Revisiting the Global Seasonal Snow Classification: An Updated Dataset for Earth System Applications

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(Manuscript received 7 April 2021, in final form 2 September 2021)

ABSTRACT: Twenty-five years ago, we published a global seasonal snow classification now widely used in snow research, physical geography, and as a mission planning tool for remote sensing snow studies. Performing the classification requires global datasets of air temperature, precipitation, and land cover. When introduced in 1995, the finest-resolution global datasets of these variables were on a $0.5^\circ \times 0.5^\circ$ latitude–longitude grid (approximately 50 km). Here we revisit the snow classification system and, using new datasets and methods, present a revised classification on a 10-arc-s $\times$ 10-arc-s latitude–longitude grid (approximately 300 m). We downscaled $0.1^\circ \times 0.1^\circ$ latitude–longitude (approximately 10 km) gridded meteorological climatologies [1981–2019, European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis, 5th Generation Land (ERA5-Land)] using MicroMet, a spatially distributed, high-resolution, micrometeorological model. The resulting air temperature and precipitation datasets were combined with European Space Agency (ESA) Climate Change Initiative (CCI) GlobCover land-cover data (as a surrogate for wind speed) to produce the updated classification, which we have applied to all of Earth’s terrestrial areas. We describe this new, high-resolution snow classification dataset, highlight the improvements added to the classification system since its inception, and discuss the utility of the climatological snow classes at this much higher resolution. The snow class dataset (Global Seasonal-Snow Classification, Version 1) and the tools used to develop the data are publicly available online at the National Snow and Ice Data Center (NSIDC).

KEYWORDS: Snow; Climate classification/regimes; Snow cover

1. Introduction

To improve our description and understanding of local to global seasonal snow covers, Sturm et al. (1995) introduced a seasonal snow classification system that has proven widely applicable (now referred to as Global Seasonal-Snow Classification, Version 0). It has been used in studies of snow remote sensing (e.g., Foster et al. 2005; Dong et al. 2005; Derksen et al. 2005, 2010; Cho et al. 2020), snow distributions (e.g., Larue et al. 2017), snow climatology and products (e.g., Brown and Mote 2009; Sturm et al. 2010; Kapnick and Delworth 2013; Metsämäki et al. 2017), cold-land ecosystems (e.g., Jones et al. 2001; Sanecki et al. 2006; Gouttevin et al. 2012; Slatyer et al. 2021), and land surface hydrology (e.g., Martinez and Gupta 2010). The classification system has also been used in several important NASA planning and science documents related to the development of general snow remote sensing tools (e.g., Maurer and Sheffield 2006; Nielsen 2014; Sturm 2018; Sturm et al. 2016; Durand et al. 2020). However, by today’s standards, the original dataset describing the global distribution of snow classes is quite coarse, limited by the $0.5^\circ \times 0.5^\circ$ latitude–longitude (approximately 50 km) spatial resolution of the data input layers available in the 1990s.

The 25 years since the classification system was introduced have seen vast improvements in global datasets and meteorological modeling tools. Since its release, the snow class dataset

has remained in high demand, with researchers frequently asking for classification maps or the data and algorithms required to produce them. The snow classification system now can be produced and applied at much higher spatial resolution. Approximately 10 years ago, we developed a higher-resolution, 30-arc-s $\times$ 30-arc-s latitude–longitude (approximately 1 km) distribution of the global snow classes and, since that time, have continued to improve the mapping procedures as better input datasets and modeling methods became available. Since its inception, we have supplied each improved iteration of the classification to investigators who requested it, but the development procedures behind the improvements, and particularly behind the 30-arc-s dataset, were not formally documented (users of this intermediate dataset include the post-2010 publications listed in the previous paragraph). In addition, the datasets prior to those presented herein were only available by contacting the authors. Here, we rectify these problems by introducing the latest version of the snow classification dataset (Global Seasonal-Snow Classification, Version 1; Liston and Sturm 2021), describing how it was created, defining and discussing the uses of the snow classes, and providing the required access information.

The core of the 1995 classification scheme was a collection of extensive field observations of snow depth, stratigraphy, temperature, and snow-grain characteristics (Fig. 1). This led to a binary decision tree (Fig. 2) that related basic climate variables to key snow characteristics observed in the field (Sturm et al. 1995). The classification applies to all non-ice-covered terrestrial regions on Earth where snow falls (see the color shades in Fig. 3). As we discuss in more detail later, the primary use of the classification system and mapping has been geographic; it has been used to divide and differentiate classes of snow over

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DOI: 10.1175/JHM-D-21-0070.1

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FIG. 1. The general stratigraphic and textural characteristics of each snow class as they would appear in middle to late winter. Symbols follow Fierz et al. (2009). Modified from Sturm et al. (1995).

regional (e.g., Derksen et al. 2010; Martinez and Gupta 2010) to global domains (e.g., Foster et al. 2005). A second use has been to validate snow remote sensing products in the absence of on-the-ground snow data, under the assumption that satellite results should not stray far from the snow “norms” suggested by the snow classification (e.g., Derksen et al. 2005).

When used for these purposes, the classification essentially describes the climatologically “most likely” snow cover that would be encountered at a given geographic location. But the classification is not limited to this use. In fact, as the snow season waxes and wanes at a location, the nature of the snow can change, in many cases shifting from one class to another as winter progresses (Sturm et al. 1995). Moreover, as the general climate changes, even the climatological “most likely” snow can evolve into a different class (e.g., Nolin and Daly 2006). The classification provides a way to estimate general snow characteristics when other data are absent, and to do so at a range of scales. For example, topography, vegetation, exposure, and elevation alter local climates at scales much smaller than those represented by the 50-km initial classification dataset. These factors, in turn, alter the local- to basin-scale

snow characteristics. Therefore, with a high-resolution classification system, it is possible to infer snow conditions from global and regional scales, down to very fine spatial scales.

Recognizing these facts, we have used the latest available atmospheric forcing and land-cover datasets to recalculate the Sturm et al. (1995) seasonal snow classes on a global, 10-arc-s $\times$ 10-arc-s latitude–longitude grid (i.e., $0.002778^\circ \times 0.002778^\circ$; approximately $300 \times 300 \text{ m}^2$), improving the mapping resolution by a factor of 180×180 (i.e., for each grid cell in the old map, there are now 32 400 grid cells in the new map). This increased resolution opens the door to many additional dataset applications. Here we provide a summary of the new dataset, describe the methods used in its creation, and discuss new ways the high-resolution product might be used.

2. Snow classification update

a. The snow classification algorithm

Sturm et al. (1995) measured snow covers across large regions of North America and Europe and found snow classes could be defined based on air temperature, precipitation, and

FIG. 2. Decision tree for identifying snow classes (following Sturm et al. 1995). In this application, land cover is used as a surrogate for wind speed (see section 2a). The two “rare” categories generally do not occur in nature and were not classified. The * indicates the application of a coastal mask to prevent the Maritime class from occurring outside of coastal regions; see section 2c for a discussion of how this was implemented.

wind speed climatologies. The classes were based on earlier, more rudimentary snow classifications by Formozov (1946), Rikhter (1954), Roch (1949), and others (see Table 1 in Sturm et al. 1995). The new classification also uses air temperature, precipitation, and wind speed climatologies, but with updated datasets to drive the classification algorithm.

