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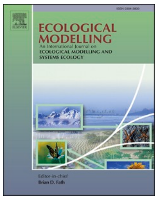

Does meter-scale snow data matter for modeling alpine plant distribution? A comparison of four data sources at two resolutions

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ABSTRACT

Snow cover is a crucial driver for plant species distributions in cold environments. The primary source of snow cover data used in distribution models is remotely sensed satellite imagery, which is characterized by coarser spatial resolutions than plot-scale observations of plant distributions. This scale-mismatch was hypothesized to limit model accuracy. Here, we used a common modeling framework to assess the contribution of snow melt-out dates derived from four data sources (satellite imagery, numerical snowpack modeling, webcam imagery and in-situ soil temperature measurements) at 1 m and 20 m spatial resolution to the predictive power of distribution models of 74 plant species in an alpine landscape of the Austrian Alps. We found that >80 % of the distribution models of all species were significantly improved by at least one snow melt-out data set when considering Area Under the Curve (AUC). Satellite-based melt-out led to significantly improved models for the highest number of species (>50 % for AUC) and increased True-Skill-Statistic and AUC on average by 16 % and 5 %, respectively. Surprisingly, fine-scale and in-situ measured melt-out data did not improve models more than the coarser scale (20 m) satellite-based melt-out data. Moreover, numerical snowpack modeling delivered results comparable to the other sources, which supports its use for projecting future species distributions. We conclude that the additional effort needed for producing high resolution, in-situ datasets as compared to commonly used satellite imagery might hence be worthwhile for some species but not for plant distribution modeling in cold ecosystems in general.

1. Introduction

Snow is a crucial factor determining plant species distributions in alpine and arctic environments (Billings and Mooney, 1968; Choler, 2018; Körner, 2021). Snow cover affects growing season length, provides protection against deep frosts in winter or early spring as well as modulates water availability at the start of the growing season (Körner, 2021). Many species are therefore well-known for their preferred or exclusive occurrence at sites characterized by either particularly long or short snow cover periods (Heegaard, 2002; Odland and Munkejord, 2008). Consequently, variables characterizing snow cover dynamics have gained increasing attention in recent years in modeling the distribution of arctic and alpine plant (Panchard et al., 2023; Niittynen and Luoto, 2018; Rissanen et al., 2023) and animal species (Keyser et al., 2023).

Species distribution modeling applications have been criticized for being based on predictor variables representing macroclimatic rather than microclimatic conditions, i.e., the climatic conditions experienced

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by the organisms, which is particularly problematic in complex alpine terrain (Hannah et al., 2014; Lembrechts et al., 2019; Maclean and Early, 2023). At the same time, there is an ongoing debate about the potential of this fine-scale microclimatic variation for mitigating the impacts of climate change on plant distribution (Graae et al., 2018; Hannah et al., 2014; Körner and Hiltbrunner, 2021; Chytrý et al., 2024). Similar to temperature conditions, snow properties can vary extensively over short distances and periods in alpine landscapes (Helfricht et al., 2014; López-Moreno et al., 2015; Miller et al., 2022). Consequently, high spatial and temporal resolution data are potentially necessary to accurately capture snow conditions determining species distributions (Dedieu et al., 2016; Randin et al., 2015). Despite this, projections of species distributions are commonly based on snow cover information derived from optical satellite imagery with spatial resolutions of tens to several hundreds of meters (Carlson et al., 2015; Niittynen and Luoto, 2018; Panchard et al., 2023; Rissanen et al., 2021). The usage of such data is motivated by the fact that snow products based on the Landsat mission, the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Advanced Very High Resolution Radiometer (AVHRR) cover two or more decades (Hall et al., 2019; Rößler and Dietz, 2022; Wulder et al., 2022), and synthesis products, such as snow cover duration or melt-out dates based on Sentinel-2 (S2), are directly available for download and thus easy to use (e.g., Barrou Dumont et al., 2025).

