

Evaluation of parameterization schemes in the detailed Snow Metamorphism and Albedo Process (SMAP) snowpack model

Teruyuki Nakahata

Niigata Local Meteorological Office

Michiko Otsuka

`michiko-otsuka@biwako.shiga-u.ac.jp`

Shiga University

Masashi Niwano

Meteorological Research Institute

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Abstract

We investigate parameterization uncertainties in the physical snowpack model Snow Metamorphism and Albedo Process (SMAP) through model sensitivity experiments involving four key physical processes: effective thermal conductivity, new snow density, compression viscosity coefficient, and water movement within the snowpack. Using high-quality surface meteorological and snow observations from Sapporo for 2006–2021, each parameterization is varied independently while the others are kept at their default settings. New snow density produces the largest short-term uncertainty during snowfall events, whereas the compression viscosity coefficient produces uncertainty that accumulates over the season through its influence on snow densification. Effective thermal conductivity affects snow depth through its influence on vertical heat transfer within the snowpack, with uncertainties increasing under dense snow conditions in late winter. In contrast, uncertainty associated with vertical water movement schemes remains comparatively small under the predominantly dry-snow conditions in Sapporo. These results provide guidance for improving snow depth forecasting and prioritizing future refinement of snowpack modeling.

1 Introduction

Accurate monitoring and forecasting of snowfall and snow depth are essential for mitigating the impacts of heavy snow, which include transportation disruptions, infrastructure damage, and increased risk of avalanches and floods associated with snowmelt. In Japan, the Japan Meteorological Agency (JMA) provides real-time snow depth analyses and short-term snowfall forecasts. Since October 2022, these products have been generated using the physical snowpack model Snow Metamorphism and Albedo Process (SMAP) (Niwano et al. 2012, 2014, 2022).

SMAP is one of several detailed multilayer physical snowpack models, alongside Crocus (Brun et al. 1989, 1992) and SNOWPACK (Bartelt and Lehning 2002; Lehning et al. 2002a, b). A distinctive aspect of SMAP is its integration of the physically based snow–albedo model PBSAM (Aoki et al. 2011), which accounts for the seasonal evolution of snow grain size and the deposition of light-absorbing impurities such as mineral dust and black carbon. This enables a more realistic representation of radiative processes within the seasonal snowpack.

Like other physical snowpack models, SMAP must approximate several snow physical processes using parameterization schemes. These approximations introduce uncertainty into snowpack simulations, particularly for complex processes such as heat conduction, densification, and vertical liquid water transport. Previous studies have investigated the contributions of parameterization, model structure, and meteorological forcing to uncertainty in snowpack simulations. Günther et al. (2019) showed that meteorological forcing generally contributes more to snowpack simulation uncertainty than model structure and parameter choice, although the relative importance of these uncertainty sources can vary with the simulated process and season. In SMAP, uncertainties associated with surface meteorological forcing, in particular precipitation phase partitioning, have also been reported (Niwano et al. 2017).

However, parameterization uncertainty within SMAP has not yet been systematically evaluated over a long period.

This study focuses on uncertainties arising from four key physical processes within SMAP that are expected to strongly influence snow depth analyses and forecasts: effective thermal conductivity, new snow density, compression viscosity coefficient, and vertical water movement within the snowpack. By isolating these four components and evaluating model responses using high-quality observations at Sapporo during the 2006–2021 winters, we aim to clarify (1) how the magnitude of uncertainty differs among schemes, and (2) under what snow and meteorological conditions each parameterization has the greatest influence.

2 Data and Method

2.1 Observational Data

We used surface meteorological and snowpack observations collected at the Institute of Low Temperature Science, Hokkaido University in Sapporo (43°05'09"N, 141°20'11"E, 15 m a. s. l.). The observations cover the 2006–2021 winters (November–April), corresponding to the study period. The dataset includes precipitation, atmospheric pressure, wind speed, air temperature, relative humidity, downward shortwave and longwave radiation, ground heat flux, and the mass concentrations of light-absorbing impurities (black carbon and mineral dust), as well as snow depth (Kuchiki et al. 2015; Ménard et al. 2019; Niwano et al. 2020). These long-term, high-quality observations provide all meteorological variables required by SMAP, allowing the effects of different parameterization schemes to be examined using a consistent observational forcing dataset. Snow depth observations were used for model evaluation.

2.2 SMAP configuration and sensitivity experiments

SMAP is a one-dimensional multilayer physical snowpack model that simulates the temporal evolution of snow depth and internal snowpack properties using meteorological forcing data. In this study, the meteorological and snowpack observations described in Section 2.1 were used as model inputs, and snow depth was evaluated as the primary output variable. Snow depth is a useful parameter for assessing a physical snowpack model because (1) it can be accurately measured automatically with high temporal resolution and (2) its variations depend on almost all snow physical processes (Armstrong and Brun 2008). SMAP was run following the settings of Niwano et al. (2012, 2014). Based on the framework of Lafaysse et al. (2017), we selected four snow physical processes—effective thermal conductivity (ETC), new snow density (NSD), compression viscosity coefficient (VC), and the vertical water movement scheme (WM)—because they were expected to strongly influence snow-depth simulations.

