1 is -92		· · ·	Fo	rmatted: Font: Italic			
(11) whe	here ρ ₀ is the init d <i>DOY</i> in this ca	ial density, ρ _{max} se begins on Jar	is the maximum mary 1. This me	n or 'final' density	for October 1 is -92		· · ·		rmatted: Font: Italic rmatted: Font: Italic			
(11) whe	here ρ ₀ is the init d <i>DOY</i> in this ca	ial density, ρ _{max} se begins on Jar	is the maximum mary 1. This me	n or 'final' density cans that their <i>DO</i>	for October 1 is -92		· · ·					
(11) whe and with	here ρ_0 is the init d <i>DOY</i> in this ca th snow class an	ial density, ρ _{max} se begins on Jar d the values dete	is the maximum nuary 1. This me ermined by Stur	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are	for October 1 is -92		· · ·					
(11) whe and with	here ρ ₀ is the init d <i>DOY</i> in this ca	ial density, ρ _{max} se begins on Jar d the values dete	is the maximum nuary 1. This me ermined by Stur	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are	for October 1 is -92		· · ·					
(11) whe and with Tab	here ρ_0 is the init d <u>DOY</u> in this ca th snow class an ble 3: Model pa inow Class	ial density, ρ _{max} se begins on Jar d the values dete rameters by snow ρ _{max}	is the maximum nuary 1. This me ermined by Stur w class for Sturr ρ_0	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are <u>n et al. (2010).</u> k ₁	for October 1 is -92 shown in Table 3.		· · ·					
(11) whe and with Tab Sr A	here ρ_0 is the init d <i>DOY</i> in this ca th snow class an ble 3: Model pa	ial density, ρ _{max} se begins on Jar d the values dete rameters by snow	is the maximum nuary 1. This me ermined by Stur w class for Sturr	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010).	for October 1 is -92 shown in Table 3.		· · ·					
(11) whe and with Tab Sr Al M Pr	here ρ_0 is the init d <i>DOY</i> in this ca th snow class an ble 3: Model par now Class lipine Maritime trairie	ial density, ρ _{max} se begins on Jar d the values deter matters by snov ρ _{max} 0.5975 0.5979 0.5941	is the maximum nuary 1. This me ermined by Stur w class for Sturn p_0 0.2237 0.2578 0.2332	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016	for October 1 is -92 shown in Table 3. k ₂ 0.0038 0.0038 0.0031		· · ·					
(11) whe and with Tab Sr Al M Pr Tu	here ρ_0 is the init d <i>DOY</i> in this can the snow class and ble 3: Model particular inow Class Alpine Aaritime rairie Tundra	ial density, ρ _{max} se begins on Jar d the values deter ameters by snow ρ _{max} 0.5975 0.5979 0.5941 0.3630	is the maximum nuary 1. This me ermined by Stur w class for Sturr p_0 0.2237 0.2237 0.2578 0.2332 0.2425	n or 'final' density eans that their DOY m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016 0.0029	k2 0.0038 0.0031 0.0031 0.0049		· · ·					
(11) whe and with Tab Sr Al M Pr Tu Ta	here ρ_0 is the init d <i>DOY</i> in this ca th snow class an ble 3: Model par now Class lipine Maritime trairie	ial density, ρ _{max} se begins on Jar d the values deter matters by snov ρ _{max} 0.5975 0.5979 0.5941	is the maximum nuary 1. This me ermined by Stur w class for Sturn p_0 0.2237 0.2578 0.2332	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016	for October 1 is -92 shown in Table 3. k ₂ 0.0038 0.0038 0.0031		· · ·					
(11) whe and with Tab Sr A M Pr Tu Ta	here ρ_0 is the init d <i>DOY</i> in this can the snow class and ble 3: Model part inow Class Alpine Araitime rairie Tundra Taiga	ial density, ρ_{max} se begins on Jar d the values deter maters by snow ρ_{max} 0.5975 0.5979 0.5941 0.3630 0.2170	is the maximum nuary 1. This me ermined by Stur w class for Sturr p_0 0.2237 0.2578 0.2332 0.2425 0.2170	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016 0.0029 0.0000	k2 0.0038 0.0038 0.0031 0.0049 0.0000	2. The coefficie	nts vary					
(11) whe and with Tab Sr Al M Pr Tu Ta To	here ρ_0 is the init d DOY in this ca th snow class an ble 3: Model para now Class Alpine Maritime rairie 'undra 'aiga	ial density, pmax se begins on Jar d the values deter matters by snow pmax 0.5975 0.5979 0.5941 0.3630 0.2170 ison, the snow c	is the maximum nuary 1. This me ermined by Stur p_0 0.2237 0.2578 0.2332 0.2425 0.2170	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016 0.0029 0.0000 IOTEL and British	k2 0.0038 0.0038 0.0031 0.0031 0.0049 0.00000 0.0000 0.0000 <td>2. The coefficie</td> <td>nts vary 1d 3 of Table</td> <td></td> <td></td>	2. The coefficie	nts vary 1d 3 of Table					