An air temperature index that combined the influence of snow-season temperature and duration was defined in terms of a cooling degree month (CDM),

$$\text{CDM} = \begin{cases} \sum_m (T_c - T_a), & \text{if } T_a < T_c \\ 0, & \text{if } T_a \geq T_c \end{cases}, \quad (1)$$

where m is the month of the year (1–12); T_a (°C) is the monthly mean screen-height (approximately 2 m) air temperature; and T_c (°C) is a critical or threshold air temperature chosen to equal 10°C to allow for snow covers that exist in locations where the monthly mean temperature may be above freezing, a condition typically found where there are wet, warm snow covers.

The CDM threshold between “high” and “very high” temperature prescribes the boundary between “Ephemeral” snow and the other seasonal snow classes (Fig. 2). Recent work by Wrzesien et al. (2019a,b), using 16 years of NASA Moderate Resolution Imaging Spectroradiometer (MODIS; Justice et al. 1998) to map an ephemeral-seasonal snow boundary, suggested that our 1995 classification system underestimated the extent of ephemeral snow because we set the CDM threshold too low (in 1995 it was set at 30°C). To determine a new very high CDM threshold, we adjusted the threshold upward until it produced the same number of seasonal snow pixels as in Wrzesien et al. (2019a,b) (within 0.1%) for all data between 20° and 60°N latitude on a 30-arc-s grid. This resulted in a very high threshold of 61°C CDM. The new value was calculated while only considering valid pixels in common between the two datasets; for example, we did not consider Wrzesien et al. (2019a,b) cloudy pixels or our glacier and ice-sheet pixels. This CDM value was then applied to the 10-arc-s input fields. The net result was to move the ephemeral-seasonal snow line further north (in the Northern Hemisphere) and to higher elevations, and to match the more accurate mapping of ephemeral

FIG. 3. Percentage of annual water-equivalent precipitation that falls as snow. Antarctica is mostly Ice and therefore not shown. These data were generated by creating annual averages of 39 years of monthly ERA5-Land water-equivalent snowfall and total precipitation data (see section 2b), calculating the ratio of the two variables, and multiplying by 100.

snow regions by Wrzesien et al. (2019a,b). The CDM between high and low air temperature (125°C) remained the same as in 1995.

A water-equivalent snowfall precipitation rate (SPR; mm day^{-1}) is also required for the snow classification. It was defined to occur during months where $T_a < T_c$, and was calculated from the monthly water-equivalent precipitation climatologies using

$$\text{SPR} = \begin{cases} \left(\frac{\sum_m P}{m} \right) / M, & \text{if } T_a < T_c, \\ 0, & \text{if } T_a \geq T_c, \end{cases} \quad (2)$$

where P is the average monthly water-equivalent precipitation rate (mm day^{-1}) for each month of the year, and M is the number of months (out of 12) where the $T_a < T_c$ requirement was met. The SPR represents the average annual water-equivalent snowfall precipitation rate during periods when the monthly air temperature is below T_c . In contrast to Sturm et al. (1995), and to account for our new, higher-resolution precipitation forcing datasets, we defined the threshold between high and low precipitation to be 4 mm day^{-1} ; Sturm et al. (1995) used 2 mm day^{-1} , likely reflecting the general low precipitation bias of the earlier, coarser-resolution, datasets.

In the absence of adequate wind speed data at spatial scales most relevant to snow processes, Sturm et al. (1995) used vegetation stature as a surrogate for wind speed, reasoning that the primary control on snow properties was whether there was enough wind to transport snow, which in turn would correspond to whether there were trees (lower wind) or no trees (higher wind). Following Sturm et al. (1995), we used vegetation as a wind proxy in our updated snow classification; our last 25 years of field observations, across all the snow classes,

suggests that this remains a viable approach (M. Sturm 2019, unpublished data). Alternatively, we could have used MicroMet (Liston and Elder 2006a) to distribute available wind speed datasets. Had we done so, MicroMet would have reduced the wind speeds in the forests by approximately 85%, essentially leading to a binary distribution of relatively low and high speeds, directly coinciding with a forest/nonforest distribution. Because both approaches produce the same result, we followed the Sturm et al. (1995) methodology for consistency. This approach is further supported by other studies looking at the effects of forest canopies on snow properties (e.g., Musselman et al. 2008; Varhola et al. 2010; Harpold et al. 2014; Tennant et al. 2017).

With these changes in thresholds, the new classification system follows the Sturm et al. (1995) decision tree presented in Fig. 2 to control the algorithm branching. To run the algorithm requires three spatially distributed input datasets: monthly climatologies of air temperature and precipitation that each span the entire year (12 months for each variable), and land-cover type. The monthly meteorological climatologies were then used to create the CDM and SPR forcing following Eqs. (1) and (2), using the methods described above. The CDM, SPR, and land-cover data were then used to produce the snow class distributions following the Fig. 2 decision tree.

There is an additional important change in Fig. 2: the new decision tree uses the following names for the snow classes: “Tundra,” “Boreal Forest,” “Montane Forest,” “Prairie,” “Maritime,” and “Ephemeral” (which extends to No Snow). The “Alpine” class from Sturm et al. (1995) is now called “Montane Forest” and, for symmetry, the “Taiga” class has been changed to “Boreal Forest.” The reasons for this are presented in section 4b. The “Ice” class continues to be used to identify glaciers and ice sheets (these are not considered

“seasonal snow” in the context of the snow classification scheme presented herein).

b. Meteorological inputs

Sturm et al. (1995) used preexisting, gridded, coarse-resolution air temperature and precipitation products to drive the Fig. 2 snow classification algorithm. Specifically, we used $0.5^\circ \times 0.5^\circ$ latitude–longitude gridded air temperature, precipitation, and land-cover data, to produce their $0.5^\circ \times 0.5^\circ$ latitude–longitude snow classification. In the updated snow classification, we employed MicroMet (Liston and Elder 2006a) to convert gridded, moderate-resolution, global air temperature and precipitation datasets into meteorological climatologies consistent with the resolution of our global land-cover dataset (i.e., $10\text{-arc-s} \times 10\text{-arc-s}$ latitude–longitude; see section 2c). MicroMet is a quasi-physically based, high-resolution (e.g., from 1-m to 10-km horizontal grid increment) weather-data distribution model. It is the meteorological driver for SnowModel, a spatially distributed snow-evolution modeling system (Liston and Elder 2006b; Liston et al. 2020) and is specifically designed for snow-related and other environmental applications. MicroMet operates as a data assimilation and interpolation model that utilizes meteorological station datasets and gridded atmospheric model or (re) analyses datasets. The model uses known relationships between meteorological variables and the surrounding landscape (primarily topography) to distribute those variables over any given landscape in physically plausible and computationally efficient ways.

