Developing a Snow Algae Model to Reconstruct Blooming at the Global Scale Using a Land Surface Model

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Abstract

Snow algae are found from spring to summer on snowfields and glaciers throughout the world. Their blooming darkens snow surfaces, reducing snow surface albedo and accelerating melting. Uncertainties remain, however, regarding the blooming season and global distribution of these algae. To reproduce snow algal bloom temporal and spatial variability, we improved an existing snow algae model using a land surface model calibrated with a global atmospheric reanalysis dataset. Snowfall and daylight length data for selected model locations were also incorporated. To evaluate its performance, we used *in situ* observational data from 15 polar to alpine area sites. The improvements made in this study allowed the reconstruction of detailed snow algal blooming reports from various locations worldwide, and the results suggested that the major factors affecting the appearance of snow algal blooming were the snow melting period duration and algal growth interruption by new snow cover. We then incorporated the updated snow algae model into a land surface model and performed a global simulation. In this case, our simulation suggested that red snow could appear on snowfields during the melting season but only in the absence of frequent new snow falls, and if the snow cover persists long enough to allow prolonged algal growth.

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3	Land Surface Model					
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10						
11	Key Points:					
12 13	• Red snow phenomena caused by snow algal blooming happen on snowfields and glaciers worldwide					
14 15	• Red snow algae model was updated with new observational data from 15 snowfields and incorporated into a land surface model					
16 17 18	• Revised model simulations achieved good agreement with red snow observations at snowfields worldwide, from polar to mid-latitudes					

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22 Uncertainties remain, however, regarding the blooming season and global distribution of these

algae. To reproduce snow algal bloom temporal and spatial variability, we improved an existing

snow algae model using a land surface model calibrated with a global atmospheric reanalysis

25 dataset. Snowfall and daylight length data for selected model locations were also incorporated.

To evaluate its performance, we used *in situ* observational data from 15 polar to alpine area sites.

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factors affecting the appearance of snow algal blooming were the snow melting period duration

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35

36 **1 Introduction**

Snow algae are photosynthetic microbes growing on snow and ice and are common globally in snowfields and glaciers. Snow algal blooms occur on thawing snow surfaces and

change the color of the snow to red, orange, or green (Hoham and Remias, 2020). In particular,

the red snow phenomenon, which is caused by blooms of *Sanguina* (S.) *nivaloides* (renamed

41 from *Chlamydomonas nivalis* by Procházková et al., 2019) and *Chloromonas* sp., have been

42 reported throughout spring and summer seasons worldwide (Thomas and Duval, 1995; Painter et

43 al., 2001; Novis, 2002; Takeuchi and Kohshima, 2004; Takeuchi et al., 2006a; Stibal et al., 2007;

44 Fujii et al., 2010; Spijkerman et al., 2012; Lutz et al., 2014, 2015, 2016; Hisakawa et al., 2015;

45 Cepák et al., 2016; Remias et al., 2016; Tanaka, 2016; Tanaka et al., 2016; Ganey et al., 2017;

Huovinen et al., 2018; Moestrup et al., 2018; Segawa et al., 2018; Onuma et al., 2018;

47 Procházková et al., 2019; Zawierucha and Shain, 2019; Vimercati et al., 2019) (Fig. 1). The

48 conditions required for snow algal growth include the availability of liquid water, solar radiation,

49 and nutrients (Hoham and Remias, 2020). Previous studies have suggested that snow algal

⁵⁰ abundance can change significantly over time, due to their growth, accumulation, and cell losses

during the snow-melting season (Müller et al., 2001; Takeuchi, 2013; Onuma et al., 2016, 2018).

52 However, it is unclear exactly when and where the red snow phenomenon appears in snowfields

53 and glaciers worldwide.

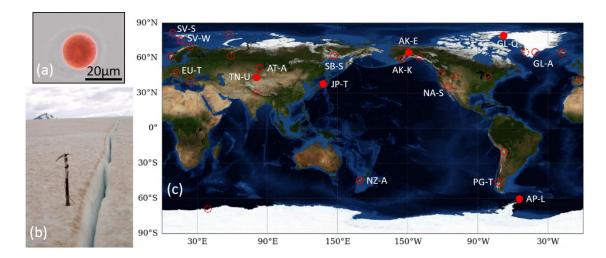




Figure 1 a red snow algae; b the red snow phenomenon on an Alaskan snowfield; c previously reported distribution of the red snow phenomena on snowfields and glaciers worldwide. Solid, open, and open-dotted marks indicate seasonal data validation sites, one-day data validation sites, and no applicable sites in this study, respectively. Only validation sites where red snow algal abundance was quantified by the cell count method were used. Site names correspond to those in Table 1

62 To reproduce snow algal growth and evaluate its impact on snow melting, a numerical equation, the "snow algae model," was recently proposed. Field observations in a Greenlandic 63 glacier showed that snow algal abundance exponentially increased with snow melting, provided 64 there was no intervening snowfall, reaching the carrying capacity of the snowpack in late 65 summer (Onuma et al., 2018). An increase in snow algal abundance with snow melting has also 66 been reported for Alaska and Japan (Takeuchi, 2013; Onuma et al., 2016). Based on these field 67 observations, Onuma et al. (2018) established a numerical model for snow algal growth. The 68 model was able to simulate the exponential growth of S. nivaloides using biological parameters 69 70 (initial cell concentration, growth rate, and carrying capacity) and the duration of snow melting. The snow algae model was then incorporated into a physically based snow albedo model (Aoki 71 et al., 2011; Onuma et al., 2020), which calculated the surface albedo of snow containing black 72 73 carbon, mineral dust, and snow algae.

74 Many studies have suggested that algal abundance can be affected by atmospheric conditions, as well as by the physical and chemical conditions of snow, such as snow melting, 75 snowfall, solar radiation, and nutrient availability (Stibal et al., 2007; Takeuchi, 2013; Lutz et al., 76 2014; Onuma et al., 2016, 2018; Hoham and Remias, 2020). The snow algae model did not 77 include such effects on algal growth, however, and it was evident that variables such as daylight 78 length and snowfall events in particular, which affect algal photosynthesis and vary across global 79 locations, should be considered if the model was to be applied to other snowfield or glacier sites. 80 Although there have been a number of studies on snow algae worldwide, most lack the *in situ* 81 data for meteorological conditions and snow physics-including air temperature, solar radiation, 82 precipitation, snow depth in water equivalent, and snow temperature—which are required to 83 evaluate the snow algae model. This suggested that a dataset of snow physics and meteorological 84 conditions obtained from a land surface model and global reanalysis data may be useful for 85

86 evaluating the snow algae model using snow algal data in published papers as well as for

simulating snow algal growth globally.

A number of land surface models, which can be driven using reanalysis data, have been 88 proposed to simulate temporal and spatial changes in snow properties on a global scale. For 89 example, CLM (Lawrence et al., 2019), ORCHIDEE (Krinner et al., 2005), ISBA (Decharme et 90 91 al., 2016), and MATSIRO (Takata et al., 2003; Nitta et al., 2014; 2017) have been established as land surface models incorporated into climate models to represent physical land processes. These 92 models can calculate temporal and spatial changes in the snow water equivalent, snow 93 temperature, water runoff, evaporation, and sublimation globally. In addition, a simulation with a 94 land surface model can be conducted independently, using atmospheric conditions near the land 95 surface as the input data. Such a simulation is termed an offline land simulation. Global 96 97 atmospheric reanalysis data are generally used as atmospheric conditions for offline land simulations, which allows temporal and spatial changes in land physical properties to be 98 reproduced without model bias that may derive from atmospheric conditions. 99

100 In this study, we first improved the snow algae model using *in situ* snow algal abundance data, as reported from 15 locations worldwide, and the physical and meteorological snow 101 conditions for these locations, as obtained from a land surface model. We incorporated the effect 102 of snowfall and daylight length into the snow algal model established by Onuma et al. (2018) 103 and then conducted offline land simulations at the study sites using various atmospheric 104 conditions and biological parameters. Finally, we performed a global simulation of the land 105 106 surface model, including the snow algae model, using atmospheric reanalysis data sets to investigate seasonal and geographical variations in snow algal blooms worldwide. 107

108

109 2 Model description and experimental design

110 2.1 Snow algae model

We used a snow algae model to calculate temporal changes in the abundance of snow algae across various snowfields. Temporal changes in the abundance of *S. nivaloides* on surface snow can be expressed using a differential logistic growth equation. The population density and growth period of the microbes were calculated as shown in Eqs (1) and (2) (Onuma et al., 2018):

$$\frac{dX}{dGP_t^M} = \mu X_0 \left(1 - \frac{X_0}{K} \right), \text{ and}$$
(1)

$$\begin{cases} GP_t^M = GP_{t-1}^M + 1 \ (T_{sn1} \ge 273.15[K]) \\ GP_t^M = GP_{t-1}^M \ (T_{sn1} < 273.15[K]) \end{cases}$$
(2)

- 115 where X and X_0 represent population densities of microbes at growth periods GP_{t}^{M} and GP_{t0}^{M} .
- respectively, and μ indicates the hourly microbe growth rate. K denotes the snow surface algae
- 117 carrying capacity, and GP^{M}_{t0} represents the day that algae first appear on the snow surface. GP^{M}_{t}
- represents the cumulative hours when the snow surface temperature, T_{snl} , is above 0 °C (as algal
- growth only occurs on the melting snow surface). Although algal cells observed in the red snow surface are often in the cyst stage (e.g. Onuma et al., 2018)—when their populations do not

actively increase—the model assumes algal growth on the snow surface, including the 121 122 condensation of algal cells grown at the subsurface, with snow melt.