To assess their individual impacts, the parameterization associated with only one process was varied at a time, while the remaining three processes were kept at their default settings. In total, 21 simulations

were performed for each winter season: 13 for ETC, 3 for NSD, 2 for VC, and 3 for WM.

2.3 Description of parameterization schemes

SMAP includes multiple selectable parameterization options for each of the four physical processes examined in this study. These options differ in their underlying assumptions and functional forms, and our sensitivity experiments evaluated the differences arising from these alternative formulations.

2.3.1 Effective thermal conductivity (ETC)

Effective thermal conductivity represents heat transfer within the snowpack and appears in the diffusion equation and boundary conditions (Niwano et al. 2012). Heat transfer in snow includes both conductive and vapor-mediated latent heat transport. Because ETC encompasses both mechanisms, it indirectly influences snow-depth evolution through its impact on snow temperature. SMAP provides 13 density-dependent parameterization options for ETC. The parameterization schemes evaluated in this study are listed in Table S1. The default ETC scheme used in SMAP follows Devaux (1933).

2.3.2 New snow density (NSD)

NSD provides the initial density of freshly deposited layers in the compaction equation. Since precipitation amount is observed, NSD directly determines the initial layer thickness and thus strongly affects simulated snow depth during snowfall events. NSD depends on snow crystal type and snow-cloud microphysics and typically increases with wind speed due to particle fragmentation (Armstrong and Brun 2008; Jordan et al. 1999).

The schemes differ in the number and type of explanatory variables; Niwano et al. (2012) adopted the Yamazaki (1998) formulation for the model simulations at Sapporo. SMAP includes two other NSD options, a formulation used in the SNOWPACK model (Vionnet et al. 2012) and the formulation by Kajikawa (1989).

2.3.3 Compression viscosity coefficient (VC)

VC controls the densification rate after snowfall due to self-weight. Snow densification proceeds through deformation of bonds between snow particles and reduction of pore volume. Fresh and lightly compacted snow have low viscosity and are compressed rapidly under overburden pressure (Armstrong and Brun 2008). VC therefore influences snow-depth evolution mainly after snowfall. Two VC parameterizations are available in SMAP: Bader and Weilenmann (1992) and Vionnet et al. (2012). The default VC scheme used in SMAP follows Vionnet et al. (2012).

2.3.4 Vertical water movement scheme (WM)

The WM describes vertical liquid-water transport within the snowpack, generated by rainfall or snowmelt. Because liquid water alters snow density and accelerates snow grain growth through wet snow metamorphism (Brun et al. 1989), WM can influence thermal conduction, densification, and radiation processes.

Three WM options are available in SMAP: a mass-fraction threshold scheme, a volume-fraction threshold scheme, and a Richards-equation scheme. The first two are simple threshold-based approaches, known as “bucket schemes”, that diagnose water movement using prescribed mass- or volume-fraction limits (Niwano et al. 2012), whereas the third is a physically based formulation that explicitly solves the one-dimensional Richards equation for liquid-water transport within the snowpack (Niwano et al. 2014).

Previous evaluations were limited to the 2007–2008 and 2008–2009 winter seasons (Niwano et al. 2014), whereas the present study extends the analysis over a much longer period.

3 Results and Discussion

3.1 Snow depth simulated by SMAP

Before examining parameterization uncertainty, SMAP was run using the default model configuration described in Section 2.2 for the period 2006–2021. Figure 1 summarizes the long-term simulation of snow depth by SMAP at Sapporo and presents a representative example of model bias during snowfall and melt events.

Figure 1a shows the time series of snow depth simulated by SMAP using the default parameterization settings (Section 2.2) and the corresponding observations at Sapporo from 2006 to 2021. SMAP reproduced the overall seasonal evolution of snow depth, although substantial positive biases were evident in some winters. Differences between simulated and observed snow depth were most evident during the snow onset and melt periods, when snow depth changed rapidly. By contrast, during the relatively stable midwinter period, simulated and observed snow depth often evolved in parallel, even when a positive bias was present.

Figure 1b presents a representative example from the snow onset period, when snowfall and melt events occurred in rapid succession. In this case, SMAP overestimated snowfall when air temperature was close to 0°C, consistent with uncertainties in rain–snow partitioning reported by Niwano et al. (2017). In addition, during melt events with surface air temperatures approximately 0–5°C, SMAP underestimated rapid decreases in observed snow depth. Similar behavior was observed in several winters shown in Fig. 1a and may contribute to the positive snow-depth biases found in some years. These results suggest that uncertainties in the representation of snow physical processes can influence snow-depth simulations, particularly during periods of rapid snow-depth change.

3.2 Sensitivity experiments for parameterization uncertainties

This section presents the results of sensitivity experiments in which the parameterizations of ETC, NSD, VC, and WM were varied individually while the remaining processes were fixed at their default settings. Figure 2 summarizes the ensemble mean and standard deviation of snow depth obtained for each

parameterization group. The standard deviation represents the spread among simulations using different parameterization schemes and is used as a measure of parameterization uncertainty.