(11) who and with Tab Sr Al M Pr Ta Ta To 1) s	here ρ_0 is the init d <u>DOY</u> in this ca th snow class an ble 3: Model para now Class Alpine daritime trairie undra 'aiga o make a compar site was determine	ial density, ρ _{max} se begins on Jar d the values deter rameters by snow ρ _{max} 0.5975 0.5979 0.3630 0.2170 ison, the snow c ned using a 1-kn	is the maximum nuary 1. This me ermined by Stur ρ_0 0.2237 0.2578 0.2322 0.2425 0.2170 class for each SN m snow class gr	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016 0.0029 0.0000 OTEL and British id (Sturm et al., 20	k2 0.0038 0.0038 0.0031 0.0049 0.0000 0.0000 0.0000	2. The coefficie	nts vary ad 3 of Table nese stations					
(11) whe and with Tab Sr Al M Pr Ta To 1) s was	here ρ_0 is the init d <u>DOY</u> in this ca th snow class an ble 3: Model para now Class Alpine daritime trairie undra 'aiga o make a compar site was determine	ial density, ρ _{max} se begins on Jar d the values deter rameters by snow ρ _{max} 0.5975 0.5979 0.3630 0.2170 ison, the snow c ned using a 1-kn	is the maximum nuary 1. This me ermined by Stur ρ_0 0.2237 0.2578 0.2322 0.2425 0.2170 class for each SN m snow class gr	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016 0.0029 0.0000 OTEL and British id (Sturm et al., 20	k2 0.0038 0.0038 0.0031 0.0031 0.0049 0.00000 0.0000 0.0000 <td>2. The coefficie</td> <td>nts vary ad 3 of Table nese stations</td> <td></td> <td></td>	2. The coefficie	nts vary ad 3 of Table nese stations					
(11) whe and with Tab Sr Al M Pr Tu Ta To 1) s was	here ρ_0 is the init d <u>DOY</u> in this ca th snow class an ble 3: Model par- now Class upine Maritime trairie 'aiga make a compar- site was determine is made up of 27	ial density, ρ _{max} se begins on Jar d the values deter ameters by snow ρ _{max} 0.5975 0.5979 0.3630 0.3630 0.2170 ison, the snow c ned using a 1-kn % Alpine, 14%	is the maximum nuary 1. This me ermined by Stur p_0 0.2237 0.2578 0.2332 0.2425 0.2170 dass for each SN m snow class gr Maritime, 10%	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010). k1 0.0012 0.0010 0.0016 0.0029 0.0000 ROTEL and British id (Sturm et al., 20 Prairie, 11% Tund	k2 0.0038 0.0038 0.0031 0.0049 0.0000 0.0000 0.0000	2. The coefficie	nts vary dd 3 of Table uese stations ation (11)					
(11) whe and with Tab Sr Al M Pr Ta To 1) s was was	here ρ_0 is the init d <u>DOY</u> in this ca th snow class an ble 3: Model par now Class Upine Aaritime rairie 'undra 'aiga a make a compar site was determi is made up of 27 as then used to en	ial density, pmax se begins on Jar d the values deter ameters by snow pmax 0.5975 0.5975 0.5941 0.3630 0.2170 ison, the snow c ned using a 1-kn % Alpine, 14% stimate snow den	is the maximum nuary 1. This me ermined by Stur w class for Sturr p_0 0.2237 0.2237 0.2578 0.2322 0.2425 0.2170 class for each SN m snow class gr Maritime, 10% nsity (and then S	n or 'final' density eans that their <i>DOY</i> m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016 0.0029 0.0000 XOTEL and British id (Sturm et al., 20 Prairie, 11% Tund SWE) for every po	k2 0.0038 0.0038 0.0031 0.0031 0.0049 0.0000 0.0000	2. The coefficie	nts vary ad 3 of Table nese stations ation (11) ed in Section	Fo				
(11) whe and with Tab Sr Al M Pr Tu Ta To 1) s was was 2.2.	here ρ_0 is the init d DOY in this ca th snow class an ble 3: Model pai now Class upine Aaritime rairie 'undra 'aiga o make a compar site was determing s made up of 27 the then used to en 2. Figure 10 com	ial density, ρ _{max} se begins on Jar d the values deter <u>pmax</u> 0.5975 0.5941 0.3630 0.2170 ison, the snow c ned using a 1-kn % Alpine, 14% stimate snow deter pares the SWE of	is the maximum nuary 1. This me ermined by Stur p_0 0.2237 0.2578 0.232 0.2425 0.2170 class for each SN m snow class gr Maritime, 10% nsity (and then S estimates from t	n or 'final' density eans that their DOY m et al. (2010) are n et al. (2010). k ₁ 0.0012 0.0010 0.0016 0.0029 0.0000 COTEL and British id (Sturm et al., 20 Prairie, 11% Tund SWE) for every po he Sturm model ar	k2 0.0038 0.0038 0.0038 0.0038 0.0031 0.0049 0.0000 0.0000 Columbia snow sur 10). The aggregated ra, and 38% Taiga d int in the validation of 0.001	2. The coefficie	nts vary ad 3 of Table uese stations ation (11) ad in Section wo-equation	Fo	rmatted: Font: Italic			