Potentially important alternative data sources for deriving snow cover dynamics are webcam imagery, soil temperature measurements and process-based snow models, some of which have also been used in ecological modeling, albeit to a lesser extent (e.g., Lookingbill et al., 2024, Randin et al., 2009, Steinbauer et al., 2022). Snow models can be run at various, even very fine, spatial resolutions, targeting the aforementioned limitations. Moreover, they provide a physically consistent representation of snow processes, allowing for mechanistic modeling of snow cover under future climate scenarios. On the contrary, satellite imagery and *in-situ* fine-scale data acquired during short monitoring periods, only allow establishing statistical relationships to project snow cover dynamics into the past and future, e.g., by relating them to topographic and/or meteorological parameters (Tappeiner et al., 2001; Carlson et al., 2015; Ma et al., 2024). However, snow cover dynamics derived from process-based snow models have rarely been used as predictors in species distribution models (SDMs) so far, and the available results (e.g., Randin et al., 2006, 2009 and Dedieu et al., 2013), are far from being conclusive regarding their predictive power when compared to models without such predictors. Alternative fine-scale datasets such as webcam imagery and soil temperature measurements acquired in the scope of short, dedicated monitoring campaigns, offer the advantage of higher spatial- (webcam) and temporal resolution (webcam, soil temperature) compared to satellite imagery and have proven to accurately reflect information on snow cover extent (Fedorov et al., 2016; Härer et al., 2016; Teubner et al., 2015). However, a disadvantage of both data sources is the time-consuming field work which prevents large-scale, continuous spatial and temporal monitoring. Moreover, derivation of snow cover from soil temperature measurements requires calibrated formulas (Steinbauer et al., 2022; Teubner et al., 2015) and deriving snow cover from webcam imagery additionally requires snow cover classification and monoplotting, i.e., projecting oblique images onto a digital elevation model to allow further processing (Fedorov et al., 2016; Härer et al., 2016). This likely explains why researchers more often adopt satellite imagery than *in-situ* loggers or webcams and raises the questions of whether accurate, high resolution datasets are advantageous when modeling species distributions and whether the effort associated with data collection is justified.

Here, we investigated how snow melt-out date (SMOD) derived from satellite imagery (S2 at 20 m resolution), a spatially-distributed numerical snow model (1 m and 20 m resolution), webcam imagery (1 m and 20 m resolution) and soil temperature measurements (point measurements) improve the accuracy of SDMs of vascular plant species in an alpine landscape in the Austrian Alps. We focus on SMOD because it is currently one of the most frequently used predictors for characterizing snow cover dynamics in SDMs. We calculated SMOD for 701 plots of 1 *m* × 1 m with known plant species composition from these datasets and subsequently evaluated the improvement of temperature- and topography-based distribution models of 74 plant species when including SMOD products. Due to the strong influence of snow cover dynamics on alpine plants (Körner, 2021; Niitynen and Luoto, 2018) we hypothesized that (1) SMOD generally improves model accuracy for all species. We expect an improved characterization of snow cover dynamics by fine scale data and hence furthermore hypothesize that (2) fine-scale (i.e., 1 m resolution and point) SMOD delivers stronger improvement of SDMs than coarse scale 20 m resolution SMOD. Finally, since *in-situ* collected data decreases or completely eliminates the influence of cloud cover (affecting satellite imagery) and the reliance on accurate model parameterization and forcing data (snow model), we hypothesize that (3) neither snow model- nor satellite-based SMOD reach the level of improvement provided by webcam- and logger-based SMOD at any of the two resolutions.

2. Materials and methods

2.1. Study site and vegetation data

The study site is Schrankogel (3497 m a.s.l., Fig. 1), a mountain in the Stubai Alps, Central Eastern European Alps (Austria). It includes areas at the foot of the mountain and on the west-, south- and east-facing slopes. The area is characterized by a large elevational gradient and typical high alpine and post-glacial landscape features, including a glacier forefield, lateral- and ground moraines and the steep slopes of Schrankogel. Meteorological data by GeoSphere Austria (2024) at a nearby station in Obergurgl (1950 m a.s.l.) for the period 1990 - 2020 indicate a mean temperature of 3.50 °C, an annual precipitation of 900 mm, of which an estimated 259 mm fall as snow (calculated as the precipitation sum below 0 °C). Automatic snow depth measurements for the very same station show a maximum snow depth of 151 cm with the last day of snow cover occurring, on average, at day-of-year 128 for the period of 2020–2024.