To produce the required high-resolution meteorological data inputs, monthly air temperature and precipitation climatologies were first defined using European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis, 5th Generation (Hersbach et al. 2020) Land (ERA5-Land; C3S 2019) products. ERA5-Land is a global, land only, atmospheric reanalysis product available on a $0.1^\circ \times 0.1^\circ$ latitude–longitude grid. We obtained monthly air temperature T_a and water-equivalent precipitation P distributions for the period January 1981–December 2019. These 39 years of monthly values were averaged to create monthly temperature and precipitation climatologies (i.e., 12 months of air temperature and 12 months of precipitation data, each representing the average of 39 years of monthly values).

MicroMet was then used to downscale these $0.1^\circ \times 0.1^\circ$ monthly meteorological distributions to our high-resolution global snow classification grid. In this application, MicroMet used a spatially and temporally constant air temperature lapse rate of $-6.9^\circ\text{C km}^{-1}$ to adjust the ERA5-Land monthly air temperature distributions to their values at sea level (using the ERA5-Land gridcell elevations). This is the annual mean of the monthly lapse rates provided by Liston and Elder (2006a); in light of the other assumptions imposed in the snow classification algorithm, using month-specific values was not justified. These $0.1^\circ \times 0.1^\circ$ sea level distributions were then spatially interpolated across the 10-arc-s snow classification grid using the Barnes objective analysis scheme (Barnes 1964, 1973; Koch et al. 1983) following standard MicroMet procedures (see Liston and Elder 2006a). The Barnes scheme applies a Gaussian distance-dependent weighting function, where the weight that an ERA5-Land grid cell contributes to

the value of a high-resolution grid point decreases with increasing distance from the ERA5-Land value. Interpolation weights were objectively determined as a function of data spacing and distribution. Then the fixed lapse rate was used to readjust the resulting spatially interpolated sea level air temperatures back across the true Earth surface using a high-resolution topography dataset (see section 2d) that corresponded to the $10\text{-arc-s} \times 10\text{-arc-s}$ latitude–longitude snow classification grid.

Similarly, MicroMet was used to distribute the ERA5-Land precipitation fields across the globe on the same 10-arc-s grid. First, we used MicroMet to create a global, 10-arc-s , ERA5-Land surface-elevation dataset using the Barnes analysis scheme and the ERA5-Land gridcell elevations. The ERA5-Land precipitation values (on its $0.1^\circ \times 0.1^\circ$ grid) were spatially interpolated to the global 10-arc-s grid, again using the Barnes scheme. These precipitation values were then adjusted to the high-resolution topographic distribution (section 2d) using a spatially and temporally constant (annual mean) precipitation adjustment parameter of 0.28 km^{-1} . This parameter is an input to Eq. (33) of Liston and Elder (2006a). It is used to calculate a nonlinear precipitation increase (or decrease) over topography that is above (or below) the ERA5-Land gridpoint elevations. Conceptually, this parameter is used to define how precipitation changes with elevation; see Liston and Elder (2006a) for additional details.

The MicroMet-modified, high-resolution, monthly air temperature and precipitation climatologies on the 10-arc-s grid were converted to the required CDM and SPR distributions using Eqs. (1) and (2), and the procedures described in section 2a. Figures 4a and 4b provide an example of the resulting CDM and SPR distributions. Sensitivity of the CDM and SPR results to the chosen air temperature lapse rate and precipitation adjustment factor indicated that using the month-specific values provided by Liston and Elder (2006a), instead of annual mean values, produced only minor changes in the CDM and SPR distributions. This is because the simulated distributions are always constrained by the ERA5-Land meteorological conditions at the ERA5-Land grid points, which exerts significant control on the resulting temperature and precipitation distributions.

c. Land-cover inputs

Creating the snow class distributions also required a global land-cover dataset. We used the European Space Agency (ESA) Climate Change Initiative (CCI) GlobCover project, $10\text{-arc-s} \times 10\text{-arc-s}$ latitude–longitude global land-cover map produced for the year 2018 (e.g., ESA 2017). The 2018 dataset was chosen as a present-day description of the global vegetation distribution, instead of using a more climatological representation; vegetation climatologies coincident with our 39-yr meteorological datasets do not exist at the 10-arc-s resolution required by this study. This GlobCover product is updated every year using observations from the 300-m Medium Resolution Imaging Spectrometer (MERIS) sensor on board the *Envisat* satellite. Because GlobCover data do not distinguish between inland and ocean water bodies, we also obtained and processed the $5\text{-arc-s} \times 5\text{-arc-s}$ latitude–longitude ESA CCI water bodies dataset (Lamarche et al. 2017). This was regridded to the 10-arc-s snow classification grid and used to

FIG. 4. Example snow classification algorithm inputs, showing Washington State in the northwestern United States. (a) Cooling degree month (CDM; °C). (b) Water-equivalent snowfall precipitation rate (SPR; mm day⁻¹). (c) Land-cover type. White is ocean.

identify which water grid cells were inland and which were ocean, thus allowing classification over inland water bodies (under the assumption that the water there would be frozen).

The GlobCover and water bodies datasets were merged to create a global distribution of four land-cover classes: short land cover, tall land cover, ice, and ocean. Consistent with using short and tall land cover to represent strong and weak winds [in terms of snow-cover controls; see [Sturm et al. \(1995\)](#)

for further description of the reasoning behind this approach], all grasses, shrubs, and similar relatively low land-cover types including inland water bodies were classified as “short” and all forest land-cover types were classified as “tall.” Prior work on snow interactions with grasses, forbs, and shrubs indicates this approach is acceptable because these vegetation types are often compressed as the snow cover builds on top of them (e.g., [Sturm et al. 2005](#); [Ray and Bret-Harte 2019](#)); therefore, they do

FIG. 5. Coastal mask, approximately 500 km wide, defined by the gray areas. The coastal snow class (i.e., Maritime) was defined to fall within the gray areas. Antarctica is mostly Ice and therefore not shown.

not prevent the wind from transporting snow. Figure 4c provides an example of the resulting land-cover distributions.

d. Topography inputs

MicroMet's downscaling procedures described in section 2b required a topographic dataset corresponding to the high-resolution, snow classification grid. Topography was defined using Global Multi-Resolution Terrain Elevation Data 2010 (GMTED2010) from the U.S. Geological Survey (USGS) and the National Geospatial-Intelligence Agency (NGA) (Danielson and Gesch 2011). The $7.5\text{-arc-s} \times 7.5\text{-arc-s}$ latitude–longitude GMTED2010 data were regridded to our 10-arc-s snow classification grid using a simple averaging procedure.