In this study, we improved this model, which may include growth and / or condensation 123 of the algal cells, to broadly reconstruct in situ observations of algal cell abundance reported for 124 snow surfaces worldwide. To calculate temporal changes in the abundance of red snow algae on 125 surface snow at various locations, we added the effects of snowfall and daylight length into the 126 original snow algae model proposed by Onuma et al. (2018). 127

128 Onuma et al. (2016) reported that the abundance of a snow alga Chloromonas (C.) nivalis on a snowpack in Japan decreased when there were occasional snowfalls in spring; however, the 129 snow algae model was not able to simulate such a decrease because it assumed a monotonic algal 130 abundance increase. Because the snow algae model could calculate temporal changes in algal 131 cell concentration in a surface snow layer to a depth of 2 cm, the accumulation of new snow 132 above the algal layer should result in a decline in algal cell concentration. In this study, we 133 updated the snow algae model to quantify the effect of snowfall on algal abundance in the top 2 134 cm layer of surface snow. 135

Daylight length is another metric with the potential of affecting algal growth because 136 snow algae grow photosynthetically. A previous study reported that snow algal blooms first 137 appeared under light conditions with a penetration of 0.1 % of the surface radiation (Curl et al., 138 1972), suggesting that snow algae on snow surfaces can grow during daylight but not during the 139 night. Therefore, we assumed that snow algae grow in sunlight and incorporated a day-night 140 141 cycle effect on snow algal growth into the snow algae model, as shown in Eq. (3):

$$\begin{cases} GP_t^{MR} = GP_{t-1}^{MR} + 1 \ (T_{sn1} \ge 273.15 \ [K] \ and \ Sw > 0 \ [Wm^{-2}]) \\ GP_t^{MR} = GP_{t-1}^{MR} \ (T_{sn1} < 273.15 \ [K] \ or \ Sw = 0 \ [Wm^{-2}]) \end{cases}$$
(3)

where GP^{MR}_{t} is defined as the cumulative hours of snow melting under daylight conditions, 142

which can increase when the snow surface temperature, T_{snl} , and downward shortwave radiation, 143 Sw, are above 273.15 K and 0 W m⁻², respectively, at t. 144

We added two further equations to the calculation of snow algal growth, to quantify the 145 effect of snowfall on snow algal abundance, as shown in Eqs (4)–(6): 146

$$X'_{t-1}^{MRF} = X_{t-1}^{MRF} \left(1 - \frac{P_{sn} * 3600 * 1000}{20 * D_{sn}} \right), \tag{4}$$

$$GP'_{t-1}^{MRF} = \frac{\log_e(\frac{b}{a})}{-\mu}, a = \frac{(K-X_0)}{X_0}, b = \frac{K}{X'_{t-1}^{MRF}} - 1, \text{ and}$$
 (5)

$$\begin{cases} GP_t^{MRF} = GP'_{t-1}^{MRF} + 1 \ (T_{sn1} \ge 273.15 \ [K] \ and \ Sw > 0 \ [Wm^{-2}]) \\ GP_t^{MRF} = GP'_{t-1}^{MRF} \ (T_{sn1} < 273.15 \ [K] \ or \ Sw = 0 \ [Wm^{-2}]) \end{cases}$$
(6)

where X_{t}^{MRF} indicates algal cell concentration during the growth period (GP_{t}^{MRF}) , including the 147 effects of snow melting, daylight length, and snowfall. X^{MRF}_{t} decreases based on the snowfall 148

rate P_{sn} (mm s⁻¹), when snowfall occurs. If the new snow cover, which is calculated using P_{sn} and snow density D_{sn} (kg m⁻³), exceeds 20 mm in 1 h, X^{MRF}_{t} is reset to X_0 . In this study, D_{sn} was 149

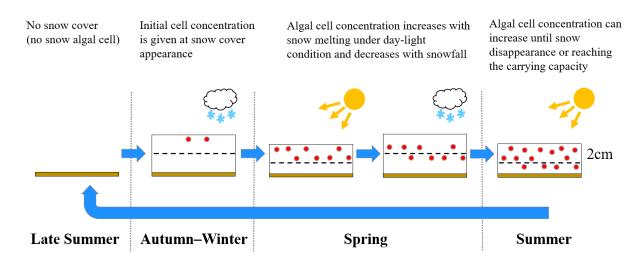
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assumed to be 300 kg m^{-3} , which is generally used for this parameter in land surface models. 151

152 $GP^{'MRF}_{t}$ in Eq. (5) has been changed from Eq. (1) and represents the growth period at $X^{'MRF}_{t}$. In 153 this study, GP^{MRF}_{t} was used as the GP^{M}_{t} in Eq. (1), to calculate hourly algal cell concentrations.

An overview of the updated snow algae model can be seen in Fig. 2. In the model, initial cell concentration, X_0 , becomes established at the first snow appearance, and then the cell concentration increases with the duration of snow melting under daylight conditions before decreasing when new snowfall covers the surface. As the model could not consider the migration of motile algal cells in a snowpack, algal cell concentrations reduced by snowfall were not conserved in the model snow layers and did not increase again until there was further snow

- 160 melting under daylight conditions. The modeled algal cell concentrations reverted to zero once
- 161 the snowpack disappeared.
- 162



163

Figure 2. Concept supporting the updated snow algae model in this study. Dashed line indicates
 the snow surface (top 2 cm) where snow algal cell can increase in snow algae model

167

2.2. Using *in situ* data for snow algal abundance to validate the snow algae model

In this study, we used temporal changes in algal cell abundance observed *in situ* at 15 locations as model validation data. An overview of the validation sites located in polar and alpine regions—six sites representing sites used in previous studies, and nine representing those observed specifically for this work—can be seen in Fig. 1c and Table 1.

Table 1. Maximum algal cell concentrations reported for red algal blooms from various snowfields

Site names	Study sites (Region)	Location	Elevation [m]	Red snow algal species	Maximum algal cell concentration [cells m ⁻²]	References
SV-S	Spitsbergen Island (North West Svalbard)	79.01N 12.48E	350	Chloromonas sp.	2.0×10^8	Lutz et al., 2015
GL-Q	Qaanaaq Area (North West Greenland)	77.5N 69.17W	944	S. nivaloides	3.5×10^{7}	Onuma et al., 2018
SV-W	Wedel Jarlsberg Land (South West Svalbard)	77.04N 15.14E	100	S. nivaloides	5.9×10^{9}	Stibal et al., 2007
GL-A	Ammassalik Island (South East Greenland)	65.6N 37.8W	150	S. nivaloides	1.8×10^{8}	Lutz et al., 2014
AK-E	Eastern Alaska Mountains (Alaska, USA)	64N 146W	1680	S. nivaloides	5.1×10^{7}	Takeuchi, 2013
SB-S	Suntar-Khayata Mountains (Siberia, Russia)	62.5N 141E	2509	Chloromonas sp.	1.8×10^8	Tanaka et al., 2016
АК-К	Kenai Mountains (Alaska, USA)	60N 150W	1100	S. nivaloides	6.7×10^{9}	Takeuchi et al., 2006b
AT-A	Altai Mountains (Altai, Russia)	49.51N 86.33E	3130	Chloromonas sp.	2.2×10^6	Takeuchi et al., 2006a
EU-T	Tyrol Mountains (Austria, Europe)	46.55N 10.55E	2975	S. nivaloides	5.0×10^8	Remias et al., 2016
TN-U	Urumqi Glacier (Tienshan, China)	43.06N 86.49E	4090	Chloromonas sp.	1.3×10^{6}	Tanaka, 2016
NA-S	Sierra Nevada Mountains (California, North America)	37.55N 119.55W	3425	S. nivaloides	1.3×10^{7}	Painter et al., 2001
JP-T	Tateyama Mountains (Japan)	36.34N 137.36E	2300	S. nivaloides	1.1×10^{8}	This study
NZ-A	Arthur's Pass Mountains (New Zealand)	42.89S 171.53E	1967	Chlainomonas kolii	1.2×10^{7}	Novis et al., 2002
PG-T	Tyndall Glacier (Southern Patagonia Ice fields, Chile)	51.15S 73.15W	1100	Chloromonas sp.	6.0×10^5	Takeuchi and Kohshima, 2004
AP-L	Livingston Island (Antarctic Peninsula)	62.39S 60.23W	13	S. nivaloides	4.9×10^8	This study

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We used *in situ* algal cell concentration per area (cells m⁻²) for model validation in this study. The algal data reported in previous studies had all been quantified using microscopic cell counts in the surface snow layer (top 2 cm). These data covered locations in NW Greenland (GL-

Q; Onuma et al., 2018), Alaska (AK-K and AK-E, Takeuchi et al., 2006b; Takeuchi, 2013), Altai

(Russia; AT-A, Takeuchi et al., 2006a), Siberia (SB-S, Tanaka et al., 2016), Tienshan (China; 180 TN-U, Tanaka, 2016), and Patagonia (PG-T, Takeuchi and Kohshima, 2004). Surface snow algal 181 abundance data reported from Svalbard (Arctic Ocean; SV-W and SV-S, Stibal et al., 2007; Lutz 182 et al., 2014), SE Greenland (GL-A, Lutz et al., 2014), Europe (EU-T, Remias et al., 2016), North 183 America (NA-S, Painter et al., 2001), and New Zealand (NZ-A, Novis et al., 2002) were also 184 used. Because most algal cell abundance data had been reported as algal cell concentration per 185 unit of melt water volume (cells L⁻¹), we converted these data to algal cell concentrations per unit 186 of area, assuming that the snow density was 500 kg m⁻³ and that the collected samples had been 2 187 cm deep. 188

We also used unpublished algal data obtained from snowfields in Japan (Mt. Tateyema) 189 and the Antarctic Peninsula (Livingston Island), in 2012 and 2015 respectively. Mt. Tateyama (N 190 36.3°, E 137.4°) is an alpine snowfield above the tree line (1850–3000 m ASL), located in W 191 Japan, and red snow algal blooming can be observed there annually as the snow pack thaws 192 (May-July) (Segawa et al., 2005). We selected a snowy plateau called Raichozawa, located at 193 2300 m, as the study site (JP-T) because the snowpack here remained until early August. 194 Livingston Island is located in the South Shetland Islands near the Antarctic Peninsula. The 195 Spanish research station, Juan Carlos I (S 62.4°, W 60.2°), and the Hurd Peninsula ice cap (S 196 62.8°, W 60.8°) are located on the Hurd Peninsula, Livingston Island. Glaciological field 197 198 observations have been conducted here to study the physical properties of ice on glacier dynamics, including surface mass balance and ice velocity on the ice cap (Navarro et al., 2013; 199 Sugiyama et al., 2019). Red snow algal blooms can be found on the coastal snowpack on 200 Livingston Island from January-February (Hodson et al., 2017). Our study site (AP-L) was 201 located on the Livingstone Island coastal snowfield. 202

203 Temporal changes in the abundance of red snow algae were quantified using surface snow samples collected through d 117–217, in 2012, at JP-T, and during 6 sampling days during 204 the period extending through d 19–30, in 2015, at AP-L. Samples were collected on each 205 206 observation date from 3 to 10 randomly selected surface locations (0-2 cm depths), using a stainless-steel scoop. The sampling areas occupied ~ 100 cm^2 and were recorded for each 207 collection. Samples were melted on-site and preserved in 3 % formalin in 30 mL clean 208 209 polyethylene bottles before being transported to Chiba University, Japan, for analysis. Algal abundances were obtained from the water samples by counting cells and was represented as the 210 cell number per unit surface area of snowpack (cells m^{-2}). This methodology has been described 211 212 in more detail in previous studies, which included those in which field observations were carried out at sites GL-Q, AK-E, SB-S, AK-K, AT-A, TN-U, and PG-T, as shown in Table 1. 213

214 2.3. MATSIRO land surface model

We used the Minimal Advanced Treatments of Surface Interaction and Runoff land surface model (MATSIRO; Takata et al., 2003; Nitta et al., 2014, 2017) to evaluate temporal changes in snow algal abundance on snowfields worldwide. This model was developed to simulate land-based physical processes in a general circulation model, and six versions—the MATSIRO6, involving up to three snow layers, six soil layers (14 m in total), and a single canopy layer—were used for the Model for Interdisciplinary Research on Climate (MIROC6; Tatebe et al., 2019).