$\begin{array}{c|c} \mbox{Table 2: Summary of performance metrics for the three regression models presented in Section 2.2.} \\ \hline \mbox{Model} & \mbox{R}^2 & \mbox{Bias (mm)} & \mbox{RMSE (mm)} \\ \end{array}$

502 to the 1:1 line). Plots of the residuals by snow class are provided in Figure 11, giving an indication of the bias of

each model for each snow class. Summaries of the model performance, broken out by snow class, are given in Table

504 4. The current model has smaller biases and RMSEs for each snow class.

506	Table 4: Compa			by Sturm et al.						Deleted: present
	Model	Sturm et al.				iable two-equ				
	Snow Class	R ²	Bias (mm)	RMSE (mm)	R ²	Bias (mm)	RMSE (mm)			
	All Data	0.928	-29.2	111	0.97 <mark>8</mark>	<u>-1.2</u>	<u>59</u>		Maria and Andrews	Deleted: 2
	Alpine	0.973	10.1	55	0.978	- <u>2.7</u>	48		A CONTRACTOR OF THE OWNER OWNER OF THE OWNER	Deleted: -0.5
	Maritime Prairie	0.968	-16.8 18.7	109 56	0.97 <u>5</u> 0.971	- <u>7.8</u> -0.7	<u>95</u> 45		M/	Deleted: 67
	Tundra	0.967	-10.5	82	0.974	-2.9	59		M///	Deleted: 1
	Taiga	0.943	-80.0	151	0.978	2.6	54	4		Deleted: 0.3
507										·
508	3.2 Comparison	n to Pistocchi	i (2016)							Deleted: 55
509	•		. ,	n the simple m	dal of Dist	occhi (2016) 1	vas also applied	to the validation		Deleted: 0
						occiii (2010) v	was also applied	to the validation		Deleted: 4.5
510	dataset. His moo	tel calculates	the bulk densi	ty as						Deleted: 105
511										Deleted: 65
512	(12) $\rho_b = \rho$	$_0 + K(DOY +$	+ 61),							Deleted: 2
513										Deleted: 51
514	where ρ_0 has a	1	3 1 K 1		3 71	DOVC	1.11			Deleted: 69
			0					~		Deleted: 6.1
515	November 1. Aj	•			-					Deleted: 67
516	These results are	e comparable	to the Sturm e	t al. (2010) mod	lel, with a l	arger bias but	smaller RMSE.			Formatted Table
517	A									Deleted: 1
518	3.3 Comparison	<u>n to Jonas et</u>	<u>al. (2009)</u>							Deleted: 4
519	A final point of	comparison c	an be provided	l by the model c	of Jonas et a	al. <u>(2009).</u> The	e full version of	that model	MM	Deleted: 62
520	contains region-	specific offse	t parameters tl	nat are not releva	ant to Nort	h America, so	the following pa	artial version of		Deleted: one
521	the model is use	d (their Eq. 4):							(Formatted: Font: Italic
522			_							Formatted: Font: 12 pt, Font color: Auto
523	(13) $\rho_b = a$	$h \perp h$								Formatted: Normal
523 524	(15) $p_b = u$	n + D,							1	Formatted: Font: 10 pt, Bold
524 525	where the paran	a b a	ary with alays	tion and month	as given b	v Table 5. No	te that coefficie	nte are not given		
525 526	for every month									
520 527	an RMSE of 69									Formatted: Not Highlight
527 528				· · ·				<u> </u>		
	the Jonas et al. (
529 520	comparison to the					iala points (ab	out 5%). When	unis is done, the		
530	current model y	ields a bias of	-0.3 mm and	an RMSE of 59	<u>mm.</u>					
531										
532	Table 5: Model	coefficients (a, b) for the Jo	onas et al. (2009) model.				ŀ	Formatted: Normal, Line spacing: single