3.2.1 ETC

Figure 2a shows the ensemble mean and standard deviation of snow depth obtained from the 13 ETC parameterization schemes. The standard deviation was generally larger from mid-December to early March, when snow depth was substantial. Pronounced standard deviation peaks of a few to several centimeters appeared during the latter part of some winters and occasionally during the early snow season.

Because ETC governs heat transfer within the snowpack, differences among ETC formulations modify snow temperature and consequently affect melt and refreezing processes. To better understand this behavior, snow-temperature profiles were compared for the Bracht (1949) and Izumi and Huzioka (1975) formulations, which produced the smallest and largest snow depths, respectively (Fig. 3). The formulation associated with larger snow depths maintained colder temperatures through a deeper portion of the snowpack, particularly during midwinter. As shown in Fig. 3b, low-temperature layers extended farther downward than in Fig. 3a, indicating more efficient penetration of atmospheric cooling into the snowpack. These differences in heat transfer between the atmosphere and the snowpack, as well as within the snowpack itself, influence melt and refreezing processes and consequently lead to divergent snow-depth evolution.

The pronounced late-season peaks occurred when snow density frequently exceeded approximately 350 kg m^{-3} , a regime in which the ETC formulations diverge substantially. Such differences become larger at high snow densities because thermal conductivity is strongly influenced by snow microstructure and bonding among snow grains (Armstrong and Brun 2008).

Although several ETC formulations specify valid temperature ranges, many snow layers within the seasonal snowpack at Sapporo remained close to 0°C throughout the season (Fig. 3), highlighting the importance of accurately representing heat transfer under near-melting snow conditions.

3.2.2 NSD

For the three NSD parameterization schemes (Fig. 2b), the standard deviation exhibited sharp increases during snowfall events, occasionally exceeding 15 cm, indicating that uncertainty associated with NSD was largest during periods of active snow accumulation. After deposition, the uncertainty decreased rapidly to a few centimeters as densification progressed. Because snowfall amount was prescribed from observations, differences among NSD formulations directly translated into differences in the thickness of newly deposited snow layers.

Although the Yamazaki (1998) formulation uses only wind speed as a predictor, it produced snow depths comparable to those obtained with the more complex formulations. Because the Yamazaki (1998) scheme was developed using observations from Sapporo, this result suggests that regional

characteristics may be more important than model complexity for estimating new snow density. Such regional dependence is expected because new snow density is influenced by snowfall particle type and snow-cloud microphysical processes. The strong dependence of NSD on meteorological conditions suggests that parameterization uncertainty may interact with uncertainty in surface meteorological forcing, particularly precipitation, wind speed, and air temperature.

3.2.3 Compression Viscosity Coefficient

The differences between the two VC formulations varied throughout the snow season and did not exhibit a clear dependence on snowfall events or the particular time of the season (Fig. 2c). Mean standard deviations for individual winter seasons ranged from approximately 0.7 to 3.3 cm, with maximum values reaching about 4–8 cm.

To better understand these differences, the distributions of VC and snow density within the snowpack were compared (Fig. 4). For a given snow density, the Vionnet et al. (2012) formulation generally produced larger VC values than the Bader and Weilenmann (1992) formulation (Fig. 4a, b). This difference arises from the different empirical formulations used to calculate VC. Although the simulated snow-density structures were broadly similar (Fig. 4c, d), the differences in VC indicate that the two formulations represent snow densification differently. Because VC directly controls snow compaction, differences in VC can lead to differences in simulated snow depth. The implications of these differences for seasonal snow-depth evolution are further examined in Section 3.3.

3.2.4 Water Movement Scheme

For the three WM parameterization schemes, the standard deviation remained small compared with the other parameterization groups (Fig. 2d). Mean standard deviations for individual winter seasons ranged from 0.2 to 1.0 cm, while maximum values ranged from approximately 2 to 5 cm. Although slightly larger spreads were observed during the melt season in several winters, the differences among the three schemes were generally small.

The increase in spread during the melt season reflects differences in the treatment of liquid-water transport among the three schemes. The mass-fraction and volume-fraction schemes diagnose water movement using prescribed threshold values, while the Richards-equation scheme explicitly simulates liquid-water transport within the snowpack. As shown in Fig. 5, these differences become apparent during the melt season, when liquid water is present within the snowpack. Because liquid water occurs only during a limited portion of the snow season at Sapporo, the overall influence of WM on simulated snow depth remained relatively small. Consequently, differences among the WM schemes cannot be fully evaluated using snow depth alone. Additional observations of snow liquid water content would be useful for evaluating their performance.

3.3 Comparison among parameterizations

In the previous section, all parameterization options currently implemented in SMAP were evaluated for each physical process. Here, we compare the resulting uncertainty characteristics among the physical processes considered in this study, with particular emphasis on their temporal behavior.

Figure 6 Parameterization uncertainty in simulated snow depth associated with ETC, NSD, VC, and WM during 2006–2021. (a) Seasonal maximum of the daily standard deviation of snow depth for each winter, representing short-term peak uncertainty. (b) Mean daily standard deviation of snow depth for each winter, representing seasonally averaged uncertainty. Boxes indicate the interquartile range, orange horizontal lines the median, green triangles the mean, whiskers 1.5 times the interquartile range, and circles outliers.