MATSIRO6 can simulate temporal and spatial changes in the snow water equivalent, snow cover fraction, and snow temperature. The snow water equivalent was simulated based on the water balance, and in MATSIRO6 it was derived from the snowfall rate, snow sublimation,

- snowmelt, and refreezing of rainfall and snowmelt. The snow cover fraction was simulated using
- a lognormal distribution function for the subgrid snow water equivalent distribution, whereas the
- 227 temperature of each snow layer was simulated using a thermal conductivity equation. The
- detailed methodology for calculating these physical properties of snow may be found in Nitta et al. (2014). Temporal changes in these snow physical properties have been validated using
- 229 al. (2014). Temporal charges in these show physical properties have been validated using 230 observations from various snowfields and derived from data for other land surface and snow
- physical models reported by the model intercomparison project (ESM-SnowMIP; Krinner et al.,
- 232 2018). In this study, we used snow surface temperatures calculated using MATSIRO6 as input
- data for snow algal simulations at the study sites.
- 234 2.4. Atmospheric forcing for land surface modeling

The atmospheric conditions used in MATSIRO6 simulations were derived from atmospheric reanalysis data (Table 2). Various datasets for atmospheric reanalysis—which were derived from global atmospheric reanalysis data near the land surface, and bias-corrected using global meteorological observations—have been established for land surface modeling. In this study, we used the atmospheric conditions derived from the reanalysis dataset for each study site, because time-series meteorological observations were not always available.

The WFDEI forcing data set (Weedon et al., 2014) was used as the atmospheric conditions for land surface modeling in this study. This atmospheric reanalysis dataset includes three-hourly information on surface air temperature, surface air pressure, downward radiation (shortwave and longwave), humidity, wind speed, and precipitation rate. While this reanalysis data set is appropriate for land surface modeling at global or regional scales, high levels of uncertainty are present when it is used for meteorological conditions at specific elevations due to its rough horizontal resolution ($0.5^{\circ} \times 0.5^{\circ}$ globally).

For this reason, we applied elevation corrections to simulate temporal changes in snow 248 algal abundance at specific sites. The surface air temperature at each site was corrected using 249 elevation information and the original air temperature and by applying a temperature lapse 250 rate, which was assumed to be - 6.5×10^{-3} Km⁻¹. The surface air pressure of each snowfield was 251 corrected using elevation information and surface air temperature (before and after the 252 correction), as recommended by the World Meteorological Organization (WMO-No. 8, in CIMO 253 Guide, Part I, Chapter 3). The specific humidity at each site was corrected from the original data 254 using the ratio of surface air pressure before and after correction, whereas the snowfall rate was 255 corrected from total precipitation data, using the ratio of rain to snow, which itself was estimated 256 using the surface air temperature, air pressure, and specific humidity given in MATSIRO6. The 257 input and output data for the offline land simulation used to calibrate MATSIRO6 in this study 258 259 can be seen in Table 2.

Variable or parameter	Description	Estimated Value	Unit					
Land surface model MATSIRO6								
Ta	Atmospheric temperature	Input	K					
Qa	Atmospheric humidity	Input	$\mathrm{kg} \mathrm{kg}^{-1}$					
Pa	Atmospheric pressure	Input	hPa					
$W\!s$	Wind speed	Input	$m s^{-1}$					
Sw	Downward shortwave radiation	Input	$W m^{-2}$					
Lw	Downward longwave radiation	Input	$W m^{-2}$					
Pr	Total precipitation rate	Input	kg m $^{-2}$ s $^{-1}$					
Psn	Snowfall rate	Calculated	kg m 2 s 1					
Sn	Snow water equivalent	Calculated	$\mathrm{kg}~\mathrm{m}^{-2}$					
Tsn	Snow temperature	Calculated	К					
Dsn Snow density		Parameter	$\mathrm{Kg}\ \mathrm{m}^{-3}$					
	Snow algae model							
X_o	Initial cell concentration	Parameter	cells m^{-2}					
μ	Growth rate	Parameter	$hour^{-1}$					
K	Carrying capacity	Parameter	cells m^{-2}					
GP	Growth period	Calculated	hour					
X	Algal cell concentration	Calculated	cells m^{-2}					

261	Table 2. V	variables and	parameters re	equired t	for land	surface	modeling	in this s	tudy

2.5. Experimental design of snow algal growth simulation

To evaluate the algal model version as improved in this study, algal growth simulations (Ag-exp) were conducted under three different conditions at 15 sites, as shown in Fig. 1c and Table 1. The three conditions covered snow algal growth with: (1) the effect of snow melting only (X^M) ; (2) effects of snow melting and daylight length only (X^{MR}) ; and (3) effects of snow melting, day-light length, and snowfall (X^{MRF}) (Table 3). The atmospheric conditions for the land offline simulations were supplied by the WFDEI forcing dataset, which had been corrected for

study site elevations in advance.

270

271 **Table 3.** Overview of sensitivity tests applied in this study

Experiment ID	Initial cell Concentration X_0 (cells m ⁻²)	Growth rate μ (hour ⁻¹)	Carrying capacity K (cells m ⁻²)	Atmospheric reanalysis data set
Algal growth simulation (Ag-exp)	6.33	0.018	Observation each site	WFDEI
Initial cell ensemble (X ₀ -exp)	$1.0 - 1.0 \times 10^3$	0.018	Observation each site	WFDEI
Growth rate ensemble (μ-exp)	6.33	0.01 - 0.025	Observation each site	WFDEI
Atmospheric reanalysis data set ensemble (Fd-exp)	6.33	0.018	Observation each site	WFDEI or GSWP3-FD or CRUJRA

272

The initial snow depth (in water equivalent) in MATSIRO6 was assumed at each study site to remain stable until the maximum algal cell concentration date. For example, the initial value was assumed to be 1000 kg m⁻² for Arctic sites and 3000 kg m⁻² for Japanese sites, which was consistent with snow depth observations (equal to 9 m in winter at JP-T, Osada et al., 2004). The snow surface temperature calculated using MATSIRO6 and the derived snowfall rate and solar radiation from atmospheric reanalysis data were used as input data for the snow algae model in this study.

Biological parameter data—such as initial cell concentration (X_0), growth rate (μ), and carrying capacity (K)—were not generally available for red snow algae in snowfields worldwide. To overcome this, we applied field observation values from the snowfield of a Greenlandic glacier, as reported by Onuma et al. (2018), for Ag-exp—and so X_0 and μ were assumed to be 6.33 cells m⁻² and 0.018 h⁻¹, respectively. Maximum algal cell concentrations observed from the sites (Table 1) were used for K because the carrying capacity of red snow algae might vary for each snowfield, as suggested by Onuma et al. (2018).

287 Simulations were conducted from January 1 to December 31 each year at the study sites,
288 except for the southern hemisphere sites NZ-A and PG-T, where 1998 and 1999 data for July 1
289 to December 31 were used.

We conducted more sensitivity testing on the updated snow algae model using two 290 291 biological parameters—initial cell concentration (X_0 -exp), and growth rate (μ -exp)—at each observation site (Table 3). Onuma et al. (2018) reported that the S. nivaloides initial cell 292 concentration and growth rate were 6.33 and 694 cells m^{-2} and 0.39 and 0.42 d^{-1} (0.016 and 0.018 293 h^{-1}), respectively, at 2 sites on a Greenlandic glacier. Field observations suggested that S. 294 nivaloides algal spores (cysts) were wind induced onto the snow surface during the early melting 295 season, and they assumed that the initial cell concentration consisted of these wind-supplied algal 296 spores before on-site algal growth initiation. Based on a previous study, the range for the initial 297 cell concentrations (X_0 -exp) was assumed for sensitivity testing to be between 1–1000 cell m⁻². 298 Because snow algae growth rates vary between snowfields worldwide, it had been suggested 299 previously that the sensitivity of the snow algae model to growth rates should be investigated. 300 Previous studies have reported that C. nivalis growth rates, as obtained from field observations 301 and cultivation, were 0.22 (Onuma et al., 2016) and 0.60 d⁻¹ (Leva et al., 2009). Based on these 302 data, we assumed that the μ -exp growth rate ranged between 0.01–0.025 h⁻¹. The maximum algal 303 cell concentration observed from the study sites was assumed to be K, for both X_0 -exp and μ -304 exp, the same as for Ag-exp. 305

In addition to applying sensitivity testing to biological variables, we reviewed model 306 sensitivity to four atmospheric conditions. Although temporal changes in snow algal abundance 307 may be affected by snow physical or atmospheric conditions, the quantitative effect of such 308 conditions on algal cell abundance remained uncertain. Therefore, Fd-exp, which is an ensemble 309 simulation using the WFDEI, GSWP3-FD, and CRUJRA forcing datasets, was conducted in this 310 study, to review the sensitivity of algal growth to atmospheric conditions (Table 3). GSWP3-FD 311 (Hurk et al., 2016; Kim, 2017) and CRUJRA (Harris, 2019) forcing datasets provided the 312 different atmospheric conditions, and an overview of the three datasets, including WFDEI, can 313 be seen in Table S1. The surface air temperature, surface air pressure, and specific humidity data 314 from GSWP3-FD and CRUJRA were corrected using each site's elevation, as was WFDEI. The 315 initial cell concentration, growth rate, and carrying capacity were taken as 6.3 cells m⁻², 0.018 h⁻¹ 316 and the observed maximum cell concentration (cells m⁻²) for Fd-exp, respectively. The 317 experimental architecture for the sensitivity tests used in this study has been summarized in 318 Table 3. 319

320 To evaluate snow algae model sensitivity to biological variables and atmospheric conditions, we used the two variables visible cell concentration of algal bloom (VCAB), and the 321 reaching time to the algal bloom (RTAB). In this study, VCAB was defined as 5.0×10^5 cells m⁻² 322 because this was the minimum algal cell concentration for a red snow phenomenon observed on 323 a Greenland glacier by Onuma et al. (2018) and was comparable to algal bloom concentrations 324 observed in other areas (e.g., 2.2×10^6 cells m⁻² at AT-A, 1.3×10^6 cells m⁻² at TN-U, and 6.0×10^6 cells m⁻² at TN-U areas (e.g., 2.2×10^6 cells m⁻² at AT-A, 1.3×10^6 cells m⁻² at TN-U, and 6.0×10^6 cells m⁻² at AT-A, 1.3×10^6 cells m⁻² at TN-U, and 6.0×10^6 cells m⁻² at AT-A, 1.3×10^6 cells m⁻² at TN-U, and 6.0×10^6 cells m⁻² at AT-A, 1.3×10^6 cells m⁻² at TN-U, and 6.0×10^6 cells m⁻² at AT-A, 1.3×10^6 cells m⁻² at TN-U, and 6.0×10^6 cells m⁻² at AT-A, 1.3×10^6 cells m⁻² at TN-U, and 6.0×10^6 cells m⁻² at AT-A, 1.3×10^6 cells m⁻² at TN-U, and 6.0×10^6 cells m⁻² at TN-U, 325 10^5 cells m⁻² at PT-G). The time taken to reach the VCAB was defined as the RTAB, and if a 326 calculated algal cell concentration did not reach the VCAB in a simulation, the date of the 327 328 calculated maximum abundance was still defined as the RTAB.