In the summers of 2021 and 2022, we established 900 vegetation plots of 1 *m* × 1 m across the accessible area within the study site (Chytrý et al., 2024). At each plot, we sampled the full vascular plant species composition. Here, we considered the subset of 701 plots which are covered by the webcams (see below) and located at elevations between ca. 2100 and 3471 m a.s.l. (i.e., covering subalpine to nival belts; Fig. 1c). For species distribution modeling we considered only species determined at least to the species level and which occurred at least in 60 plots ($n = 74$ species). Plant nomenclature follows the Euro+Med database (emplantbase.org, accessed 2022–10–18).

2.2. Snow cover datasets

2.2.1. Satellite imagery

We employed the S2 Level 3B SMOD product provided by Theia (2024) for the years 2022 and 2023, which covers the entire study site (Fig. 1c). The S2 Level 3B SMOD product is derived from the S2 Level 2B snow cover product which is characterized by a spatial- and temporal resolution of 20 m and 5 days, respectively (Theia, 2024). Level 2B products are derived from S2 surface reflectance by employing the ‘Let-it-snow’ (LIS) algorithm (Gascoin et al., 2019). The snow detection of LIS is based on thresholding of the Normalized Difference Snow Index (Dozier, 1989) with specific adjustments to avoid misclassification of water surfaces. The SMOD is computed by hydrological year (i.e., starting Sep 1st each year) as the last day of the longest period of consecutive snow cover and characterized by a root mean square error and mean absolute error of 24 and 9 days, respectively, when compared against *in-situ* data in the Alps and Pyrenees (Barrou Dumont et al., 2025).