		11	1				1					
	Month	<i>z</i> > 2000 <i>m</i>	2000 m > z > 3	1400 m	1400	m > z					•	Formatted Table
	January	(206, 52)	(208, 47))	(235	5,31)						
	February	(217,46)	(218, 52))	(27	9,9)						
	March	(272, 26)	(281, 31))	(33	3, 3)						
	<u>April</u>	(331,9)	(354, 15))	(347	7,25)						
	May	(378,21)	(409, 29))	(413	8,19)						
	June	(452, 8)	<u>n/a</u>		<u>n</u>	<u>/a</u>					+	Formatted: Centered
1	July	(470, 15)	<u>n/a</u>		<u>n</u>	<u>/a</u>						Formatted: Centered
	August	<u>n/a</u>	<u>n/a</u>		<u>n</u>	<u>/a</u>						Formatted: Centered
	September	<u>n/a</u>	<u>n/a</u>		<u>n</u>	<u>/a</u>					-	Formatted: Centered
	October	<u>n/a</u>	<u>n/a</u>		<u>n</u>	<u>/a</u>						Formatted: Centered
	November	(206, 47)	(183, 35))	(149	9,37)						
	December	(203,52)	(190, 47))	(201	,26)						
553	I										-	Deleted: ¶
554	3.4 Results fo	r Northeast USA	\									Formatted: Font color: Auto
555			s study were devel	oped usin	ig a large	collection	n of snow	pillow sit	es in CO	NUS. AK		Formatted: Line spacing: 1.5 lines
556	-	•	are limited to loca	·								Deleted: 3
557			USA (Section 2.1		••	-			, ,	0		⁵ (Deleted: SNOTEL
558			ically distant from	<i>,</i>		5						Deleted: are
559			ring, with the exc		-			-				Deleted: ,
560			s, providing an int	·			_	0 1				Deleted: present
561				U		5						(
562	Figure 12 grap	hically summariz	zes the datasets an	d the perf	ormance	of the mu	lti-variał	le two-equ	ation mo	odel of the	,	
563		-	es are comparable									
564	comparatively	thinner snowpac	ks in the northeas	t, represei	nt a large	r relative e	error (Tal	ole 5). The	bias of t	he model		
565	is consistently	positive, in contr	rast to the western	stations v	where the	bias was	negligibl	e. Note the	at Table 5	5 also		
566	includes result	s from the applic	ation of the other	three mod	lels discu	ssed. Stur	m et al. (2010) can	not be ap	plied to		
567	several of the	datasets since the	ir available 1 km	snowclass	dataset o	cuts off at	-71.6° lo	ngitude. T	he curren	nt model		Formatted: Font: Not Italic
568	and the Jonas	et al. (2009) mod	el perform better t	than the o	ther two	models, w	ith the cu	irrent mod	el genera	<u>illy</u>		Formatted: Font: Not Italic
569	outperforming	the Jonas et al. (2009) model. The	two datas	sets wher	e the Jona	<u>s et al. (</u> 2	009) mod	el has a s	lightly		~
570	better perform	ance are the two	smallest datasets (less than	1000 mea	asurement	s; see Ta	ble 1).				
571												
572			or various models			heastern U	JSA data	sets. Bold	font is u	sed to		Deleted: the multi-variable two-equation model
573	highlight the n	nodel with the be	st performance for Multi-varial		aset. Sturm e	×t al	Jonas e	tal	Pistoce	hi]	Deleted: various
			two-equatio		(2010)	<u></u>	(2009)		(2015)	***		
	Dataset Nam	e		RMSE	Bias (mm)	RMSE (mm)	Bias (mm)	RMSE (mm)	Bias (mm)	RMSE (mm)		