Because GMTED2010 does not include Antarctica, Greenland, and the Arctic Ocean (e.g., areas from 56° to 90°S latitude and from 84° to 90°N latitude are undefined in GMTED2010), we used the GTOPO30 topography dataset to fill in the missing GMTED2010 values. GTOPO30 is a $30\text{-arc-s} \times 30\text{-arc-s}$ latitude–longitude dataset that covers the globe with no missing values (available through the USGS Earth Resources Observation Systems (EROS) Data Center; Gesch et al. 1999). GTOPO30 was regridded to our 10-arc-s snow classification grid using a linear-weighting interpolation function, and the resulting topographic values were used to replace any undefined values in the GMTED2010 dataset. The outcome was a global topography dataset, on a $10\text{-arc-s} \times 10\text{-arc-s}$ latitude–longitude grid, with no missing values. There are two reasons why this approach was acceptable for this application: 1) most of the GMTED2010 undefined areas are glaciers and ice sheets where the topographic variability is relatively small, and 2) these ice areas are not used in the seasonal snow classification scheme (they are identified as Ice, not snow, in the classification).

e. Coastal mask

In some areas of the world, far from any coast, the classification algorithm labeled the snow as “Maritime.” This only occurred in high mountain areas where orographic lifting

produced large precipitation values, despite the relatively large distance from ocean moisture sources (e.g., in the Rocky Mountains and Himalayas). To prevent the creation of Maritime snow in nonmaritime environments, we created a coastal mask that encompassed all areas within ~ 500 km of a coastline and used it to prevent the coastal (i.e., Maritime) snow class from occurring outside this masked area. In our implementation of the Fig. 2 decision tree, if “high temperature” and “high precipitation” occurred outside of this coastal mask, then the algorithm followed the “low precipitation” branch and was classified as either Prairie or Montane Forest, depending on the wind speed conditions. This coastal mask dataset and coastal requirement were not used by Sturm et al. (1995) because the coarser dataset generally did not produce the same high precipitation anomalies far from a coast.

The coastal mask was created by first extracting every 60th grid cell from our 10-arc-s ocean grid cell distribution, to create a $10\text{-arc-min} \times 10\text{-arc-min}$ latitude–longitude ocean–land dataset. All land points on this grid were defined to have a value of 1000, and all ocean points were given a value of 0. Then a 9-point smoother was applied to this distribution 200 times, and values ≤ 998 were defined to be coastal (this clipping value defined how wide the coastal mask was). The resulting coastal distribution was then regridded back to the original $10\text{-arc-s} \times 10\text{-arc-s}$ latitude–longitude grid using a simple nearest-neighbor interpolation; therefore, no information was added at the higher resolution. Then, the original ocean grid cells were applied as an ocean mask. The result was a relatively smooth global coastal mask that was approximately 500 km wide along all coastlines (Fig. 5). The resulting snow class map was largely insensitive to this 500-km distance, e.g., coastal mask widths of 300 or 700 km produced nearly identical snow class distributions.

3. Results

The Sturm et al. (1995) snow classification algorithm (Fig. 2) was run over the entire globe using the new high-resolution data distributions and the threshold values defined in section 2a.

FIG. 6. Global snow classification. Antarctica is mostly Ice and therefore not shown.

While rerunning the algorithms for this snow classification update, the coastal mask presented in Fig. 5 (see section 2e) was implemented. The resulting global snow classification is presented in Fig. 6.

The global area (km^2) covered by each of the seasonal snow classes is presented in Table 1. Also shown is the percentage of total snow cover area covered by each class. This calculation excludes the Ephemeral class, which roughly coincides with locations where snowfall is $\leq 5\%$ of the annual precipitation (Fig. 3). The Tundra class covers the most area, followed by Boreal Forest, Prairie, Montane Forest, and then Maritime. It is noteworthy that the majority (56.2% ; $24.2 \times 10^6 \text{ km}^2$) of the world's seasonal snow cover is wind affected (Tundra and Prairie combined; Table 1), and when the snow cover of the Ice areas is added, the total area of Earth covered by wind-affected snow is 60% greater ($38.8 \times 10^6 \text{ km}^2$) than the wind-affected seasonal snow-covered area ($24.2 \times 10^6 \text{ km}^2$).

Figure 7 displays the snow classes for the United States and much of Canada, and Fig. 8 displays the classes for western Eurasia. Both figures highlight the strong control that air temperature, precipitation, and land cover play in controlling the type of snow found in each region. In these maps, which use long-term average values for the entire winter, the snow classifications are truly *snow-climate* classes, with the spatial patterns reflecting the main winter climatology found in each area. The reason this weather- or climate-driven approach to classifying snow works is because the physical properties of the snow cover are the direct result of the winter weather (i.e., a product of the winter climate), and the key weather variables that impact winter snow properties are air temperature, precipitation amount, and wind speed. These three weather controls combine to produce unique, snow-class specific thermal regimes that regulate snow temperatures, snow temperature gradients, and heat and vapor flow in the snow. And these, in turn,

drive snow-evolution processes that impact snow properties such as grain size, bonding, and habit, and thermal conductivity, stratigraphy, density, depth, and snow water equivalent. This weather–snow property linkage is the basis for physically based snow models that evolve snow in response to weather forcing (e.g., Liston and Elder 2006b; Liston et al. 2020). Both the classification and the models work because of the intimate connection between the snow cover and the weather that produced it.

In principle, the snow classification scheme could also be run using early- or middle-winter values to identify how the different classes evolve in time at different locations. As an example of this temporal evolution, during the last few days of a snowpack's melt, all of the classes take on the physical characteristics of Ephemeral snow. The scheme could also be run with different land-cover representations (e.g., prior to 2018) to assess how forest-cover changes might impact the resulting snow class distributions.

TABLE 1. Terrestrial area of the globe covered by the different snow classes. The Ice class includes Antarctica, Greenland, and all other glaciers. Also shown is the percentage of land covered by each class, relative to the area covered by all classes except the Ice and Ephemeral classes (so the percentages total 100.0%).

Snow class	Area (10^6 km^2)	Percent Coverage (%)
Ice	14.6	—
Tundra	13.7	31.8
Boreal Forest	12.2	28.3
Montane Forest	6.0	13.8
Prairie	10.5	24.4
Maritime	0.7	1.7
Ephemeral (or No Snow)	89.5	—

FIG. 7. United States and Canada snow classification.

To see the class differences between the Sturm et al. (1995) distribution [this was based on a 60-yr observed air temperature and precipitation climatology for the period 1920–80 by Legates and Willmott (1990a,b)] and the updated classification, we regridded the new classification to the original $0.5^\circ \times 0.5^\circ$ latitude–longitude grid by selecting the dominant class in the higher-resolution dataset. Figure 9 displays the seven classification changes that occurred over the greatest number of $0.5^\circ \times 0.5^\circ$ latitude–longitude grid cells. In general, jumps between classes that are normally separated by large distances did not occur. For example, there are no instances where Tundra became Montane Forest, Tundra became Prairie, Boreal Forest became Montane Forest, Boreal Forest became Prairie, or Prairie became Boreal Forest.

Most of the differences between the two classifications, we believe, are the result of changes in the classification algorithms and the threshold values that separate the classes, rather than changes in climate between the original 60-yr climatology of the first paper and the 39-yr climatology used in this paper. For example, the large increase in Ephemeral snow at the expense of Prairie and Maritime snow in the western United States and across Eurasia (e.g., the green and red colors, respectively, in Fig. 9) is a direct result of the higher threshold CDM we now use; this was now defined using the Wrzesien et al. (2019a,b) ephemeral-seasonal snow classification.