NSD produced the largest short-term uncertainty, as shown by the relatively large maximum standard deviations (Fig. 6a). Because new snow density directly determines the initial thickness of freshly deposited layers, uncertainty associated with NSD increased rapidly during snowfall events. However, such periods were generally short-lived and therefore contributed less strongly to seasonally averaged uncertainty (Fig. 6b).

In contrast, VC tended to produce larger seasonally averaged uncertainty than the other parameterizations. Although the differences between the two VC formulations did not exhibit a distinct seasonal pattern (Section 3.2.3), their influence on snow densification accumulated throughout the snow season. Consequently, small differences accumulated over time and became evident in the seasonal mean uncertainty.

The resulting uncertainty from ETC was generally smaller than the short-term peaks associated with NSD but became more pronounced under high-density snow conditions, particularly during the latter part of the snow season. As described in Section 3.2.1, these differences are associated with the increasing divergence among ETC formulations at high snow densities.

WM produced the smallest uncertainty among the four parameterization groups. Although differences among WM schemes became apparent when meltwater was present within the snowpack, their influence on snow depth remained limited under the predominantly dry-snow conditions at the Sapporo site.

These results demonstrate that the importance of parameterization uncertainty depends strongly on the time scale considered. NSD primarily influences short-term variability during snowfall events, whereas VC exerts a more persistent influence through cumulative snow densification. ETC affects snow-depth evolution through heat-transfer processes, particularly under dense-snow conditions, while WM plays a comparatively minor role in the dry-snow environment considered here.

4. Conclusions

This study evaluated the effects of four key snow physical processes in the SMAP model by varying one parameterization at a time during the 2006–2021 winters in Sapporo. The results show that uncertainty characteristics differ substantially among parameterizations. NSD produces the largest short-term uncertainty during snowfall events, while VC exerts a persistent medium- to long-term influence through cumulative snow densification. ETC contributes uncertainty primarily through differences in snowpack cooling and under high-density snow conditions, whereas WM has only a minor impact under the predominantly dry-snow conditions at Sapporo.

These findings indicate that improving snow-depth simulations by SMAP requires prioritizing refinements to NSD and VC parameterizations. As discussed in Section 3.2.2, NSD parameterizations depend strongly on surface meteorological conditions, particularly precipitation, wind speed, and air temperature. Combining NSD-scheme selection with meteorological ensemble forecasts may therefore further enhance the accuracy of ensemble snowfall predictions.

The results also suggest that improved representation of vertical heat transfer under near-melting snow conditions may further reduce uncertainty associated with ETC parameterizations. Although WM had only a limited influence on snow depth at Sapporo, additional observations of liquid-water content would be valuable for evaluating the realism of water movement schemes.

Future work should examine additional output variables, such as snow water equivalent and snow temperature, assess the role of compensating errors, extend the evaluation to a wider range of climatic regions, and develop a more comprehensive understanding of predictive uncertainty.

Declarations

Competing interests

M.N. is a member of the editorial board of SOLA.