(mm)

(mm)

(mm)

(mm)

<u>(mm)</u>

RMSE (mm)

(mm)

<u>(mm)</u>

Maine Geological Survey, ME	13.1	3 <u>4.0</u>	n/a	n/a	25.1	46.0	59.2	77.1	
Hubbard Brook (Station 2), NH	21.8	66.6	34.2	76.9	19.4	65.4	52.0	90.8	
Thompson Farm, NH	7.1	20.2	<u>n/a</u>	<u>n/a</u>	5.6	<u>19.9</u>	20.4	<u>32.3</u>	
NRCS SCAN	1.2	39.2	<u>8.4</u>	<u>45.0</u>	<u>-2.8</u>	<u>40.6</u>	<u>23.4</u>	<u>56.9</u>	Τ
Sleepers River, VT	14.4	28.2	36.5	48.9	20.4	33.5	55.8	67.1	Τ
New York Snow Survey	14.8	31.2	21.0	49.3	16.3	33.0	41.3	56.1	

583 <u>3.5 Results for NRCS Snow Course / Aerial Marker Data</u>

584 The NRCS snow course and aerial marker data were also left out of the model building process so they provide an

585 additional and completely independent comparison of the various models considered. Recall that these data come

586 from snow course (coring measurements) and aerial surveys, which are different measurement methods than the

587 snow pillows which provided the data for construction of the current regression model. Table 6 shows the results

588 and demonstrates that the current model has the best performance.

589

590 <u>Table 6: Performance metrics for various models applied to the NRCS snow course and aerial marker dataset. Bold</u> 591 font is used to highlight the model with the best performance.

	Multi-varia		<u>Sturm et</u> (2010)	al.	<u>Jonas et</u> (2009)	al.	Pistocchi (2015)		
Dataset Name	Bias (mm)	<u>RMSE</u> (mm)	<u>Bias</u> (mm)	RMSE (mm)	Bias (mm)	<u>RMSE</u> (mm)	<u>Bias</u> (mm)	RMSE (mm)	
<u>NRCS Snow Course / Aerial</u> <u>Marker</u>	<u>0</u>	<u>59</u>	<u>-24</u>	<u>123</u>	<u>24</u>	<u>72</u>	<u>71</u>	<u>99</u>	

592 **4** Discussion

593 The results presented in this study show that the regression equation described by equations (5, 7-8) is an

594 improvement (lower bias and RMSE) over other widely used bulk density equations. The key advantage is that the

595 <u>current</u> method regresses in relevant parameters directly, rather than using discrete bins (for snow class, elevation,

596 month of year, etc.), each with its own set of model coefficients. The comparison (Figs. 10-11; Table 4) to the model

597 of Sturm et al. (2010) reveals a peculiar behavior of that model for the Taiga snow class, with a large negative bias

598 in the Sturm estimates. Inspection of the coefficients provided for that class (Table 3) shows that the model simply

599 predicts that $\rho_b = \rho_{max} = 0.217$ for all conditions.