Other changes can be explained by movements in the boundaries of landscape units due to better land-cover datasets. For example, the northward shift in the northern edge of North America's boreal forest (e.g., the dark pink

color in Fig. 9) is best explained this way. The new land-cover dataset is both more accurate and has much higher spatial structure than that used in 1995. This produces realistic patchy spatial structures in the new classification that could not be resolved in the 1995 maps.

4. Discussion

a. Increased resolution

Improvements in available high-resolution meteorological and land-cover data, and the ability to downscale the meteorological forcing using MicroMet, allowed us to reclassify the world's seasonal snow cover in much greater detail than 25 years ago. The new map products show a degree of snow class heterogeneity, driven by elevation, vegetation variations, and local differences in climatology, that could not be addressed using the coarse input data available in 1995. Figure 10 shows the original (1995) and current snow classification for Washington State, highlighting the realistic, fine-scale heterogeneity revealed in the new classification.

The substantial increase in spatial resolution provides the ability to resolve microsnow climatologies on the map and in the data products. Essentially, we can resolve vegetation, elevation, and wind-driven variations (from vegetation classes) of snow conditions across the globe using a climatological approach. These variations have long been recognized, but they have never been quantified and mapped, at this resolution, over such a large area. For example, Fig. 10 showcases how the snow classes change on a transect across the Washington Cascades. These changes have been known to locals for centuries, but not mapped. Figure 11 zooms in to that area and

FIG. 8. Western Eurasia snow classification.

shows the boundaries between the Tundra and Boreal Forest and Montane Forest snow in this region, and the resulting correspondence between the snow class maps and the Landsat imagery. Figure 12 zooms in even further.

Sturm et al. (1995) classified nearly the entire Cascade Mountain Range as Maritime snow. However, in the new classification, the east side of the range, where winter precipitation and air temperatures are lower, it is now categorized as Montane Forest snow (Fig. 10b). This snow class has fewer melt-freeze layers and less wet snow texture than Maritime snow, and it is less deep and more powdery, consistent with the general climatology of this region (Steenburgh et al. 1997). At higher elevations in this same area, there is even some Boreal Forest and Tundra snow; the latter classification occurring where the vegetation conditions allow the wind to erode and redistribute the snow (Figs. 11 and 12).

An example of the detail provided by the new classification is further highlighted in Fig. 11, which shows the snow classification over the large black rectangle located in the upper center of Fig. 10b. Figure 11a is a mosaic of four Landsat-8 images from

three dates: 7 and 16 June 2015 and 2 July 2015 (image numbers, LSS_PPPRRR_YYYYMMDD: L08_046027_20150607, L08_046026_20150607, L08_045027_20150616, L08_045026_20150702). Figure 11b shows the corresponding regional, west-to-east variation in snow classes, including the transition from Ephemeral, to Maritime, to Montane Forest, and to Prairie at the dry, lower elevations east of the main mountain divide, and then to Ephemeral where the elevation drops low enough to produce the relatively high temperatures associated with ephemeral snow. This mosaicked image showcases the ability of the new snow classification dataset to realistically categorize relatively fine-scale snow conditions over a large spatial area.

Figure 12 displays the more local snow class variations that exist in the new dataset. Figure 12a presents a Landsat-8 image from 7 June 2015 (image number: L08_046026_20150607), and Fig. 12b displays the corresponding snow classification distribution. In this area of the North Cascade Mountain Range, there are small areas of Tundra above tree line, and just below tree line (in places where it is cold enough) there are small

FIG. 9. Differences between the Sturm et al. (1995) snow classification and the updated classification, on the original $0.5^\circ \times 0.5^\circ$ latitude–longitude grid. Shown are the seven classification changes that occurred over the greatest number of $0.5^\circ \times 0.5^\circ$ latitude–longitude grid cells. In the color legend, T = Tundra, BF = Boreal Forest, MF = Montane Forest, P = Prairie, M = Maritime, and E = Ephemeral. The small arrows pointing to the right indicates a change from the 1995 classification (left of the arrow) to the new classification (right of the arrow).

areas of Boreal Forest snow. Figures 11 and 12 also make clear that one need not travel great distances to move from one snow class to another. This can occur over relatively short horizontal distances, by moving up- or downslope to a different elevation.

b. Snow classes based on physical properties

The new snow classification dataset suggests that the fundamental basis of the 1995 classification has not changed despite the high-resolution update. Table 2 provides an updated and expanded description of each snow class, while Table 3 provides summary snow depth, density, and snow water equivalent (SWE) statistics for each snow class. Tables 2 and 3 and Fig. 1 highlight the basic premise that there are distinct classes of snow, and that they are defined by snow texture; the number, thickness, and nature of the layers; the snow and ground temperatures; and the snow surface characteristics.

c. Clarifying misconceptions

The original goal of the Sturm et al. (1995) naming convention was for each snow class name to invoke a conceptual image of the associated snow physical properties and structural characteristics. In addition, we sought to follow historical practices when choosing some of the class names (see Formozov 1946; Roch 1949; Rikhter 1954; Espenshade and Schytt 1956; Sturm et al. 1995). Despite this intention, there has been occasional confusion surrounding the names we used. For example, the Tundra class was meant to evoke an image of snow in cold, dry, windswept areas located on top of low-stature vegetation in

high-latitude and high-elevation environments. The associated snow would consist of alternating layers of wind slab and depth hoar, be quite thin (<0.8 m), and would include surface features such as dunes, barchans, and sastrugi created by the wind. Such snow would be found in Arctic tundra regions, but it could also be found near or on the summit of some peaks in the Rocky Mountains or the Alps and perhaps, during exceptionally cold weather, on the prairies. However, the snow class names were frequently considered to be representative of geographic classifications only, and under this assumption, tundra snow would only be found where there was tundra. While this interpretation may be appropriate in some cases, it is not always suitable. For example, above-tree-line snow in midlatitude high mountain regions often is texturally what Sturm et al. (1995) called Tundra snow; even though it is not in an Arctic tundra region, it looks like Tundra snow, and it is likely to be found on talus or fellfield terrain.

The snow class name that has proven most problematic is the original Alpine class. The word alpine has many definitions. For plants, the term evokes low-stature species occurring above tree line: mainly graminoids, forbs, mosses, lichens, and shrubs. Tundra plants cannot hold much snow or block wind, so snow in alpine plant environments is usually thin and wind-scoured, with isolated, deep snowdrifts; the qualities of the relatively thin snowpack are basically those of Tundra snow. At the same time, alpine can also mean mountain snow (as is its connotation for many skiers) and, in that context, suggests a deep, dry powdery snowpack that is often located in mountain forests. Sturm et al. (1995)

FIG. 10. Comparison of the new snow-class distribution for two different grid resolutions, highlighting the added information provided by the increased resolution of the new classification. (a) On a $0.5^{\circ} \times 0.5^{\circ}$ latitude–longitude grid (approximately 50 km); this is the resolution of the [Sturm et al. \(1995\)](#) snow classification. (b) On the 10-arc-s $\times$ 10-arc-s latitude–longitude grid (approximately 300 m); this is the resolution of the new classification dataset. The two black rectangles in (b) identify the locations of the plots in [Figs. 11](#) and [12](#).

intended the term Alpine to mean this latter type of midlatitude forest snow (i.e., generally below-freezing air temperatures typically found in middle-latitude mountains; moderate precipitation; and low wind speeds). The “low wind speed” control means the Alpine class does not represent above-treeline, mountain snow.