329 **3 Results**

330 3.1. Simulation and evaluation of algal cell concentrations achieved using the original331 snow algae model

The algal growth simulations, Ag-exp, produced RTABs ranging from d 155–220; the 332 date depended on their Northern Hemisphere locations, with mid-latitude site RTABs being 333 generally earlier than those for polar sites. Specifically, the RTAB ranged from d 155- to 220 334 335 (early June to early August), at the Northern Hemisphere mid-latitude sites (N 30–60°; AT-A, EU-T, TN-U, NA-S, and JP-T), and from d 175–220 for the polar sites (N 60–90°; SV-S, SV-W, 336 GL-Q, GL-A, AK-E, AK-K, and SB-S). The algal cell concentration, X^{M} , at JP-T, which was 337 calculated using snow melting duration only, showed no significant increase from d 1-70, and 338 then increased, reaching VCAB on d 155 (RTAB = d 155) (Fig. 3). X^{M} values for mid-latitude 339 sites were found to reach the VCAB earlier than the polar sites. Similarly, X^{M} at Southern 340 341 Hemisphere mid-latitude sites (S 30-60°; NZ-A and PG-T) reached the VCAB earlier than it did at the single Southern Hemisphere polar site (S 60–90°; AP-L). The RTAB estimated from X^{MR} , 342 which was calculated from the duration of snow melting under daylight conditions, did not 343 significantly differ from that estimated at the study sites using X^{M} (Fig. 3). 344 345

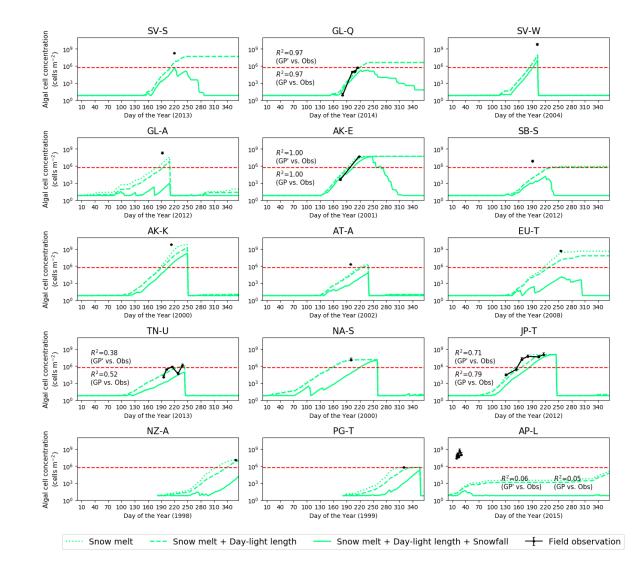




Figure 3. Temporal changes in red snow algal cell concentrations at each site. Dotted, dashed and solid lines indicate X^M , X^{MR} and X^{MRF} , respectively

The simulation achieved using the original snow algae model showed algal cell 351 concentration changes over time which agreed with in situ values for snowfields at GL-Q, AK-E, 352 TN-U, and JP-T. For example, Ag-exp showed that the RTAB estimated for GL-Q from X^M was 353 d 215, which was the same date that the maximum cell concentration was observed at the site 354 (Fig. 3). The RTABs for sites AK-E, EU-T, TN-U, JP-T, and NZ-A also agreed well with the 355 observations, whereas the changes in X^{MR} over time did not significantly differ from those for 356 X^{M} , at any of the sites. The determination coefficients for temporal change in X^{M} (and X^{MR}), 357 compared with those for the observed algal cell concentrations, were 0.97 (P < 0.05), 1.00 (P < 0.05) 358 359 (0.05), (0.38) (P > 0.05), and (0.71) (P < 0.05), at GL-Q, AK-E, TN-U, and JP-T, respectively.

360 3.2. Simulation and evaluation of algal cell concentrations achieved using the improved361 snow algae model

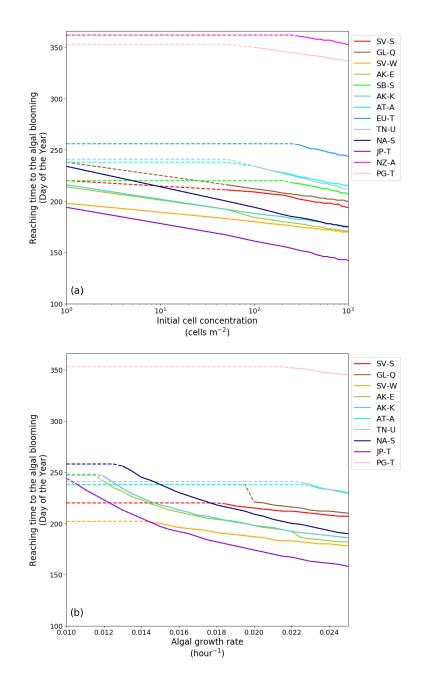
RTABs simulated using the updated snow algae model ranged from d 180–240 in the 362 Northern Hemisphere, showing that the snow algal bloom timing estimates were significantly 363 later than those simulated using the original snow algae model, at all sites. For example, the algal 364 cell concentration, X^{MRF} , at JP-T, which was simulated using snow melting, daylight length, and 365 interruption by new snow cover effects, kept X_0 from d 1–100, and then reached the VCAB on d 366 180 (RTAB = d 180) (Fig. 3). The RTAB ranged from d 180–255 (late June to early September) 367 at the Northern Hemisphere mid-latitude sites, and from d 185–220 in the polar sites. In Southern 368 Hemisphere, RTABs were 365, 355, and 40, at sites NZ-A, PG-T, and AP-L, respectively. These 369 results showed that RTABs for X^{MRF} were later than had been the case for X^{M} and X^{MR} . We also 370 saw that there were no significant differences in the RTABs estimated using X^{MRF} among the 371 sites at different latitudes, unlike the case for those estimated using either X^{M} or X^{MR} . 372

Snow algal abundances simulated using the updated model produced seasonal change 373 results which agreed better with observational data than those simulated using the original snow 374 algae model. Ag-exp showed that X^{MRF} at GL-Q started to increase on d 175 and then reached the 375 VCAB on d 220. The temporal changes estimated using X^{MRF} agreed with the site observation 376 data better than those achieved using either X^{M} or X^{MR} (Fig. 3). The determination coefficients 377 for the temporal change in X^{MRF} against the observation data were 0.97 (P < 0.05), 1.00 (P < 378 0.05), 0.52 (P > 0.05), and 0.79 (P < 0.05), for sites GL-A, AK-E, TN-U and JP-T, respectively. 379 These coefficients were slightly higher than those for the X^M and X^{MR} , whereas the RTABs 380 calculated using X^{MRF} agreed with the timing of the red snow phenomenon observed at the other 381 sites, including SV-S, SV-W, EU-T, NA-S, NZ-A, PG-T, and AP-L. 382

383 3.3. Model sensitivity testing in relation to biological parameters and atmospheric384 conditions

Testing X_0 -exp sensitivity to the initial algal cell concentration showed that the RTAB 385 was approximate 15–30 d earlier where the initial cell concentration was 100-fold greater than 386 the original concentration (1.0 cells m^{-2} , Fig. 4a). For example, the RTABs in the simulation of 387 the minimum initial cell concentration (1.0 cells m⁻²) were on d 215 and 195, at AK-E and JP-T, 388 respectively. Simulation results showed that the AK-E RTABs were on d 200, 180, and 175, for 389 the cases in which the minimum initial cell concentrations increased by a factor of 10, 100, and 390 1000, respectively. Under similar circumstances, the RTABs for JP-T were on d 180, 160, and 391 145. X^{MRF} did not reach the VCAB before the disappearance of snow in either GL-A or AP-L, in 392 any of the simulations. 393

The test of μ -exp sensitivity to algal growth rate showed that, in the case of a 10 % greater growth rate, the RTAB was approximately 10 d earlier than the original rate (Fig. 4b). RTABs simulated using a growth rate of 0.018 h⁻¹ (original case) were 210 and 180 d at AK-E and JP-T, respectively. The RTABs at AK-E were simulated to be d 200, 195, and 190, for growth rates 10, 20, and 30 % greater than that of the original rate, respectively. Under similar circumstances, the JP-T RTABs were simulated to be d 170, 160, and 155. X^{MRF} did not reach the level of algal blooming at GL-A, SB-S, EU-T, NZ-A, or AP-L, in any of the simulations.



402

Figure 4. Sensitivity of snow algal growth rate to biological parameters at each site: a initial cell
 concentration sensitivity; b algal growth rate sensitivity

405

Testing Fd-exp sensitivity to atmospheric conditions showed that the RTAB estimate 406 results significantly varied among the atmospheric reanalysis datasets, even at the same site. The 407 minimum, median, and maximum RTABs, derived from simulations using the WFDEI, GSWP3-408 FD, and CRUJRA datasets, can be seen for each site in Fig. 5-which also shows the 409 atmospheric reanalysis data set uncertainties for the RTABs. The RTABs varied significantly 410 among the data sets at sites SV-S, GL-A, SB-S, AT-A, EU-T, TN-U, and NA-S. The differences 411 412 in the RTABs estimated between the data sets were equal to 100 d at EU-T and just 5 d at site JP-T. 413

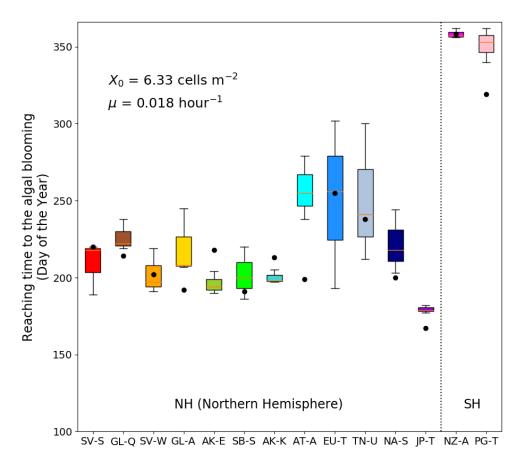


Figure 5. Modeled algal growth uncertainties under different meteorological conditions