600

501	When our multi-variable two-equation model, developed solely from western North American data, is applied to
502	northeast USA locations, it produces SWE estimates with smaller RSME values and larger biases than the western
503	stations. When comparing the SWE-h scatter plots of the SNOTEL data (Figure 4b) to those of the east coast data
504	sets (left column; Figure 12), it is clear that the northeast data generally have more scatter. This is confirmed by
505	computing the correlation coefficients between SWE and h for each dataset. It is unclear if this disparity in
506	correlation is related to measurement methodology or is instead a 'signal to noise' issue. Comparing Figures 4 and
507	12 shows the considerable difference in snowpack depth between the western and northeastern data sets. When the
508	western dataset is filtered to include only measurement pairs where $h < 1.5$ m, the correlation coefficient is reduced
509	to a value consistent with the northeast datasets. This suggests that the performance of the current (or other)

610 regression model is not as good at shallow snowpack depths. This is also suggested upon examination of the time

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626 series of observed $\rho_b = SWE/h$ for a given season at a snow pillow site. Very early in the season, when the depths 627 are small, the density curve has a lot of variability. Later in the season, when depths are greater, the density curve 628 becomes much smoother. Very late in the season, when depths are low again, the density curve becomes highly 629 variable again. 630 631 Measurement precision and accuracy affect the construction and use of a regression model. Upon inspection of the 632 snow pillow data, it was observed that the precision of the depth measurements was approximately 25 mm and that 633 of the SWE measurements was approximately 2.5 mm. To test the sensitivity of the model coefficients to the 634 measurement precision, the depth values in the training dataset were randomly perturbed by +/- 25 mm and the SWE 635 values were randomly perturbed by +/- 2.5 mm and the regression coefficients were recomputed. This process was 636 repeated numerous times and the mean values of the perturbed coefficients were obtained. These adjusted 637 coefficients were then used to recompute the SWE values for the validation data set and the bias and RMSE were 638 found to be -10.5 mm and 72.7 mm. This represents a roughly 10% increase in RMSE, but a considerable increase in 639 bias magnitude (see Table 4 for the original values). This sensitivity of the regression analysis to measurement 640 precision underscores the need to have high-precision measurements for the training data set. Regarding accuracy, 641 random and systematic errors in the paired SWE - h data used to construct the regression model will lead to 642 uncertainties in SWE values predicted by the model. As noted in the introduction, snow pillow errors in SWE 643 estimates do not follow a simple pattern. Additionally, they are complicated by the fact that the errors are often 644 computed by comparing snow pillow data to coring data, which itself is subject to error. Lacking quantitative 645 information on the distribution of snow pillow errors, we are unable to quantify the uncertainty in the SWE 646 estimates. 647 648 Another important consideration has to do with the uncertainty of depth measurements that the model is applied to. 649 For context, one application of this study is to crowd-sourced, opportunistic snow depth measurements from 650 programs like the Community Snow Observations (CSO; Hill et al., 2018) project. In the CSO program, 651 backcountry recreational users submit depth measurements, typically taken with an avalanche probe, using a 652 smartphone in the field. The measurements are then converted to SWE estimates which are assimilated into 653 snowpack models. These depth measurements are 'any time, any place' in contrast to repeated measurements from 654 the same location, like snow pillows or snow courses. Most avalanche probes have cm-scale graduated markings, so 655 measurement precision is not a major issue. A larger problem is the considerable variability in snowpack depth that 656 can exist over short (meter scale) distances. The variability of the Chugach avalanche probe measurements was 657 assessed by taking the standard deviation of 8 h measurements per site. The average of this standard deviation over 658 the sites was 22 cm and the average coefficient of variation (standard deviation normalized by the mean) over the 659 sites was 15%. This variability is a function of the surface roughness of the underlying terrain, and also a function of 660 wind redistribution of snow. Propagating this uncertainty through the regression equations yields a slightly higher 661 (16%) uncertainty in the SWE estimates. CSO participants can do three things to ensure that their recorded depth 662 measurements are as representative as possible. First, avoid measurements in areas of significant wind scour or