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Figures

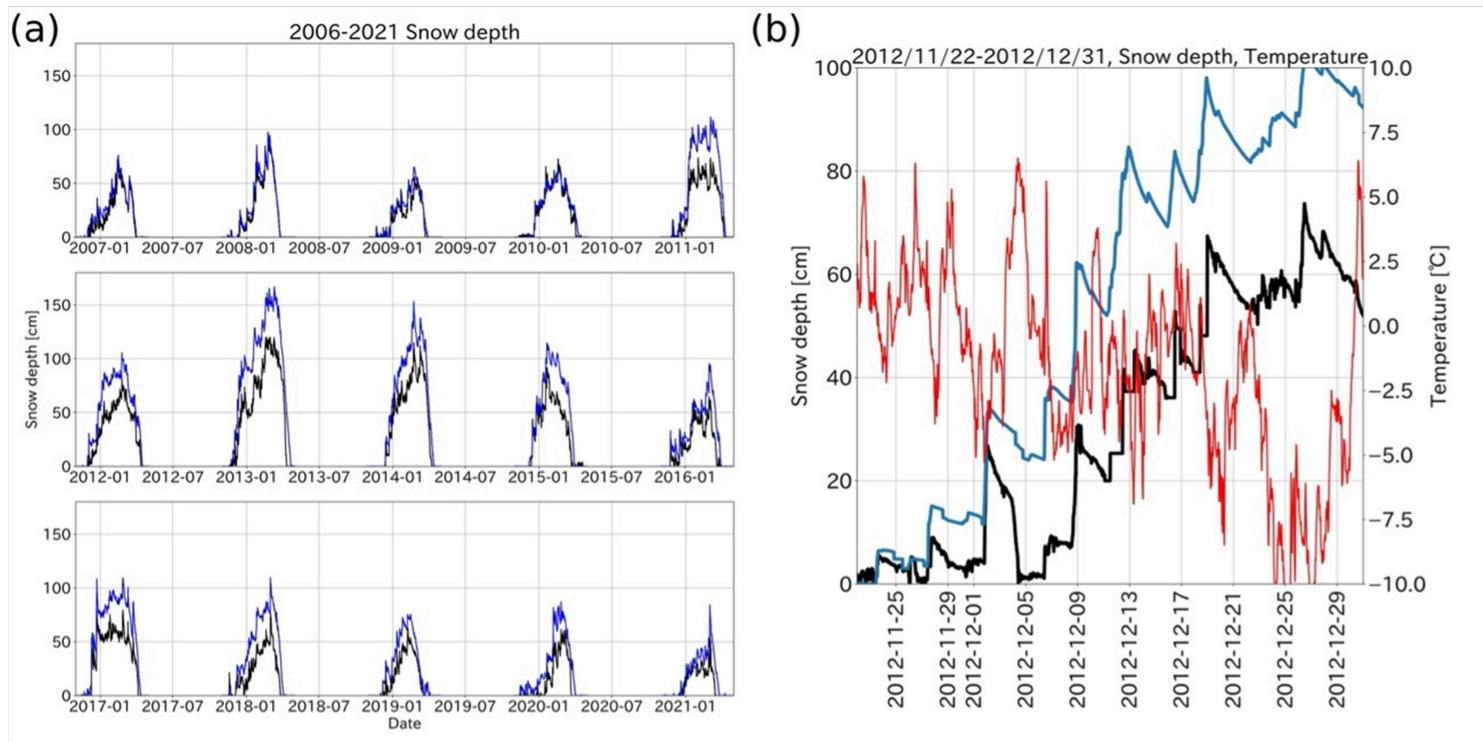


Figure 1

Observed and simulated snow depth at Sapporo. (a) Time series of snow depth from 2006 to 2021. Blue and black lines indicate simulated and observed snow depth, respectively. (b) Example from November–December 2012 showing simulated and observed snow depth together with surface air temperature (red line).

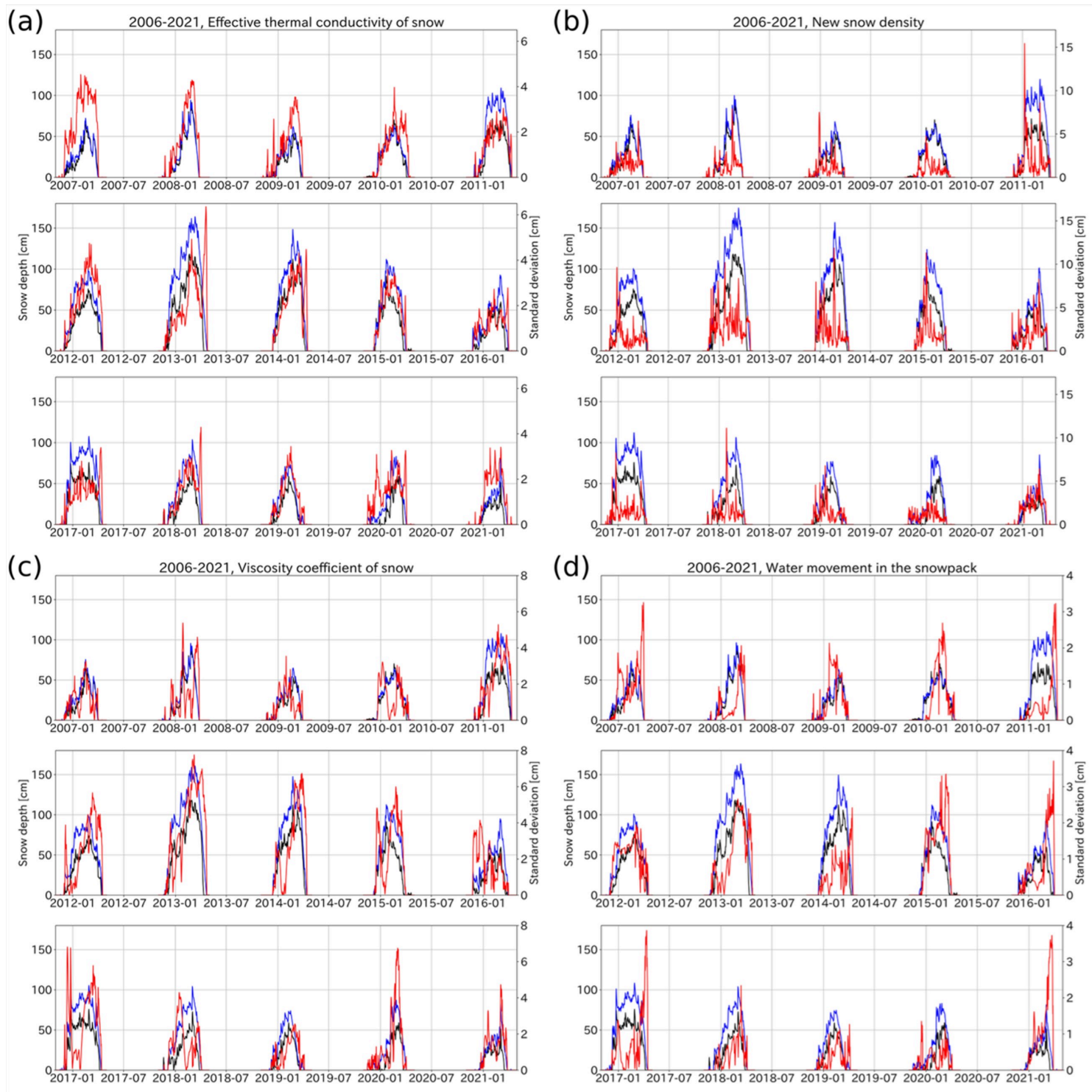


Figure 2

Ensemble statistics of snow depth obtained by varying parameterization schemes for (a) ETC, (b) NSD, (c) VC, and (d) WM. The blue and red lines indicate the ensemble mean and standard deviation of simulated snow depth, respectively, and the black line indicates observed snow depth.