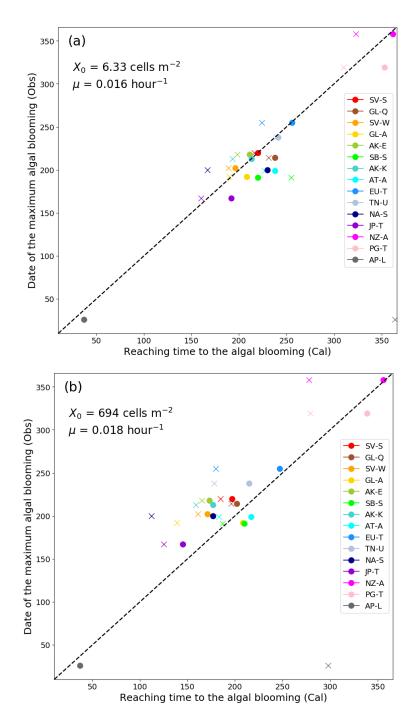
417 4 Discussion

418 4.1. Effect of daylight length on algal bloom simulation results

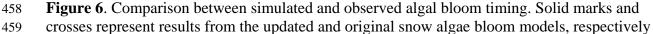
The simulations showed that RTABs did not differ significantly in cases where daylight 419 length was or was not taken into account, indicating that daylight length did not affect snow algal 420 bloom timing to a significant extent. Ag-exp showed that GP^M , which represents cumulative 421 snow melting time, was longer than GP^{MR} , excluding night time (Fig. S1). In the simulations, 422 surface snow could melt at night when the daily surface air temperature was > 10 °C at mid-423 latitude sites (Fig. S2). However, even if the surface snow had melted, snow algae would be 424 unlikely to grow during the night because they cannot not photosynthesize without solar 425 radiation. In experimental studies, the snow algae Cr. tughillensis and Cr. chenangoensis showed 426 the greatest increases in response to the longest daylight scenario (light:dark 24:0 h) (Hoham et 427 al., 2000, 2009), suggesting that snow algal growth depended on daylight length. Hence, GP^{MR} , 428 excluding nighttime, was expected to simulate algal growth better than GP^{M} —however, there 429 were no significant differences in the RTABs calculated using X^M and X^{MR} , at any site (Fig. 3). 430 This indicated that snow did not melt during the night before algal blooming commenced. The 431 432 atmospheric reanalysis data set showed that surface air temperatures often fell below freezing 433 during the night in the early melting season, indicating that snow melting during the night would have been rare. 434

435 4.2. Effect of snowfalls on algal bloom simulations

Updated model simulations which included the effects of snowfall and daylight length 436 were more accurate than those produced using the original model, at most sites, suggesting that 437 snowfall significantly affected algal growth, including algal bloom timing. The RTAB in the 438 case of X^{MRF} was later than it was the case of X^{MR} , at all sites (Fig. 3), whereas comparing temporal changes in the X^{MRF} with those in the X^{MR} showed that the rate of increase in X^{MRF} 439 440 declined due to frequent snowfall during the early melting season at the study sites. For example, 441 daily surface air temperature at site JP-T first exceeded 0 °C on d 90, but snowfalls continued to 442 occur quite frequently, up to d 110. The algae gradually increased from d 90 to 110 at this site, in 443 the case of X^{MR} , whereas X^{MRF} showed no increase during the same period. These results 444 indicated that frequent snowfall events delayed the RTAB. Model simulations showed that 445 increasing trends in X^{MRF} agreed well with observed algal cell concentrations at sites GL-Q, AK-446 E, TN-U, and JP-T (Fig. 3). Figure 6 indicates that the updated snow algae model was generally 447 more accurate than the former model at many study sites, suggesting that incorporating snow 448 cover on the algal growth surface had improved model accuracy. Although the effect of snowfall 449 on an algal surface had been previously reported (Tanaka, 2016; Onuma et al., 2016), it had not 450 been quantified in field observations. Further periodical observations during the early snow 451 melting season are now needed to further improve spring to summer snow algal bloom prediction 452 accuracy. 453







460 4.3. Sensitivity of algal growth simulation to initial cell concentration and growth rate

Testing biological parameter sensitivity suggested that the initial snow algae cell
 concentrations and growth rate estimates in each test were significantly affected by the RTAB. In
 this study, we conducted simulations using the updated snow algae model with an initial cell

concentration of 6.33 cells m^{-2} , and a growth rate of 0.018 h^{-1} . However, these parameters may 464 have introduced some uncertainty, as they were derived using in situ Greenland glacier data 465 (Onuma et al., 2018). S. nivaloides blooming was previously reported as appearing on d 180 and 466 215 at two different sites, with the initial cell concentration and the growth rate at the former site 467 (694 cells m^{-2} and 0.018 h^{-1}) higher than those at the latter site (6.33 cells m^{-2} and 0.016 h^{-1}). 468 Differences in biological parameters would cause uncertainty in the timing of snow algal 469 blooming, and thus, we quantified the range of RTAB uncertainty which could be attributed to 470 the biological parameters observed in the previous study. 471

RTABs simulated using the highest (694 cells m^{-2} and 0.018 h^{-1}) and lowest (6.33 cells 472 m^{-2} and 0.016 h^{-1}) reported biological parameters can be seen in Figs 6a and 6b, respectively, 473 where it can be seen that the RTABs in Fig. 6b were 10-30 d earlier than those in Fig. 6a. Snow 474 475 algal blooming was generally observed on the day between the RTABs in Figs 6a and b, suggesting that the RTAB simulated with the updated snow algae model changed by 476 approximately 10 d, compared with the observed blooming date of the snow algae. Although 477 snow algae initial cell concentrations and growth rates may depend on the amount of mineral 478 dust supplied from the atmosphere and on nutrient conditions (nitrogen and phosphorus), as 479 suggested by Onuma et al. (2016; 2018), the major factors affecting the biological parameters 480 remain uncertain. Field data on snow algae biological parameters from various snowfields and 481 glaciers worldwide are needed. However, our simulations suggested that the updated snow algae 482 model could forecast snow algal bloom timing with an accuracy of approximately 10 d. 483

484 Sensitivity testing suggested that the RTAB range was likely to be related to site latitude. For example, the RTAB at JP-T (36° N) ranged from d 145–195, whereas at SV-W (77° N), it 485 ranged from d 180–200 in X₀-exp (Fig. 4a). Similarly, the RTAB at JP-T ranged from d 160– 486 250, whereas it ranged from d 180–200 in μ-exp (Fig 4b). These differences in the RTAB among 487 the sites could be explained by their different GP^{MRF} results. GP^{MRF} accumulated during the 488 davtime only at JP-T, whereas at site SV-W, it also accumulated during the night (Fig S1). The 489 sensitivity tests showed similar trends at the other sites. At polar sites, snow algae are likely to 490 grow for a shorter period because of the longer daylight length during summer, leading to a 491 shorter range for the RTAB in each sensitivity test. For example, the RTAB simulated with the 492 initial cell concentration of 694 cells m^{-2} was 15 d earlier than that simulated using 6.3 cells m^{-2} 493 at SV-W and 30 d earlier in the case of JP-T. In μ -exp, the RTAB with a growth rate of 0.018 h⁻¹ 494 was 10 d earlier than that simulated with an initial cell concentration of 0.016 h⁻¹, at SV-W, 495 496 whereas it was 25 d earlier in the case of JP-T. Although differences in biological parameters could lead to uncertainty in algal bloom timing, the uncertainty may be smaller in polar regions 497 than in mid-latitude regions. The results here suggested that the timing estimates for the red snow 498 499 phenomenon achieved using the updated snow algae model were more reliable at polar sites.

500 501 4.4. Algal bloom simulation uncertainties caused by different atmospheric reanalysis data sets

Fd-exp showed that sensitivity to meteorological conditions was higher in the Asian high mountain areas than in polar snowfields, suggesting that RTAB estimation uncertainty was larger in areas where precipitation mainly occurred in summer. RTABs simulated with the updated snow algae model using the WFDEI, GSWP3-FD, and CRUJRA atmospheric reanalysis datasets varied greatly at some sites (Fig. 5). Notably, the difference in the RTAB between the 25th and 75th percentiles was 50 d at sites EU-T and TN-U. The differences were smaller, approximately

20 d, at some alpine sites (SB-S, AT-A, and NA-S) and polar maritime snowfield sites (SV-S, 508 509 SV-W, and GL-A). This RTAB difference was probably due to the frequency of snowfall during summer in each dataset. As reported previously, most Asian high mountain glaciers are 510 characterized by summer accumulation due to the influence of the Asian monsoon (Fujita and 511 Ageta, 2000; Fujita, 2008; Sakai and Fujita, 2017). According to meteorological conditions 512 derived from the atmospheric reanalysis data sets, study sites SB-S, AT-A, EU-T, and TN-U 513 could probably be classified as summer accumulation-type glaciers (Figs S2 and S4). The higher 514 sensitivity of the RTAB to atmospheric conditions was probably caused by frequent summer 515 snowfalls at these sites, which would greatly affect the algal growth in the X^{MRF} . Furthermore, a 516 previous study showed that precipitation amounts derived from atmospheric reanalysis datasets 517 still have levels of uncertainty in high elevation and polar maritime areas (Weedon et al., 2014). 518 Large RTAB variations may also be influenced by dataset accuracy at specific sites—although 519 there were no significant differences in the RTABs estimated using the different datasets at sites 520 GL-Q, AK-E, and JP-T. The determinant coefficient in the algal cell concentrations achieved by 521 simulation and observation at these sites was > 0.8 (Fig. 4), suggesting that the updated snow 522 algae model was capable of reproducing red snow bloom timing in these regions, even if the 523 524 dataset contained uncertainties regarding atmospheric conditions. Notably, the updated snow algae model performed very reasonably in reproducing snow algal bloom timing at sites where 525 the atmospheric reanalysis data were highly accurate. 526

The model needs to be improved if it is to reproduce red snow blooming accurately on a global basis—especially in summer accumulation-type glaciers. At such sites, model validation using *in situ* observational meteorological conditions would be necessary. It has also become apparent that the level of snow algal bloom sensitivity to meteorological conditions in summer may vary depending on seasonal precipitation patterns. Further, the snow algae model could be a useful tool for revealing snow algal growth sensitivity to meteorological conditions.

4.5. Other possible factors affecting red snow algal blooming

The current status of snow algal growth numerical modeling in snowfields has been 534 summarized in this section, with aspects of the updated snow algae model which still require 535 improvement being identified. The updated model can estimate algal bloom timing better than 536 what had been achievable in simulations using the previous model (Onuma et al., 2018) at 537 comparable sites (Fig. 6). As noted in 4.2, this was probably due to incorporating the effect of 538 snowfall on algal abundance in surface snow into the model. The result also showed, however, 539 that algal cell concentrations simulated using the updated model underestimated observed 540 541 concentrations at the study sites, resulting in algal blooming not appearing during the thaw season at the polar sites GL-A, SB-S, and AP-L. This may be attributed to uncertainties in both 542 the biological parameters and the atmospheric reanalysis data (especially those for snowfall 543 544 amount and frequency) at the sites. Other biological process issues may also be contributing to these underestimations. Previous studies have suggested that snow algae motile cells could swim 545 up to the snow surface from the soil, or from ice below the surface snow (Müller et al., 2001; 546 Remias, 2012). The snow depth at site AP-L ranged from 5–20 cm during the observation period, 547 and thus, as Müller et al. (2001) suggested that such motile cell vertical movement occurred at 548 snow depths < 40 cm, snow algal cells originating from the ground may have contributed to 549 underestimating the simulated algal cell concentration at AP-L. We need to consider 550 incorporating such biological processes into snow algae models in the future. Although the snow 551 algae model could simulate temporal changes in cyst cell concentrations, some of these cells 552

might transform into vegetative cells during the thaw (Remias, 2012). Further field observation

and cultivation are needed to quantify such algal stage changes so that they can be incorporated into the snow algae model.