We have renamed the original Alpine snow Montane Forest snow in order to rectify some of the confusion, though we recognize that this does not provide a perfect solution. In fact, the snow class itself occupies both the montane and subalpine life zones (e.g., [Bailey 1980](#); [Lugo et al. 1999](#)), but for simplicity and to avoid confusing subalpine with alpine, we use the simpler

FIG. 11. (a) Mosaic of *Landsat-8* imagery from June and July 2015 for the large rectangle in Fig. 10b. For reference, the greater Seattle area is located along the western edge, and Mount Rainier is in the lower left. (b) The snow classification for area in (a). Shown are the strong mountain-related gradients in snow classes. The black rectangle in (b) identifies the region plotted in Fig. 12. Lakes are assumed to be frozen with snow on them.

FIG. 12. (a) *Landsat-8* image from June 2015 for the small rectangle in Fig. 10b and Fig. 11b. (b) The snow classification for (a). Shown is the Maritime snow in the west; Tundra snow in the highest elevations above tree line; Boreal Forest snow in the highest, coldest forests; Montane Forest snow in the lower, warmer forests; and Prairie and Ephemeral snow in relatively warm areas with short land cover. Lakes are assumed to be frozen with snow on them.

designation of Montane Forest. This pairs nicely with the Boreal Forest class (previously called Taiga), the former being deeper and warmer, the latter being colder and thinner and containing a higher percentage of depth hoar (Table 2). In keeping with the

original intention of the snow class names to evoke a picture of the general snow conditions, in Table 4 we provide some alternate class names that may help people associate the snow with a distinct ecosystem, vegetation class, or life zone.

TABLE 2. Description of snow class physical properties.

Snow class	Description
Tundra	<p>Depth: Thin: 0.2–0.8 m. Anything above 0.8 m tends to be a snowdrift. Snowdrifts range from 1 to over 8 m in depth.</p> <p>Density: Bimodal, because the snow cover typically consists of wind slab ($400\text{--}600\text{ kg m}^{-3}$) over depth hoar ($200\text{--}270\text{ kg m}^{-3}$), with the bulk density the average of these two dissimilar types and densities of snow. The combination tends to converge at 300 kg m^{-3}, which for all seasonal snow can be considered a “universal” average.</p> <p>Liquid water: Rare until spring. When it does occur (due to rain or melt), the meltwater percolates rapidly (in minutes to hours), down through the cold snow (from -5° to -20°C), forming superimposed ice at the ground surface, and often thin ice layers within the snowpack.</p> <p>Mechanical properties: Depth hoar is stiff in compression and weak in shear. Since these basal layers of depth hoar are often moderately loaded by overlying slab layers, the hoar layers can collapse, making a “whomp” sound, and leading to instant settlement of several centimeters. Slab layers are extremely strong in both compression and tension, hence will fracture into blocks during snowpack collapse. Large drifts are primarily wind slab, well sintered, and often quite dense ($>400\text{ kg m}^{-3}$). Thin hoar layers can be found interbedded within the drifts, but these rarely lead to avalanching or fracture, except if there is a cornice breaking cycle at the end of large wind transport events.</p> <p>Stratigraphy: Intertussock and hummock areas mainly become low density, weak depth hoar, which then become capped by one or more wind slabs with depth hoar partings. New and recent snow at the top of the snow cover rarely lasts long due to wind transport with percussive forces fracturing the new grains.</p> <p>Other: Snow distribution patterns are set by the interaction of the wind and topography; hence they repeat from year to year (Sturm and Wagner 2010; Parr et al. 2020; Pflug and Lundquist 2020).</p> <p>References: Bilello (1957), Benson and Sturm (1993), Pomeroy and Gray (1995), Sturm and Liston (2003), Domine et al. (2016).</p>
Boreal Forest	<p>Depth: Thin to moderate: 0.3–1.3 m, though heavy winters might result in as much as 1.5 m on the ground.</p> <p>Density: This is the lowest density snow cover of all the classes due to 1) the absence of wind during and after snowfalls (initial snowfall densities can be as low as 50 kg m^{-3}), 2) the development of extensive depth hoar and a concomitant upward loss of snow mass from the depth hoar layers, and 3) little overburden and/or melt events to hasten densification. Bulk density values in autumn are about 150 kg m^{-3}, and often never reach 200 kg m^{-3} prior to spring melting. New and recent snow layers at the surface of the snow retain their basic snow crystal structures for days due to the low temperatures and absence of wind; they may remain at densities of less than 100 kg m^{-3} for weeks. The overall low density of the snow, as well as the low density depth hoar at the base of the snow, is favorable for subnivean animals.</p> <p>Liquid water: Rare, and when it occurs the amount of water input is low, producing little alteration of the snow grains or stratigraphy.</p> <p>Mechanical properties: High permeability, high porosity, fluffy, and weak.</p> <p>Stratigraphy: The most notable characteristic is the presence of depth hoar occupying 2/3 to virtually all the snow cover; this is a product of intense upward vapor movement under strong vertical temperature gradients. This depth hoar metamorphism is enhanced by 1) proximity to the ground (warmer), 2) a moisture flux from the soil, 3) higher vapor pressure (with higher temperatures) near the ground, and 4) elapsed time. Consequently, depth hoar grains are largest near the ground and progressively smaller (and of different crystal habit) with height in the snowpack. Depending on the time since last snowfall, there may or may not be any recent/new snow at the surface, but nighttime surface hoar development can be intense and relict surface hoar layers are common.</p> <p>Other: Local distribution patterns are controlled by canopy structure.</p> <p>References: Pruitt (1957), Trabant and Benson (1972), Akitaya (1974), Benson (1980), Sturm (1991).</p>

TABLE 2. (Continued)