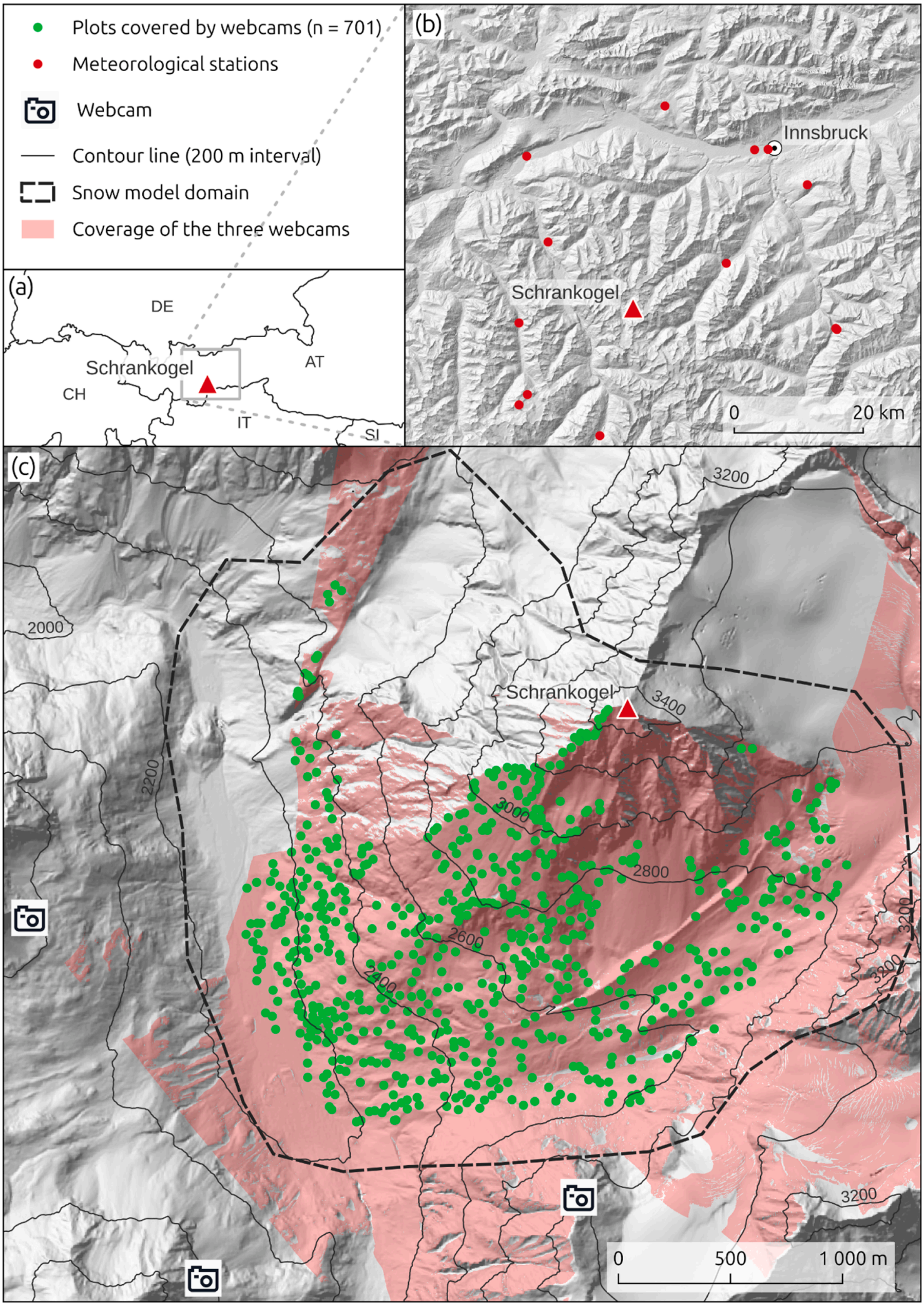

Fig. 1. (a) Location of the study site, (b) meteorological stations used to force the snow model openAMUNDSEN, (c) combined coverage of the three webcams and the 701 vegetation plots used for modeling at Schrankogel, Stubai Alps (Austria).

2.2.2. Snow model

We employed openAMUNDSEN, a spatially-explicit, physically based snow model for mountain regions (Strasser et al., 2024). openAMUNDSEN models the evolution of alpine snowpacks on a gridded representation of the earth's surface by calculating relevant energy- and mass fluxes based on meteorological forcing data and a digital elevation model (DEM) at user-specified timesteps (the 1 m DEM was obtained from the Department of Geoinformation, State of Tyrol, Austria, 2024). As meteorological forcing data we used hourly meteorological input data (2 m air temperature, relative humidity, incoming shortwave radiation, precipitation, wind speed) of 13 stations (GeoSphere Austria, 2024), resampled to 3-hourly time steps. The mean distance of the stations to the study site is 26 km (Fig. 1b), the full list of stations is given in the supplementary (Table S.4). openAMUNDSEN generates spatially-distributed meteorological forcing data by interpolating temperature and precipitation using elevation dependent lapse rates; actual solar radiation is obtained by correcting potential solar radiation which is calculated based on local topography, with a spatially interpolated cloud factor, the latter being parameterized by relative humidity in our particular model setup. Here, we started modeling in 2020 to account for eventually occurring perennial snow from the previous winter season and modeled until the end of August 2024. The model was run at 3-hourly time steps using the energy-balance melt-scheme considering lateral snow redistribution by wind by means of a snow redistribution factor which is applied to spatially correct the interpolated fields of solid precipitation. openAMUNDSEN was run at resolutions of 1 m and 20 m resulting in two snow model datasets for the snow model domain indicated in Fig. 1c. For the 20 m resolution, the DEM was aggregated from 1 m to 20 m before the modeling (method: average). We configured the model to produce maps of mean daily snow water equivalent, which was converted to binary snow cover by applying a minimum threshold of 1 mm for each pixel (Hanzer et al., 2016).