556 Overall, we have concluded that challenges remain in the effective and accurate 557 reproduction of snow algal abundance temporal changes using the updated snow algae model 558 presented here. Despite this, we have, however, been able to demonstrate that the snow algae 559 model reasonably reproduced algal bloom start times at the study sites, from which we can 560 conclude that the snow algae model has the potential to predict the appearance of red surface 561 snow worldwide.

562 4.6. Global simulation of red snow algae blooms

Based on evaluating algal cell abundance and bloom timing using the updated snow algae 563 model in the previous sections, we incorporated the snow algae model described in Section 2.1 564 into a scheme of snow physical processes in MATSIRO6. We named this version for snow algal 565 simulation Bio-MATSIRO, using the same naming convention applied to the water isotope 566 simulation, Iso-MATSIRO, by Yoshimura et al. (2006). Bio-MATSIRO can be used to calculate 567 temporal changes in algal cell concentration (cells m⁻²) at regional and global scales, using 568 atmospheric conditions near the land surface as input data. The model input data for simulations 569 using Bio-MATSIRO in this work have been summarized in Table 2. 570

571 To evaluate snow algal seasonal growth changes and global distribution qualitatively, we conducted a two-dimensional offline land simulation, using Bio-MATSIRO. For this, we 572 conducted three global simulations, using Bio-MATSIRO with the WFDEI, GSWP3-FD, and 573 CRUJRA data sets. The horizontal resolution and calculation period for these simulations were 574 575 0.5° and from January 1, 1980 to December 31, 2014, respectively, to ensure that we had common horizontal resolutions and data periods for the three data sets. Land physical properties, 576 such as snow water equivalent, were derived in advance from spin-up simulations (35 y total), 577 using the same reanalysis data set, and were used as initial conditions for the three simulations. 578 The initial cell concentration and algal growth rate were the same as Ag-exp in this study (6.33 579 cells m⁻², and 0.018 h⁻¹, respectively) because these preliminary biometrics seemed to facilitate 580 better model simulation performance. As there is little information available on carrying 581 capacity, which is likely to vary between sites (snowfields or glaciers) and years, it was assumed 582 to be 3.5×10^7 cells m⁻², which was the carrying capacity suggested by Onuma et al. (2018), for 583 Greenlandic Glacier sites. 584

The global simulation established using Bio-MATSIRO showed that snow algae grew 585 from spring to summer in both hemispheres, and that their blooming sites were generally 586 consistent with red snow sites reported previously, suggesting that Bio-MATSIRO had the 587 potential to reconstruct snow algal blooms at the global scale. The global distribution of snow 588 algal blooming was derived from the monthly means of the X^{MRF} (1980–2014 climatological 589 mean), which were the algal cell concentrations simulated with Bio-MATSIRO using each 590 atmospheric reanalysis data set. Red snow blooming $(X^{MRF}, atmospheric reanalysis data set:$ 591 WFDEI) distribution for each month's snow cover can be seen in Fig. 7. In the Northern 592 Hemisphere, snow algae gradually increased from March to August, and their blooming area 593 gradually extended from mid- to high-latitude areas. The area covered by the red blooms then 594 extended southward because snowfall events frequently occurred in high latitudes. Red snow 595 596 algal blooming simulated with Bio-MATSIRO appeared between June and August, and the

- blooming area agreed well with the red circles (red snow phenomenon reported by previous 597 598 studies) shown in Fig. 1. Red snow in European and North American snowfields had been reported previously over periods extending from summer to early autumn (Thomas and Duval, 599 1995; Remias et al., 2016), and the reported areas were consistent with simulated red snow algal 600 bloom areas. In the Southern Hemisphere, the model simulation presented red snow algae 601 gradually increasing from September to March, especially in Patagonia and on the Antarctic 602 Peninsula. The red snow phenomenon has been reported as occurring between November and 603 March in these regions (Takeuchi and Kohshima, 2004; Gray et al., 2020). Interestingly, the red 604 snow algal bloom simulation hardly showed any occurrences in either N Russia or NW 605 Canada—and there have actually been few reports of this phenomenon there. Frequent snowfall 606 events during the snow melting season would interrupt snow algal bloom appearance in these 607 regions because X^{MRF} drastically decreased to X_0 in August. Simulations using GSWP3-FD and 608 CRUJRA showed spatial and seasonal changes in X^{MRF} similar to those simulated using WFDEI 609 (Figs S5 and S6), with these results suggesting that Bio-MATSIRO had the potential to 610 reproduce seasonal and geographical changes in red snow algal abundance globally. 611
- 612

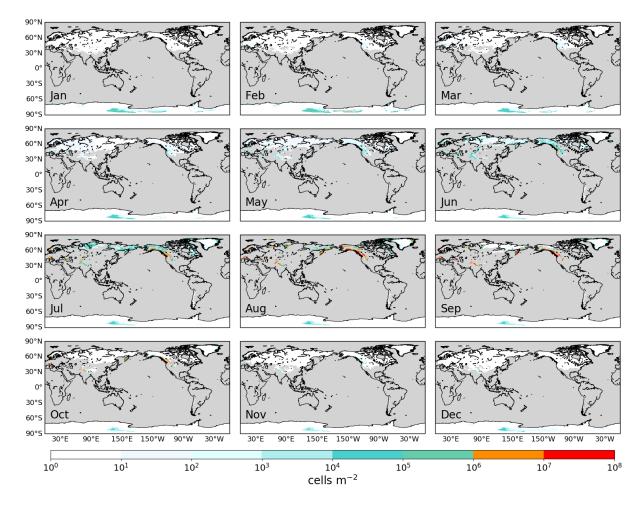


Figure 7. Distribution of red snow algal abundance on the surface snow, as simulated using the
 land surface model with the atmospheric reanalysis data set WFDEI (1980–2014)

Because we used constants for the biological parameters (initial cell concentration,

growth rate, and carrying capacity) and atmospheric reanalysis data at the scale of 0.5° globally,

the algal cell concentrations derived from our simulations contained some uncertainty levels in

this study. Further observational and modeling studies are necessary to improve the snow algae model. Satellite observations of red and green snow algae blooms have been conducted recently

(Hisakawa et al., 2015; Ganey et al., 2017; Huovinen et al., 2018; Gray et al., 2020; Khan et al.,

2021), and validating model simulations with satellite observations would also be useful, at the

624 glacial or regional scales. In addition, global simulation of red snow algal blooming, using a land

surface model, could provide an important contribution to understanding climate change effects

- on snow and ice distribution in time and space.
- 627

628 **5 Conclusions**

We updated the existing snow algae model based on observational data from 15 snowfields and 629 incorporated it into a land surface model to quantify time and space changes in snow algal 630 abundance worldwide. The existing snow algae model (Onuma et al., 2018) could simulate 631 temporal changes in the abundance of red snow algae in surface snow, using snow temperature, 632 but up until now had only been applied to simulate the abundance of Greenlandic glacier 633 snowpack. In this study, the effects of daylight length and snowfall rate on algal cell abundance 634 were incorporated into the model, and the revised model simulations achieved good agreement 635 with observations at snowfields worldwide, from polar to mid-latitude areas-particularly in 636 637 regions with fewer summer snowfalls.

Based on these encouraging results, we incorporated the updated snow algae model into a land surface model and conducted a global snow algal simulation, using Bio-MATSIRO. This simulation produced results showing prominent algal blooms taking place in areas generally consistent with regions where the red snow phenomenon had been reported in either *in situ* or satellite observations. Our simulations suggested that Bio-MATSIRO has the potential to simulate temporal and spatial changes in red snow algal abundance and to predict the timing and coverage of the red snow phenomenon.

Snow algal distribution may be a key to revealing the geographic specifications of 645 microbes worldwide (Lutz et al., 2016; Segawa et al., 2018; Procházková et al., 2019; 646 Zawierucha and Shain, 2019). The snow algae model may be useful not only for providing such 647 biological information but also for quantifying snow algal contributions to thaw events 648 worldwide (by reducing snow surface albedo), revealing trends over time. This contribution has 649 been reported in many studies as a bioalbedo effect and has been quantified using in situ 650 observations, satellite observations, and numerical simulations (Thomas and Duval, 1995; 651 Painter et al., 2001; Takeuchi et al., 2006b; Aoki et al., 2013; Lutz et al., 2016; Cook et al., 2017; 652 Ganey et al., 2017; Mauro et al., 2017; Gray et al., 2020; Onuma et al., 2020). Because these 653 studies focused on specific mountains or glaciers, comprehensive bioalbedo effects should be 654 investigated at the global scale in the future using numerical simulation. To simulate bioalbedo 655 effects at such a scale, a numerical bioalbedo model that has the capacity to calculate snow 656 albedo (with the effect of snow algae included) needs to be incorporated into land surface models 657 and climate models. Although further observations and simulations would further improve snow 658 algae models, our study has provided an important first step towards revealing the global 659 660 geographic characteristics of snow algae and their contribution to snow melting.

661 Author contributions

462 YO, KY, and NT designed the study and the paper. YO and NT collected snow samples and 463 quantified snow algal abundance. YO developed the snow algae model and prepared the 464 atmospheric reanalysis data at the validation sites, then conducted the numerical model 465 simulation.