Snow class	Description
Montane Forest	<p>Depth: At maximum accumulation, montane snow is typically on the order of 0.5–3.0 m deep, depending on year and location.</p> <p>Density: The density of montane snow varies notably through the season and how close you are to the edge of conifer canopies. Early in the season, values around 100–200 kg m^{−3} are common. Some of the lightest surface snow densities can be as low as 50 kg m^{−3}, particularly during cold and calm conditions. Snow densifies gradually through winter, often not reaching 300 kg m^{−3} until warmer conditions emerge in spring when surface melt starts and when liquid water appears in the snow. Density values are typically in the 300–400 kg m^{−3} range through the melt season. Snow density can also vary depending on whether the snow is in a forest gap or under a canopy. Unloaded snow can produce localized increases in density, due to the impact of snow clumps falling out of the canopy to the snowpack below, and due to higher density material coming from the canopy (e.g., icy/melt-freeze material).</p> <p>Liquid water: Liquid water is rare in montane forests through much of the winter. Drip from melting icicles in the canopy may produce some localized areas with liquid water. Intermittent warm periods in the winter may result in some liquid water, which may refreeze in the snowpack. These ice layers often cause faceting both above and below the crust.</p> <p>Mechanical properties: Snow hardness varies somewhat with depth, with less hard snow at the surface and harder snow toward the base of the snowpack. Intermittent/discontinuous melt-freeze layers may be present and introduce thin layers of anomalously high hardness. Depth hoar is often present at the base of the snowpack, such that there is almost always a small decrease in density, and often a large decrease in strength, at the base.</p> <p>Stratigraphy: The surface snow tends to be lower density than the rest of the snowpack, because the montane forest shelters it from wind. Depth hoar is common at the base of the snowpack. Between the surface/fresher snow and the base, rounded grains are typically found. There may be variable/discontinuous and thin layers of melt-freeze, depending on the canopy structure (more or less shortwave shading) and weather conditions through winter. The stratigraphy under canopy can be more variable than in forest gaps due to the unloading of canopy snow. Surface hoar is common, especially in the forest gaps, and can persist for months in some locations that are wind and sun protected.</p> <p>Other: Local distribution patterns are controlled by canopy structure.</p> <p>References: Keeler and Weeks (1967), Armstrong and Armstrong (1987), Elder et al. (2009), Raleigh and Deems (2016).</p>
Prairie	<p>Depth: Prairie snow is highly susceptible to redistribution by the wind and often has a veneer facies covering broad level areas whose depth is controlled by whether there is stubble from crops or bare earth (fallow fields), with deep drifts behind windrows, buildings, and in natural depressions and gullies. Variability in depth for prairie snow exceeds that of tundra snow, ranging from around 0.3 m to more than 1 m outside of drifts. Overall snow depths differ in prairie zones where all the winter snow remains vs locations where the snow cover forms, melts, then reforms during the next storm cycle. Increasing latitude and continentality in climate tends to produce more stable snow covers. In more southerly locations, prairie snow takes on characteristics of ephemeral snow, forming and melting away several times in a winter.</p> <p>Density: Outside of drifts, prairie snow densities range from 200 to 350 kg m^{−3}, with the density increasing slowly through the winter. Locally, basal melting and wind transport can produce higher densities.</p> <p>Liquid water: Rain-on-snow and melt events (chinooks) are common, and when they occur, they produce melt features within the snowpack and water at the base.</p> <p>Mechanical properties: Little information exists on this topic, but the mechanical properties are likely to be similar to descriptions of wind slab for tundra snow.</p> <p>Stratigraphy: Unlike tundra snow, basal melting is common in prairie snow, and gradients sufficient to produce depth hoar are limited. Consequently, layers of fine-grained snow alternate with denser wind slabs, with melt features often present.</p> <p>Other: Prairie snow is a critical source of water for agriculture and soil moisture recharge.</p> <p>References: Gray (1970), Greb (1980), Gray and Granger (1985), Pomeroy and Gray (1995).</p>

TABLE 2. (Continued)

Snow class	Description
Maritime	<p>Depth: Maritime snow ranges up to 8 m deep, with 2 m a valid average value, though 4 m (without drifting) is not unheard of.</p> <p>Density: Density is high, with a “best guess value” for bulk snow being 400 kg m^{-3} for most of the winter and early spring, getting up to 500 kg m^{-3} in spring during periods of active melt or right after a major rain on snow event. New snow densities are typically $100\text{--}250\text{ kg m}^{-3}$, with densities below 100 kg m^{-3} very rare.</p> <p>Density increases steadily, nearly linear with time, due to the number and frequency of additional layers of snow that form the overburden for lower layers.</p> <p>Liquid water: Maritime snow is frequently rained upon. The snow is typically saturated and isothermal (meltwater goes right through it), often with ponded excess water in some layers. Sometimes at the base of a snow pit there will be standing, or even flowing, water (lovely working conditions).</p> <p>Mechanical properties: The snow creeps and slides and runs, often slowly, and drags things with it. The snow bridges a lot (bad for snow pillows) and the freeze–thaw cycles will destroy instruments even faster than very low air temperatures. The snow is very sticky. The strength changes rapidly during thaws and rain, both of which cause rapid densification and strengthening. In this environment the avalanche danger typically drops just 48 h after big storms, with persistent weak layers being rare.</p> <p>Stratigraphy: Initial snowfall densities can be exceptionally high, even approaching 400 kg m^{-3} due to wet snow. These new layers undergo wet snow metamorphism rapidly, producing icy layers, preferential flow paths, and creating generally uniform rounded snow grains. Surface hoar, from moisture condensing on the snowpack, can occur and produce avalanche risk, but rarely lasts very long, due to large loads and high temperatures, in contrast to colder snow climates. Depth hoar never occurs.</p> <p>Other: Rime occurs a lot where there is wind, due to the high humidity.</p> <p>References: Armstrong and Armstrong (1987), Sturm and Holmgren (1998), Conway and Benedict (1994), Lundquist et al. (2008), Pflug and Lundquist (2020).</p>
Ephemeral	<p>Depth: Ephemeral snow depth ranges from a few cm to up to 1 m. It typically includes only the snowfall from a single storm.</p> <p>Density: This snow is characterized by high densities (e.g., 400 kg m^{-1}) associated with relatively high temperatures and rapid evolution from snow accumulation to melting.</p> <p>Liquid water: The snow is typically isothermal and saturated soon after snowfall.</p> <p>Mechanical properties: The snow’s warm, wet conditions mean it has little strength. It is generally wet and heavy.</p> <p>Stratigraphy: Since the snowpack is comprised of snowfall from a single storm, any stratigraphy is formed from within-storm changes in snowfall conditions.</p> <p>Other: The defining characteristic of this snow class is its short duration. It typically only lasts a few hours or a few days from onset to complete depletion. Often it is defined to be a snowpack that lasts less than 60 days.</p> <p>References: Petersky and Harpold (2018), Wrzesien et al. (2019a,b).</p>

TABLE 3. Representative, late winter, snow depth and density statistics for each climate class (these data were adapted from [Sturm et al. 2010](#)); n = number of observations, SD = standard deviation, SWE = snow water equivalent depth.

	n	Depth (m)	Depth SD (m)	Density (kg m^{-3})	Density SD (kg m^{-3})	SWE (m)	SWE SD (m)
All data	25 688	1.08	1.11	312	93	0.39	0.49
Tundra	31%	0.44	0.25	284	75	0.13	0.08
Boreal Forest	6%	0.60	0.23	217	56	0.13	0.06
Montane Forest	18%	1.30	0.83	335	86	0.46	0.36
Prairie	13%	0.89	0.73	312	85	0.30	0.31
Maritime	32%	1.77	1.50	343	101	0.68	0.67
Ephemeral	—	—	—	—	—	—	—

d. Seasonal changes

Another aspect of the classification that has not been fully understood by some users is how it relates to the time-varying nature of winter snow covers. For example, in the Northern Hemisphere, seasonal snow usually starts out in autumn as Ephemeral snow. The ground is generally warm, it is not yet fully winter, and the first snowfall of the season often melts away before the second snowfall arrives. Under these conditions, during the initial period when this first snowfall is on the ground, the snow is indeed Ephemeral. We have also seen early-winter snow conditions in a Colorado mountain forest that would be called Boreal Forest snow because it is mostly depth hoar and only 0.5 m deep. But, later in the winter, when this snow is deeper, the percentage of depth hoar is lower, it includes more fine-grained cold snow, and it is warmer than Boreal Forest snow, it would be called Montane Forest snow.