2.2.3. Webcam

Three webcams were installed on slopes opposite of Schrankogel (Fig. 1c) and delivered images at sub-hourly intervals since July 2021. A Random Forest classification (Breiman, 2001) was employed to derive daily snow cover from individual images following the method described by Fedorov et al. (2016). This method relied on pixel-wise image classification that was based on 33 predictor variables. For each image pixel the classifier received the local intensity of each pixel in a 3 pixel × 3 pixel wide window (9 features in total), the local intensity average of a 15 pixel × 15 pixel wide window and the global average of the entire mountain. These 11 predictors were computed for all of the three RGB channels, resulting in a total of 33 predictors. As a response we used binary snow/no-snow labels for each pixel and image compiled by visual interpretation. These pixels were sampled from approximately 50 images for each webcam. Georectification of the oblique webcam images was done with the software package PRACTISE (Härer et al., 2016). Given a DEM of the study site, ground control points and initial estimates of camera parameters, for each pixel in an image, PRACTISE computes the corresponding DEM pixel, i.e., the real-world location. Using the same DEM as for snow modeling, this procedure was applied to all images from the webcams, i.e., the entire time series, to derive daily, webcam-based snow cover maps at 1 m resolution. Images with low visibility were filtered out, which introduced few gaps into the time series. Afterwards, snow cover maps from all three webcams were merged into a single daily map for the extent indicated in Fig. 1c, using the mode in those parts of the study site where maps overlapped. In case a pixel was only visible from two cameras, pixels were assumed to be covered by snow if at least one of the cameras detected snow.

2.2.4. Soil temperature loggers

At each vegetation plot (Fig. 1c), we installed a temperature logger (GeoPrecision M-Log 5 W) 10 cm below ground. Using hourly measurements from the years 2022 and 2023, we identified days when the site was covered with snow based on a daily soil temperature amplitude smaller than 0.2 °C and a maximum soil temperature of 2 °C, corresponding to a high probability for snow cover (Teubner et al., 2015). In the context of this study, the soil temperature-derived snow cover does not suffer from any geometric inaccuracy, since it is located right at the plot. For improved readability, logger-derived snow cover data is included in the 1 m resolution group, despite being a point measurement.

2.3. Computation of SMOD

The SMOD for the snow model-, webcam- and logger-based data was computed by relating the binary data of a single pixel of one of the three snow cover sources to its day-of-year of observation using a Generalized Linear Model (GLM, binomial distribution, logistic link) following Niittynen & Luoto (2018). SMOD was defined as the first day of the year when the GLM predicts a value of ≤ 0.5 (i.e., the day from which the probability to be covered by snow was below 50 %). Only data from pixels corresponding to the locations of the 701 plots were used in the GLMs for snow cover maps derived from the webcams and the snow model. For all computations only observations of the day-of-year 1 to 250 (compare Niittynen and Luoto 2018; Panchard et al., 2023) of the years 2022 and 2023 were considered and data from both years are merged into a single dataset using their day-of-year. In the case of the satellite imagery, SMOD is defined as the last day of the longest period of consecutive snow cover in a hydrological year (Barrou Dumont et al., 2025). In order to align the period of data collection with the other data sources, we defined satellite-based SMOD in our study as the mean S2 SMOD of the years 2022 and 2023. Since the annual S2 SMOD, pre-computed by Theia (2024), is based on the hydrological year, starting at Sep 1st, all values were shifted by 122 days, so that S2 SMOD also refers to melt-out with respect to Jan 1st, as it is the case for all other data sources. The 20 m resolution webcam SMOD was computed as the average SMOD of the 1 m cells falling into a 20 m resolution cell. In total, we obtained the following six SMOD products: snow model-based as well as webcam-based SMOD at 1 m and 20 m resolution, satellite-based SMOD at 20 m resolution and logger-based SMOD at 1 m resolution.

We calculated the pairwise Spearman rank correlation between the SMOD products, to quantify the agreement between the data sets.

2.4. Supporting environmental predictors

In addition to SMOD, we used further variables characterizing the topography and the climate of plots as predictors of plant occurrences. Their choice was mainly guided by their use in previous studies (Niittynen and Luoto, 2018; Panchard et al., 2023; Rissanen et al., 2021, 2023), including a study conducted at our study site (Chytrý et al., 2024). As topographic variables, we selected slope, topographic wetness index (TWI) and sum of potential solar radiation (from July to September) based on a 10 m resolution Digital Elevation Model (DEM). As a climatic predictor, we computed the mean air temperature (from July to September) for a 30-year period from 1991 to 2020 based on spatially interpolated temperature grids. These grids were obtained by interpolation of data from the meteorological stations that were also used by the process-based snow model (Fig. 1b) onto a DEM with 10 m spatial resolution by running the meteorological preprocessor of openAMUNDSEN. The temperature interpolation is based on a combination of inverse-distance-weighting and an elevational lapse-rate that varies by month to account for elevation dependence (Strasser et al., 2024). Since the focus of the study was to show the added value of different SMOD products at various resolutions in SDMs, only data source and spatial resolution of SMOD was varied across models while those of mean air temperature and the topographic predictors were kept constant.