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678 Data Availability

- All of the observation data, output data and scripts for the figures in this study are available at
- 680 the following DOI.
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682 Supporting Information

683 Supporting tables and figures are uploaded separately.

684 **References**

- Aoki, T., Kuchiki, K., Niwano, M., Kodama, Y., Hosaka, M., & Tanaka, T. (2011), Physically
- based snow albedo model for calculating broadband albedos and the solar heating profile in
- snowpack for general circulation models. J. Geophys. Res., 116, D11114.
- 688 doi:10.1029/2010JD015507
- 689
- Aoki, T., Kuchiki, K., Niwano, M., Matoba, S., Uetake, J., Masuda K., & Ishimoto, H. (2013),
- Numerical Simulation of Spectral Albedos of Glacier Surfaces Covered with Glacial Microbes in
- 692 Northwestern Greenland. RADIATION PROCESSES IN THE ATMOSPHERE AND OCEAN
- (IRS2012), Robert Cahalan and Jürgen Fischer (Eds), ALP Conf. Proc., 1531, 176.
- 694 doi:10.1063/1.4804735
- 695
- 696 Cepák, V., Kviderová, J., & Lukavský, J. (2016), The first description of snow algae on Mount
- 697 Olympus (Greece). *Nova, Hedwigia*, 103:457–73. doi:10.1127/nova_hedwigia/2016/0365
- 698
- 699 CIMO Guide, Part I, Chapter 3, https://www.wmo.int/pages/prog/www/IMOP/CIMO-
- 700 Guide.html
- 701

- Cook. J. M., Hodson, A. J., Taggart, A. J., Mernild, S. H., & Tranter, M. (2017), A predictive
- model for the spectral "bioalbedo" of snow. J. Geophys. Res. Earth Surf., 122.
- 704 doi:10.1002/2016JF003932 705
- Curl Jr., H., Hardy, J. T., & Ellermeier, R. (1972), Spectral absorption of solar radiation in alpine
 snow fields. *Ecology*, 53, 1189–1194. doi:10.2307/1935433
- 708
- Decharme, B., Brun, E., Boone, A., Delire, C., Le Moigne, P., & Morin, S. (2016), Impacts of
- snow and organic soils parameterization on northern Eurasian soil temperature profiles simulated
- by the ISBA land surface model. *Cryosphere*, 10, 853–877. doi:10.5194/tc-10-853-2016
- Fujii, M., Takano, Y., Kojima, H., Hoshino, T., Tanaka, R., & Fukui, M. (2010), Microbial
 community structure, pigment composition, and nitrogen source of red snow in Antarctica.
- 715 *Microb. Ecol.*, 59:466–75. doi:10.1007/s00248-009-9594-9
- 716
- Fujita, K. (2008), Effect of precipitation seasonality on climatic sensitivity of glacier mass
 balance. *Earth Planet. Sc. Lett.*, 276, 14–19. doi:10.1016/j.epsl.2008.08.028
- 719
- Fujita, K., & Ageta, Y. (2000), Effect of summer accumulation on glacier mass balance on the
- Tibetan Plateau revealed by mass-balance model. J. Glaciol., 46 (150), 244–252.
 doi:10.3189/172756500781832945
- 723
- Ganey, G. Q., Loso, M. G., Burgess, A. B., & Dial, R. J. (2017), The role of microbes in
 snowmelt and radiative forcing on an Alaskan icefield. *Nature Geoscience*.
 doi:10.1038/NGEO3027
- 726 doi: 727
- Gorton, H. L., & Vogelmann, T. C. (2003), Ultraviolet radiation and the snow alga
- 729 Chlamydomonas nivalis (Bauer) Wille. *Photochem. Photobiol*, 77:608–15.
- 730
- Gray, A., Krolikowski, M., Fretwell, P., Convey, P., Peck, L. S., Mendelova, M., Smith, A. G.,
- 732& Davey, M. P. (2020), Remote sensing reveals Antarctic green snow algae as important
- 733 terrestrial carbon sink, *Nat. Commun.*, 11, 2527. doi:10.1038/s41467-020-16018-w
- 734
- Harris, I. C. (2019), CRU JRA v2.0: A forcings dataset of gridded land surface blend of Climatic
- Research Unit (CRU) and Japanese reanalysis (JRA) data. Centre for Environmental Data
- 737 Analysis, https://catalogue.ceda.ac.uk/uuid/7f785c0e80aa4df2b39d068ce7351bbb.
- 738
- Hisakawa, N., Quistad, S. D., Hestler, E. R., Martynova, D., Maughan, H., Sala, E., Gavrilo, M.
- V., & Rowher, F. (2015), Metagenomic and satellite analyses of red snow in the Russian Arctic.
- 741 *Peer J*, 3, e1491. doi:10.7717/peerj.1491
- 742
- Hodson, A. J., Nowak, A., Cook, J., Sabacka, M., Wharfe, E. S., Pearce, D. A., Convey, P., &
- Vieira, G. (2017), Microbes influence the biogeochemical and optical properties of maritime
- 745 Anatarctic snow. J. Geophys. Res. Biogeosci., 122, 1456–70. doi:10.1002/2016JG003694
- 746

- Hoham, R. W., Frey, F. M., Berman, J. D., Ryba, J. B., Duncan, J. E., Forbes, A. A., Goodridge, 747 748 B. M., & Miller, P. R. (2009), The effects of irradiance level, photoperiod, and cell density on sexual reproduction in the green snow alga, Chloromonas chenangoensis (Chlorophyta, 749 750 Volvocales), from Upstate New York. Nova. Hedwigia, 89:1-16. 751 Hoham, R. W., Marcarelli, A. M., Rogers, H. S., Ragan, M. D., Petre, B. M., Ungerer, M. D., 752 Barnes, J. M., & Francis, D. O. (2000), The importance of light and photoperiod in sexual 753 reproduction and geographical distribution in the green snow alga, Chloromonas sp.-D 754 (Chlorophyseae, Volvocales). Hydrol. Process, 14:3309-21. 755 756 Hoham, R. W., & Remias, D. (2020), SNOW AND GLACIAL ALGAE: A REVIEW. J. Phycol., 757 12952. doi:10.1111/jpy.12952 758 759 Huovinen, P., Ramírez, J., & Gómez, I. (2018), Remote sensing of albedo-reducing snow algae 760 and impurities in the Maritime Antarctica. ISPRS J. Photogramm, Remote Sens., 146, 507-517. 761 doi:10.1016/j.isprsjprs.2018.10.01510 762 763 Khan, A. L., Dierssen, H., Scambos, T., Höfer, J., & Cordero, R. R. (2021), Spectral 764 characterization, radiative forcing and pigment content of coastal Antarctic snow algae: 765 766 approaches to spectrally discriminate red and green communities and their impact on snowmelt. Cryosphere, 15, 133–148. doi:10.5194/tc-15-133-2021 767 768 Kim, H. (2017), Global Soil Wetness Project Phase 3 Atmospheric Boundary Conditions 769 (Experiment 1) [Data set], Data Integration and Analysis System (DIAS). 770 doi:10.20783/DIAS.501. 771 772 Krinner, G., Derksen, C., Essery, R., Flanner, M., Hagemann, S., Clark, M., Hall, A., Rott, H., 773 Brutel-Vuilmet, C., Kim, H., Ménard, C. B., Mudryk, L., Thackeray, C., Wang, L., Arduini, G., 774 Balsamo, G., Bartlett, P., Boike, J., Boone, A., Chéruy, F., Colin, J., Cuntz, M., Dai, Y., 775 Decharme, B., Derry, J., Ducharne, A., Dutra, E., Fang, X., Fierz, C., Ghattas, J., Gusev, Y., 776 Haverd, V., Kontu, A., Lafaysse, M., Law, R., Lawrence, D., Li, W., Marke, T., Marks, D., 777 778 Ménégoz, M., Nasonova, O., Nitta, T., Niwano, M., Pomeroy, J., Raleigh, M. S., Schaedler, G., 779 Semenov, V., Smirnova, T. G., Stacke, T., Strasser, U., Svenson, S., Turkov, D., Wang, T., Wever, N., Yuan, H., Zhou, W., & Zhu, D. (2018), ESM-SnowMIP: assessing snow models and 780 quantifying snow-related climate feedbacks, Geosci. Model Dev., 11, 5027-5049, 781 doi:10.5194/gmd-11-5027-2018. 782 783 Krinner, G., Viovy, N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, 784 785 P., Sitch, S., & Prentice, IC. (2005), A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system, Global Biogeochem. Cycles, 19(1), GB1015. 786 doi:10.1029/2003GB002199. 787
- 788
- Lawrence, D. M., Fisher, R. A., Koven, C. D., Oleson, K. W., Swenson, S. C., Bonan, G., et al.
- (2019), The Community Land Model version 5: Description of new features, benchmarking, and
- impact of forcing uncertainty. *Journal of Advances in Modeling Earth Systems*.
- 792 doi:10.1029/2018MS001583

794 Leya, T., Rahn, A., Lütz, C., & Remias, D. (2009), Response of arctic snow and permafrost algae to high light and nitrogen stress by changes in pigment composition and applied aspects for 795 796 biotechnology. FEMS Microbiol. Ecol., 67, 432-443. doi:10. 1111/j. 1574-6941.2008.00641.x 797 Lutz, S., Anesio, A. M., Jorge Villar, S. E., & Benning, L. G. (2014), Variations of algal 798 799 communities cause darkening of a Greenland glacier. FEMS Microbiol. Ecol., 89, 402–414. doi:10.1111/1574-6941.12351 800 801 Lutz, S., Anesio, A. M., Field, K., & Benning, L. G. (2015), Integrated 'omics', targeted 802 803 metabolite and single-cell analyses of Arctic snow algae functionality and adaptability. Front. Microbiol, 6, 1323. doi:10.3389/fmicb.2015.01323 804 805 806 Lutz, S., Anesio, A. M., Raiswell, R., Edwards, A., Newton, R. J., Gill, F., & Benning, L. G. (2016), The biogeography of red snow microbiomes and their role in melting arctic glaciers. 807 Nature Communications, doi:10.1038/ncomms11968 808 809 Mauro, B. D., Baccolo, G., Garzonio, R., Giardino, C., Massabo, D., Piazzalunga, A., Rossini, 810 M., & Colombo, R. (2017), Impact of impurities and cryoconite on the optical properties of the 811 812 Morteratsch Glacier (Swiss Alps). Cryosphere, 11 (6), 2393-2409. doi:10.5194/tc-11-2393-2017 813 814 Moestrup, Ø., Nicholls, K. H., & Daugbjerg, N. (2018), Studies on woloszynskioid dinoflagellates IX: ultrastructure, cyst formation and phylogeny of the 'red-snow' alga 815 Borghiella pascheri (Suchlandt) Moestrup (= Glenodinium pascheri, Woloszynskia pascheri, 816 Gyrodinium nivalis). Eur. J. Phycol., 53, 393-409 817 818 Müller, T., Leya, T., & Fuhr, G. (2001), Persistent snow algal fields in Spitsbergen: field 819 observations and a hypothesis about the annual cell circulation. Arct. Antarct. Alp. Res., 33, 42-820 51. doi:10.2307/1552276 821 822 Nagatsuka, N., Takeuchi, N., Nakano, T., Shin, K., & Kokado, E. (2014), Geographical 823 variationsin Sr and Nd isotopic ratios of cryoconite on Asian glaciers. Environ. Res. Lett., 9, 824 825 045007, doi:10.1088/1748-9326/9/4/045007 826 Navarro, F.J., Jonsell U.Y., Corcuera M.I., & Martín-Español A. (2013), Decelerated mass loss 827 of Hurd and Johnsons Glaciers, Livingston Island, Antarctic Peninsula. J. Glaciol., 59(213), 828 115-128. 829 830 831 Nitta, T., Yoshimura, K., & Abe-Ouchi, A. (2017), Impact of arctic wetlands on the climate system: Model sensitivity simulations with the MIROC5 AGCM and a snow-fed wetland 832 scheme, J. Hydrometeorol., 18, 2923–2936 833 834 Nitta, T., Yoshimura, K., Takata, K., O'ishi, R., Sueyoshi, T., Kanae, S., Oki, T., Abe-Ouchi, A., 835 & Liston, G. E. (2014), Representing variability in subgrid snow cover and snow depth in a 836 837 global land model, J. Climate, 27, 3318-3330. doi:10.1175/JCLID-13-003 838