To address a more time-varying application or question, a snow season at a given location could be subdivided into early-, middle-, and late-season components, and the associated air temperature and precipitation climatology subsets used to quantify the nature (class) of the snow for the shorter period. In addition to seasonal variations, snow distributions and properties can exhibit important interannual variability in response to variations in air temperature and precipitation. These could be large enough to modify the resulting snow class in a given year, at a given location. In this paper we have not applied the snow classification system in a seasonal or interannual fashion but, in principle, the classification scheme could be used to describe the

textural evolution of snow in a particular location as a function of the seasonal progression of fall, winter, and spring, or to address how snow conditions vary from one year to the next. In addition, new methods are available to visualize these kinds of progressions and changes (e.g., [Roth et al. 2010](#)).

e. Vegetation changes

Because we lacked a 39-yr climatological land-cover dataset at the required spatial resolution, we used a global 2018 land-cover distribution to generate our updated snow classification. Forests evolve over time, in response to insect disturbance, harvest, regrowth, and fire (e.g., [Hansen et al. 2013](#)). Depending on the application, these vegetation variations can be important at fine spatial scales, and they can make important contributions over time. For example, a large fire in 2015 might cause the GlobCover map to register that area as nonforested, when in fact it was forested for most of the ~ 40 -yr period considered in this snow classification update. In addition, there are now global forest-cover and forest canopy height data available at 30-m spatial resolution ([Potapov et al. 2020](#)) that could be used to create an even higher-resolution snow classification dataset. Because of this, we have made the notes and programs required to perform the classification available to the user so they can tailor the data inputs and generate snow classifications specific to their needs.

f. Snow density calculations using the new classification

The 1995 snow classification has been widely used as input to the [Sturm et al. \(2010\)](#) snow-density model (e.g.,

TABLE 4. Snow classification naming conventions, and a conceptual description of the general environment, properties, and geographic location associated with each snow class.

Recommended (adopted herein)	Sturm et al. (1995)	Physical environment	Snow property	Geographic description
Tundra	Tundra	Cold, windy	Shallow, hard wind slabs	High mountain and polar
Boreal Forest	Taiga	Cold, forested	Shallow, depth hoar	Subpolar
Montane Forest	Alpine	Warm, forested	Moderate depth, mixed types, warm snow	Mountains
Prairie	Prairie	Warm, windy	Shallow, soft wind slabs, some melting	Plains
Maritime	Maritime	Warm, high precipitation	Deep, wet	Coastal influence
Ephemeral	Ephemeral	Very warm	Always melting, intermittent, not persistent	Everywhere in autumn, always in temperate and subtropic locations

TABLE 5. Snow property coefficient of variation values, adapted from Liston (2004), for each snow class.

Snow class	Coefficient of variation
Tundra	0.4
Boreal Forest	0.1
Montane Forest	0.1
Prairie	0.5
Maritime	0.7
Ephemeral (or No Snow)	0.1

Bormann et al. 2013; Tedesco and Jeyaratnam 2016; Luoju et al. 2013; Ntokas et al. 2021; Venäläinen et al. 2021). The Sturm et al. (2010) model defines snow-class-specific coefficients as part of its snow density calculations. Because the snow field observations used in that study were classified similarly for the old and new snow classification, the coefficients and methodologies described in Sturm et al. (2010) can still be used with the more accurate new snow classification. It should work better in regions where the classification has changed due to better input data (see Fig. 9); this is particularly true for regions where the class changed from a seasonal snow class to the Ephemeral class (Fig. 9), because of the dramatic differences in physical properties between the Ephemeral class and the other snow classes (Table 2).

g. Mountain snow

Sturm et al. (1995) noted that mountain snow covers often have high spatial variability. As an example, in mountains above tree line, it can be common to find significantly different snow conditions on windward and lee sides of a ridge. This issue of spatial variability over a global domain was addressed by Liston (2004). For snow classification users interested in the spatial variability of snow properties within each class, Table 5 provides coefficient of variation (CV) values, from Liston (2004), for the updated snow classes. In addition, the new, high-resolution classes could be aggregated to coarser resolution to provide a measure of cross-class spatial heterogeneity or variability.

5. Conclusions

A new high-resolution global seasonal snow classification (Global Seasonal-Snow Classification, Version 1; Liston and Sturm 2021) was presented that replaces the original coarse-grid system of Sturm et al. (1995) (Global Seasonal-Snow Classification, Version 0). The new system resolves 10-arc-s $\times$ 10-arc-s latitude–longitude (approximately 300 m) variations in snow classes. This resolution captures regional to local changes in snow characteristics that are driven by high-resolution, microclimatological differences associated with air temperature, estimated snowfall quantities, and approximated wind speed classes. The snow representation in this dataset makes this new seasonal snow classification directly applicable to environmental studies and applications that require high-quality information about regional-to-local variations in snow characteristics.

Acknowledgments. The authors thank Christopher Hiemstra for his useful suggestions during the development of this dataset, Mark Raleigh for his insightful comments about the snow class naming convention, and Michael Durand and Melissa Wrzesien for the suggestion to use their MODIS product to define the ephemeral-seasonal snow boundary. We also greatly appreciate Jessica Lundquist, Mark Raleigh, and HP Marshall for their contributions to Table 2. Adele Reinking, C. Hiemstra, M. Raleigh, Christoph Marty, and one anonymous reviewer are acknowledged for their constructive edits of this manuscript. We also gratefully acknowledge the ESA CCI GlobCover Project for providing the GlobCover and water bodies datasets; the USGS for providing the GMTED2010 and GTOPO30 topographic datasets, and the Landsat-8 images; and the Copernicus Climate Change Service for providing the ERA5-Land atmospheric forcing datasets. Finally, we thank Carl Benson, who first suggested to us the idea of snow climate classes. This work was supported by United States National Science Foundation Grants ARC-0629279 and ARC-0632133, National Aeronautics and Space Administration Grants NNX08AI03G and 80NSSC18K0571, and Department of Energy ARM Program Contract 0F-60237.

Data availability statement. The new, high-resolution, snow classification dataset is available at the National Snow and Ice Data Center (NSIDC), Boulder, Colorado: Liston, G. E., and M. Sturm; Global Seasonal-Snow Classification, Version 1; <http://dx.doi.org/10.5067/99FTCYYYLAQ0>. The dataset is available covering the entire globe, and key subdomains, at the following resolutions: 10 arc s ($\sim$ 300 m); 30 arc s ($\sim$ 1 km); 2.5 arc min ($\sim$ 5 km); 0.5° ($\sim$ 50 km). The data are provided in the following formats: geotiff, netcdf, and ascii. Also included in this archive are all the notes and codes required to reproduce this dataset. The original Sturm et al. (1995) dataset (Global Seasonal-Snow Classification, Version 0) is also available at the same website.

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