663 deposition. Second, avoid measurements in terrain likely to have significant surface roughness (rocks, fallen logs, 664 etc.). Third, take several measurements and average them. 665 666 Expansion of CSO measurements in areas lacking SWE measurements can increase our understanding of the 667 extreme spatial variability in snow distribution and the inherent uncertainties associated with modeling SWE in 668 these regions. It could also prove useful for estimating watershed-scale SWE in regions like the northeastern USA, 669 which is currently limited to five automated SCAN sites with historical SWE measurements for only the past two 670 decades. Additionally, historical snow depth measurements are more widely available in the Global Historical 671 Climatology Network (GHCN-Daily; Menne et al. 2012), with several records extending back to the late 1800s. 672 While many of the GHCN stations are confined to lower elevations with shallower snow depths, the broader 673 network of quality-controlled snow depth data paired with daily GHCN temperature and precipitation measurements 674 could potentially be used to reconstruct SWE in the eastern US given additional model development and refinement. 675 **5** Conclusions 676 We have developed a new, easy to use method for converting snow depth measurements to snow water equivalent 677 estimates. The key difference between our approach and previous approaches is that we directly regress in 678 climatological variables in a continuous fashion, rather than a discrete one. Given the abundance of freely available 679 climatological norms, a depth measurement tagged with coordinates (latitude and longitude) and a time stamp is 680 easily and immediately converted into SWE. 681 682 We developed this model with data from paired SWE-h measurements from the western United States and British 683 Columbia. The model was tested against entirely independent data (primarily snow course; some snow pillow) from 684 the northeastern United States and was found to perform well, albeit with larger biases and root-mean-squared-685 errors. The model was tested against other well-known regression equations and was found to perform better. The 686 model was also tested against a large dataset of independent snow course and aerial marker measurements from 687 western North America. For this second independent test, the current model outperformed the other models 688 considered. 689 690 This model is not a replacement for more sophisticated snow models that evolve the snowpack based on high 691 frequency (e.g., daily or sub-daily) weather data inputs. The intended purpose of this model is to constrain SWE 692 estimates in circumstances where snow depth is known, but weather variables are not, a common issue in sparsely 693 instrumented areas in North America.

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698 7 Data Access

699	Numero	ous online datasets were used for this project and were obtained from the following locations:		
700	1.	NRCS Snow Telemetry: https://www.wcc.nrcs.usda.gov/snow/SNOTEL-wedata.html		Formatted: Default Paragraph Font, Font: (Default) +Body
701	2.	NRCS Soil Climate Analysis Network: https://www.wcc.nrcs.usda.gov/scan/		(Calibri), 12 pt
702	3.	British Columbia Automated Snow Weather Stations:		Formatted: Default Paragraph Font, Font: (Default) +Body (Calibri), 12 pt
703		https://www2.gov.bc.ca/gov/content/environment/air-land-water/water/water-science-data/water-data-		Formatted: Default Paragraph Font, Font: (Default) +Body
704		tools/snow-survey-data/automated-snow-weather-station-data		(Calibri), 12 pt
705	4.	Maine Cooperative Snow Survey: https://mgs-maine.opendata.arcgis.com/datasets/maine-snow-survey-data		Formatted: No underline, Font color: Auto
706	5.	New York Snow Survey: http://www.nrcc.cornell.edu/regional/snowsurvey/snowsurvey.html		Formatted: Default Paragraph Font, Font: (Default) +Body
707	6.	Sleepers River Research Watershed. Snow data not available online; request data from contact at:		(Calibri), 12 pt
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708		https://nh.water.usgs.gov/project/sleepers/index.htm		Formatted: Default Paragraph Font, Font: (Default) +Body
709	<u>7.</u>	Hubbard Brook Experimental Forest: https://hubbardbrook.org/d/hubbard-brook-data-catalog		(Calibri), 12 pt
710	<u>8.</u>	Climatological Data: https://adaptwest.databasin.org/pages/adaptwest-climatena	\mathbb{N}	Formatted: Default Paragraph Font, Font: (Default) +Body (Calibri), 12 pt
711 712	<u>9.</u>	NRCS Snow Course / Aerial Marker Data: https://wcc.sc.egov.usda.gov/reportGenerator/		Formatted: No underline, Font color: Auto
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715		//github.com/communitysnowobs/snowdensity).		Formatted: Font: (Default) Times New Roman, No underline, Font color: Auto
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 Figure 3: Sample time series of SWE and h from the Rex River (WA) SNOTEL station. Observations of h at times

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 when SWE is zero are likely spurious.



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Depth (mm)









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RMSE/SV









left column shows the SWE-h data for each dataset. Note that the black symbols are points removed by the outlier

Figure 12: Results from application of the multi-variable, two-equation model to numerous east coast datasets. The

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