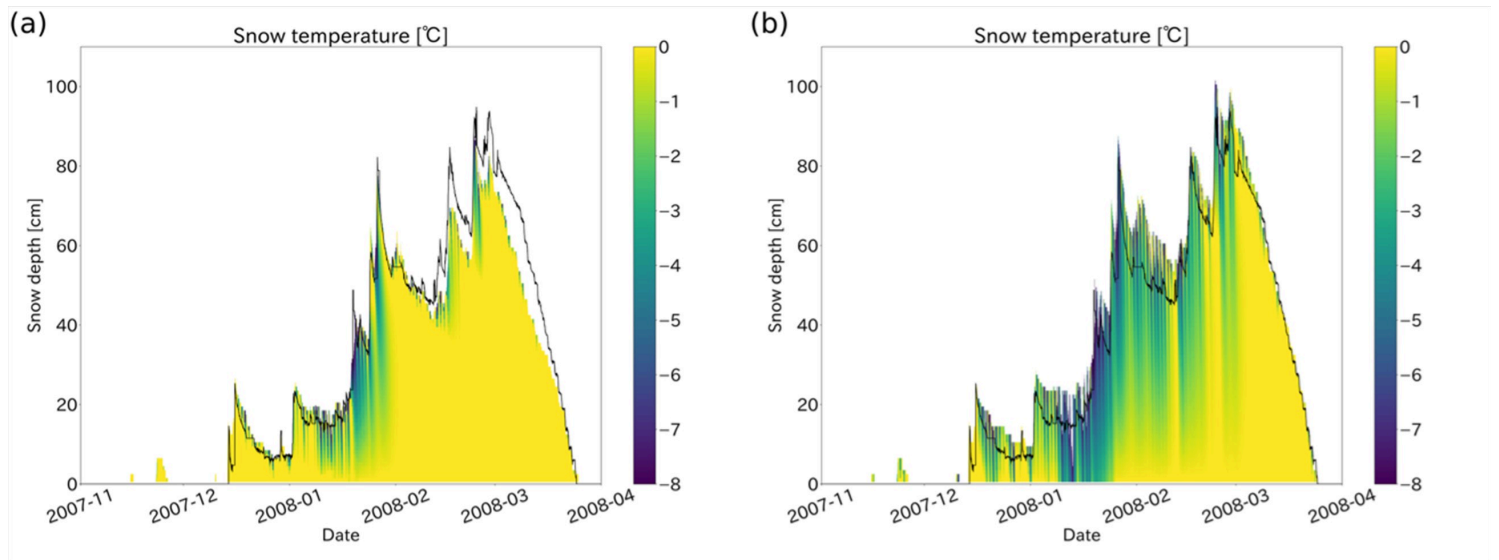


Figure 3

Snow-temperature profiles simulated by SMAP for the 2007–2008 winter using two selected ETC parameterizations. The color shading indicates snow temperature ($^{\circ}\text{C}$), and the black line indicates snow depth (cm). The profiles compare the parameterization producing (a) the smallest snow depth (Bracht 1949) and (b) the largest snow depth (Izumi and Huzioka 1975).