- Novis, P. M. (2002), Ecology of the snow alga Chlainomonas kolii (Chlamydomonadales,
- Chlorophyta) in New Zealand. *Phycologia*, 41 (3), 280–292. doi:10.2216/i0031-8884-41-3-280.1
- Osada, K., Ida, H., Kido, M., & Matsunaga, K. (2004), Iwasaka, Y.: Mineral dust layers in snow
- at Mount Tateyama, Central Japan: formation processes and characteristics. *Tellus*, 56B, 382392. doi:10.3402/tellusb.v56i4.16436
- Onuma, Y., Yoshimura, K., & Takeuchi., N. (2021). Data set regarding snow algal modeling
- 847 (Version v1.2) [Data set]. Zenodo. doi:10.5281/zenodo.4626347
- 848

- Onuma, Y., Takeuchi, N., & Takeuchi, Y. (2016), Temporal changes in snow algal abundance on
 surface snow in Tohkamachi, Japan. *Bull. Glaciol. Res.*, 34, 21-31. doi:10.5331/bgr.16A02
- 851
- Onuma, Y., Takeuchi, N., Tanaka, S., Nagatsuka, N., Niwano, M., & Aoki, T. (2018),
- Observations and modelling of algal growth on a snowpack in north-western Greenland.
- 854 Cryosphere, 12, 2147–2158. doi:10.5194/tc-12-2147-2018
- 855
- Onuma, Y., Takeuchi, N., Tanaka, S., Nagatsuka, N., Niwano, M., & Aoki, T. (2020), Physically
- based model of the contribution of red snow algal cells to temporal changes in albedo in
 northwest Greenland. *Cryosphere*, 14, 2087-2101. doi:10. 5194/tc-14-2087-2020
- 859
- Painter, T. H., Duval, B., & Thomas, W. H. (2001), Detection and quantification of snow algae
 with an airborne imaging spectrometer. *Appl. Environ. Microbiol.*, 67, 5267–5272.
- doi:10.1128/AEM.67.11.5267-5272.2001
- Procházková, L., Leya, T., Křížková, H., & Nedbalová, L. (2019), Sanguina nivaloides and
 Sanguina aurantia gen. et spp. nov. (Chlorophyta): the taxonomy, phylogeny, biogeography and
 ecology of two newly recognised algae causing red and orange snow. *FEMS Microbiol. Ecol.*,
 95:fiz064, doi:10.1093/femsec/fiz064
- 868
- Remias, D. (2012), Cell structure and physiology of alpine snow and ice algae, in: Plants in
 alpine regions, Cell physiology of adaption and survival strategies. edited by: Lütz, C., *Springer Wien*, 202, 175–186. doi:10.1007/978-3-7091-0136-0_13.
- 871 872
- Remias, D., Albert, A., & Lütz, C. (2010), Effects of realistically simulated, elevated UV
 irradiation on photosynthesis and pigment composition of the alpine snow alga Chlamydomonas
- nivalis and the arctic soil alga Tetracystis sp. (Chlorophyceae), *Photosynthetica*, 48, 269–277.
- 876
- 877 Remias, D., Pichrtová, M., Pangratz, M., Lütz, C., & Holzinger, A. (2016), Ecophysiology,
- 878 secondary pigments and ultrastructure of Chlainomonas sp. (Chlorophyta) from the European
- Alps compared with Chlamydomonas nivalis forming red snow, FEMS Microbiol. Ecol.,
- 880 92:fiw030. doi:10.1093/femsec/fiw030
- 881
- 882 Sakai, A., & Fujita, K. (2017), Contrasting glacier responses to recent climate change in
- highmountain Asia. Sci. Rep., 7: 13717. doi:10.1038/s41598-017-14256-5
- 884

Segawa, T., Matsuzaki, R., Takeuchi, N., Akiyoshi, A., Navarro, F., Sugiyama, S., Yonezawa, 885 T., & Mori, H. (2018), Bipolar dispersal of red-snow algae. Nat. Commun., 9:3094. 886 doi:10.1038/s41467-018-05521-w 887 888 Segawa, T., Miyamoto, K., Ushida, K., Agata, K., Okada, N., & Kohshima, S. (2005), Seasonal 889 Change in Bacterial Flora and Biomass in Mountain Snow from the Tateyama Mountains, Japan, 890 Analyzed by 16S rRNA Gene Sequencing and Real-Time PCR. App. Environ. Microbiol., 71 (1), 891 123-130. doi:10.1128/AEM.71.1.123-130 892 893 Spijkerman, E., Wacker, A., Weithoff, G., & Leya, T. (2012), Elemental and fatty acid 894 895 composition of snow algae in arctic habitats. Front. Microbiol., 3:380. 896 Stibal, M., Elster, J., Sabacká, M. and Kaŝtovská, K. (2007), Seasonal and diel changes in 897 photosynthetic activity of the snow alga Chlamydomonas nivalis (Chlorophyceae) from Svalbard 898 determined by pulse amplitude modulation fluorometry. FEMS. Microbiol. Ecol., 59, 265–273. 899 doi:10.1111/j.1574-6941.2006.00264.x 900 901 Sugiyama, S., Navarro, F. J., Sawagaki, T., Minowa, M., Segawa, T., Onuma, Y., Otero, J., & 902 Vasilenko, E. J. (2019), Subglacial water pressure and ice-speed variations at Johnsons Glacier, 903 904 Livingston Island, Antarctic Peninsula. J. Glaciol., 65(252), 689-699. doi:10.1017/jog.2019.45 905 Takata, K., Emori, S., & Watanabe, T. (2003), Development of the Minimal Advanced 906 907 Treatments of Surface Interraction and RunOff (MATSIRO). Global Planet. Change, 38, 209-222. 908 909 Takeuchi, N. (2013), Seasonal and altitudinal variations in snow algal communities on an 910 Alaskan glacier (Gulkana glacier in the Alaska range). Environ. Res. Lett., 8, 035002. 911 doi:10.1088/1748-9326/8/3/035002 912 913 Takeuchi, N., & Kohshima, S. (2004), snow algal community on a Patagonian glacier, Tyndall 914 glacier in the Southern Patagonia Icefield. Arct. Antarct. Alp. Res., 36, 91-8. 915 916 917 Takeuchi, N., Uetake, J., Fujita, K., Aizen, V. B., & Nikitin, S. D. (2006a), A snow algal 918 community on Akkem Glacier in the Russian Altai Mountains. Ann. Glaciol., 43, 378-84. 919 Takeuchi, N., Dial, R., Kohshima, S., Segawa, T., & Uetake, J. (2006b), Spatial distribution and 920 abundance of red snow algae on the Harding Icefield, Alaska derived from a satellite image. 921 Geophys. Res. Lett., 33, L21502. doi:10.1029/2006GL027819 922 923 924 Tanaka, S. (2016), Seasonal and inter-annual variabilities of snow and ice algal community on glaciers in the Asia and Arctic regions. Graduate School of Science, Chiba Univ., Doctoral 925 926 thesis. 927 Tanaka, S., Takeuchi, N., Miyairi, M., Fujisawa, Y., Kadota, T., Shirakawa, T., Kusaka, R., 928 929 Takahashi, S., Enomoto, H., Ohata, T., Yabuki, H., Konya, K., Fedorov, A., Konstantinov, P.

- 930 (2016), Snow algal communities on glaciers in the Suntar-Khayata Mountain Range in eastern
- 931 Siberia. *Russia. Polar Sci.*, 10, 3, 227-238, doi:10.1016/j.polar.2016.03.004.
- 932
- Tatebe, H., Ogura, T., Nitta, T., Komuro, Y., Ogochi, K., Takemura, T., Sudo, K., Sekiguchi, M.,
- Abe, M., Saito, F., Chikira, M., Watanabe, S., Mori, M., Hirota, N., Kawatani, Y., Mochizuki,
- 935 T., Yoshimura, K., Takata, K., O'ishi, R., Yamazaki, D., Suzuki, T., Kurogi, M., Kataoka, T.,
- 936 Watanabe, M., & Kimoto, M. (2019), Description and basic evaluation of simulated mean state,
- internal variability, and climate sensitivity in MIROC6. *Geosci Model Dev.*, 12, 2727–2765.
- 938 doi:10.5194/gmd-12-2727-2019
- 939
- Thomas, W. H., & Duval, B. (1995), Sierra Nevada, California, USA, snow algae: snow albedo
 changes, algal-bacterial interrelationships, and ultraviolet radiation effects. *Arct. Alp. Res.*, 27,
 389–99.
- 942 943
- van den Hurk, B., Kim, H., Krinner, G., Seneviratne, S. I., Derksen, C., Oki, T., Douville, H.,
- 945 Colin, J., Ducharne, A., Cheruy, F., Viovy, N., Puma, M. J., Wada, Y., Li, W., Jia, B.,
- Alessandri, A., Lawrence, D. M., Weedon, G. P., Ellis, R., Hagemann, S., Mao, J., Flanner, M.
- 947 G., Zampieri, M., Materia, S., Law, R. M., & Sheffield, J. (2016), LS3MIP (v1.0) contribution to
- 948 CMIP6: the Land Surface, Snow and Soil moisture Model Intercomparison Project aims, setup 940 and expected outcome. *Crossii Model Day*, 0, 2800, 2832, doi:10.5104/gmd 0.2800, 2016
- and expected outcome. *Geosci. Model Dev.*, 9, 2809–2832. doi:10.5194/gmd-9-2809-2016
- Vimercati, L., Solon, A. J., Krinsky, A., Arán, P., Porazinska, D. L., & Darcy, J. L. (2019),
- Nieves penitentes are a new habitat for snow algae in one of the most extreme high-elevation
- environments on Earth. Arct. Antarct. Alp. Res., 51:1, 190-200.
- 954 doi:10.1080/15230430.2019.1618115
- 955
- Weedon, G. P., Balsamo, G., Bellouin, N., Gomes, S., Best, M. J., & Viterbo, P. (2014), The
- 957 WFDEI meteorological forcing data set: WATCH Forcing Data methodology applied to ERA
- 958 Interim reanalysis data. *Water Resour. Res.*, 50, 7505–7514. doi:10.1002/2014WR015638 959
- 960 Yoshimura, K., Miyazaki, S., Kanae, S., & Oki, T. (2006), Iso-MATSIRO, a land surface model
- that incorporates stable water isotopes. *Global Planet. Change*, 51, 90–107.
- 962 doi:10.1016/j.gloplacha.2005.12.007
- 963
- Zawierucha, K., & Shain, D. H. (2019), Disappearing Kilimanjaro snow—Are we the last
- generation to explore equatorial glacier biodiversity? *Ecol. Evol.*, 9, 8911–8918.
- 966