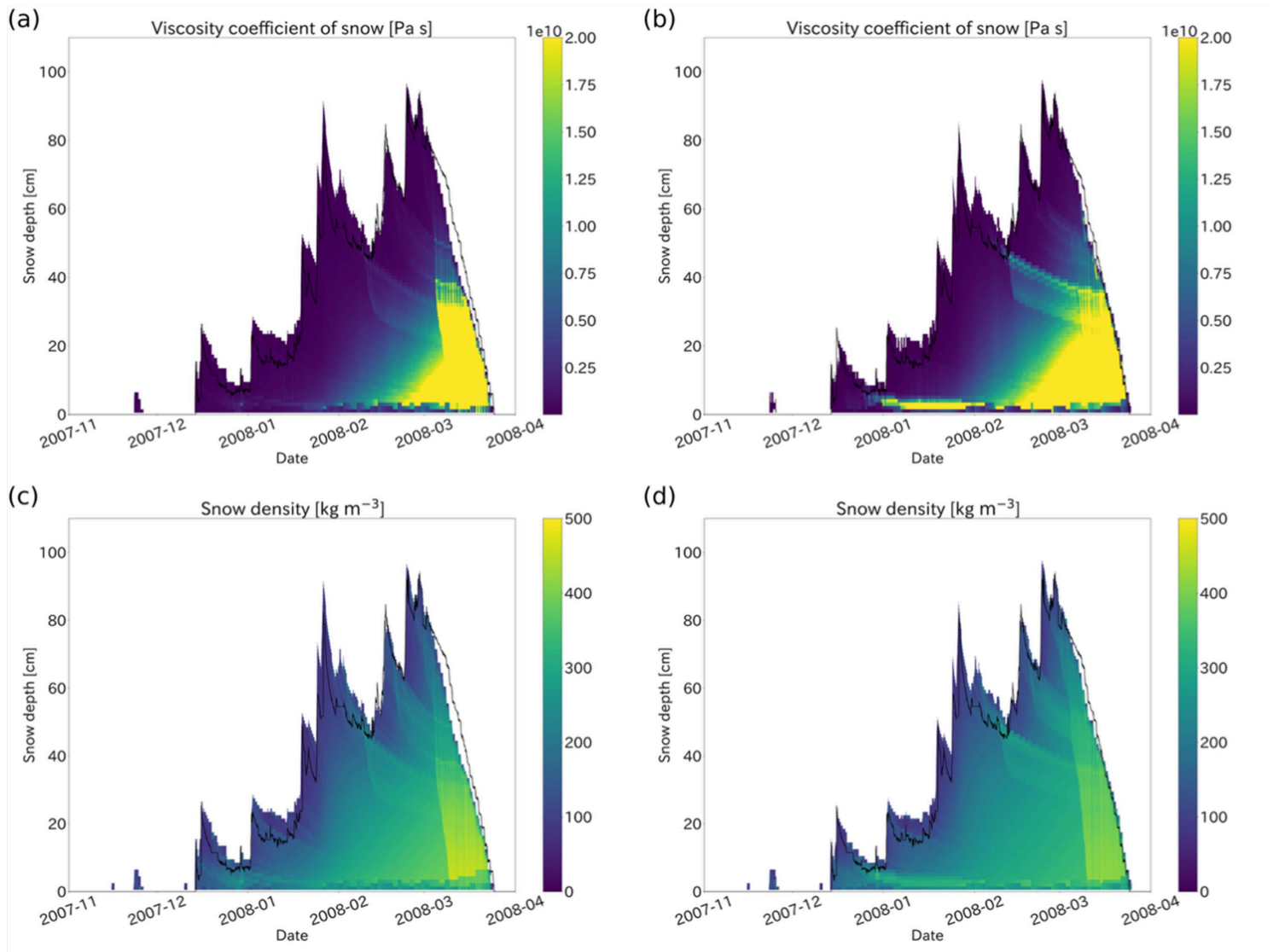


Figure 4

VC and snow density simulated by SMAP for the 2007–2008 winter using the Bader and Weilenmann (1992) and Vionnet et al. (2012) formulations. Panels (a) and (b) show VC, and panels (c) and (d) show snow density. Color shading indicates VC (Pa s) in (a,b) and snow density (kg m⁻³) in (c,d); black lines indicate snow depth (cm).

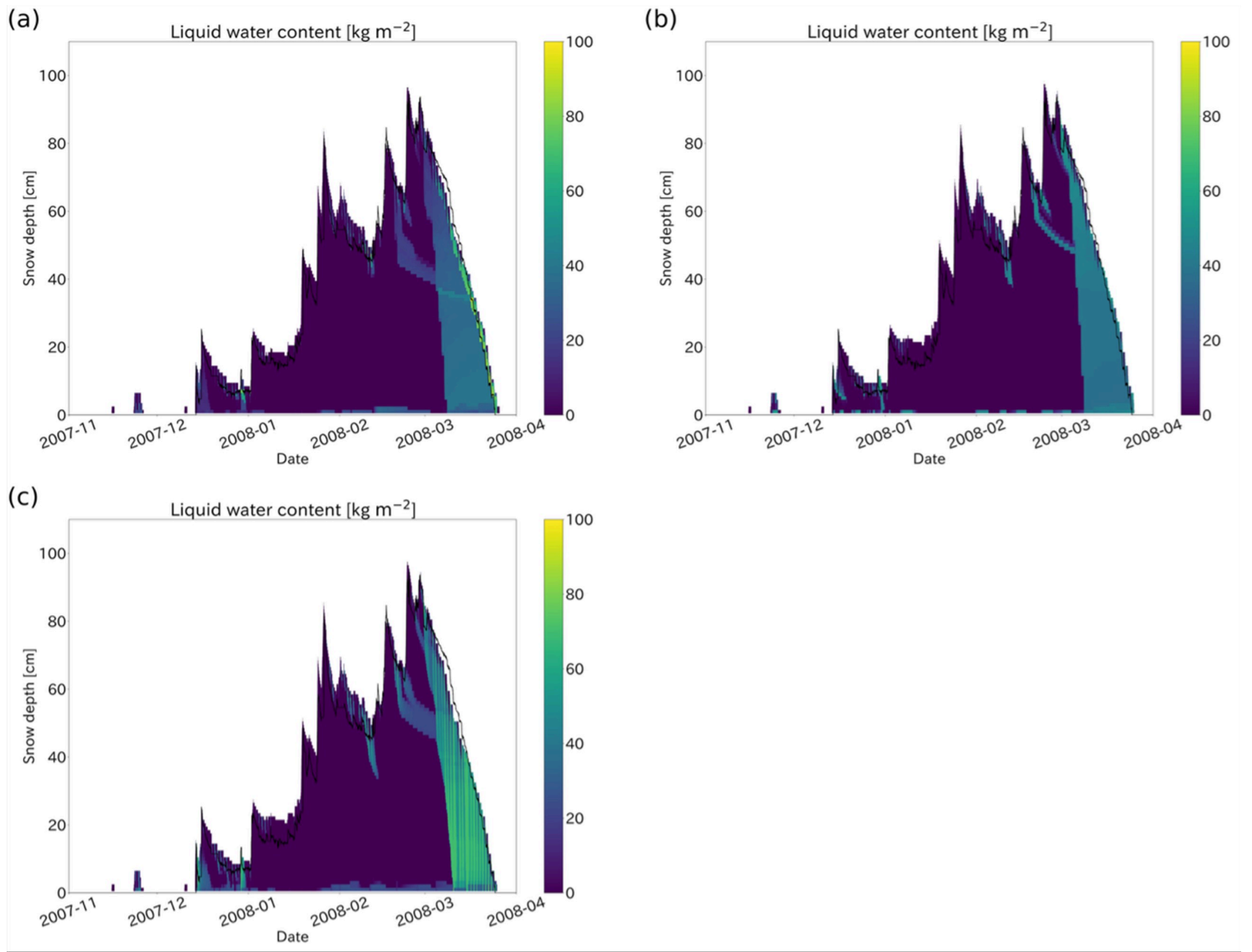


Figure 5

Liquid-water content simulated by SMAP for the 2007–2008 winter using three WM schemes: (a) mass-fraction threshold, (b) volume-fraction threshold, and (c) Richards equation. Color shading indicates liquid-water content (kg m^{-2}), and black lines indicate snow depth (cm).

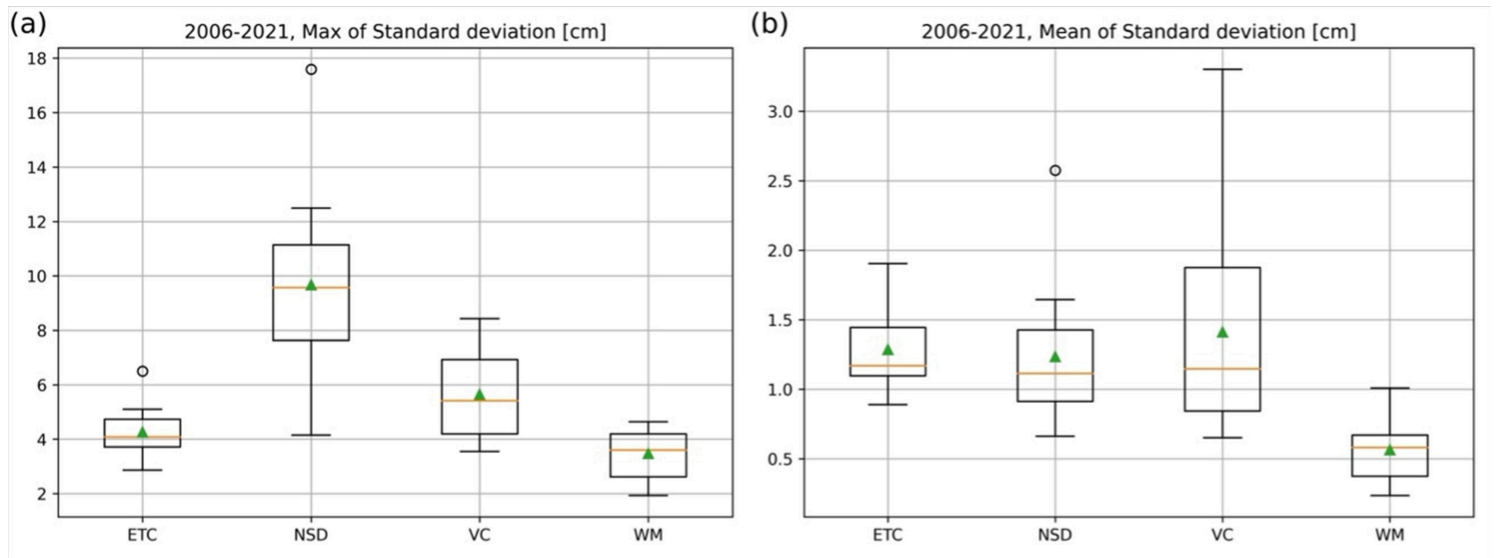


Figure 6

Parameterization uncertainty in simulated snow depth associated with ETC, NSD, VC, and WM during 2006–2021. (a) Seasonal maximum of the daily standard deviation of snow depth for each winter, representing short-term peak uncertainty. (b) Mean daily standard deviation of snow depth for each winter, representing seasonally averaged uncertainty. Boxes indicate the interquartile range, orange horizontal lines the median, green triangles the mean, whiskers 1.5 times the interquartile range, and circles outliers.

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