2.5. Species distribution modeling & analysis

For all SDMs, we used an ensemble model consisting of a Random Forest (Breiman, 2001), a Generalized Additive Model (Hastie and Tibshirani, 1986) and a Generalized Linear Model (Nelder and Wedderburn, 1972). For each of the 74 species and each SMOD dataset, we separately fitted three (sets of) models to predict the species' occurrence: (1) A baseline model using the supporting environmental predictors only (slope, TWI, solar radiation, air temperature), (2) a SMOD model based on the supporting environmental predictors plus one of the six SMOD datasets, (3) 100 permutation models based on the predictors of (2) but with the SMOD variable randomly permuted. The baseline model, the "real"-SMOD model and all 100 permutation models were evaluated on independent data via 10-fold cross validation, stratified on the occurrence of the target species, using the same splits across all models, resulting in a total of 452,880 models (6 SMOD products x 10 folds x 102 models x 74 species). As a measure of the goodness of fit, we computed the mean True-Skill-Statistic (TSS, Allouche et al., 2006), mean area under the receiver operating characteristic curve (AUC, Fielding and Bell, 1997) and mean Boyce index (Hirzel et al., 2006) of the 10 cross-validation runs, resulting in 45,288 (6 SMOD products x 102 models x 74 species) validation metrics for TSS, AUC and Boyce index, respectively, each of which we refer to as a "single" SDM from here on (despite being actually based on 10 ensemble models from the cross-validation). We denote metrics for the baseline and SMOD SDMs as $TSS_{baseline}$ ($AUC_{baseline}$, $Boyce_{baseline}$) and TSS_{SMOD} (AUC_{SMOD}, $Boyce_{SMOD}$), respectively. Since TSS has been shown to have a more constant response to species prevalence, it is considered superior to Kappa (Allouche et al., 2006) which was therefore deliberately excluded from the results.

In order to test for a significant improvement when adding a SMOD product, we flagged the improvement for a specific combination of species and SMOD product as 'significant' if TSS_{SMOD} (AUC_{SMOD}, $Boyce_{SMOD}$) was greater than the 95 % quantile of TSS (AUC, Boyce index) scores from the 100 permutation models. This type of permutation test is often applied in a similar context (cf. Niittynen and Luoto, 2018, Panchard et al., 2023) and we show that the 95 % quantile is a more conservative estimate of model improvement than checking for TSS_{SMOD} (AUC_{SMOD}, $Boyce_{SMOD}$) being greater than $TSS_{baseline}$ ($AUC_{baseline}$, $Boyce_{baseline}$, supplementary, Fig. S.1). The effect of adding SMOD to the SDMs was quantified using the absolute as well as proportional change in TSS score, calculated as $TSS_{absolute} = TSS_{SMOD} - TSS_{baseline}$ and $TSS_{prop} = TSS_{absolute} / TSS_{baseline}$ (likewise for AUC and Boyce index). Since permuting SMOD values could break spatial autocorrelation in the dataset, hence potentially lowering $TSS_{baseline}$ ($AUC_{baseline}$, $Boyce_{baseline}$) and thereby increasing the risk to falsely conclude that SMOD increases predictive power, we additionally provide a set of autocovariate models in the supplementary (Dormann 2007) to show that the change given by $TSS_{absolute}$ ($AUC_{absolute}$, $Boyce_{absolute}$) is still largely positive when explicitly accounting for spatial autocorrelation in the baseline models (supplementary Fig. S.8, S.9).

In order to check if SMOD generally improves model accuracy for all species (hypothesis 1), we record the number of significantly improved SDMs per SMOD product and rank each SMOD product accordingly to characterize differences in predictive power of SMOD products (hypothesis 2 and 3). We also checked for significant differences in evaluation metrics between generalist and snowbed species within a SMOD data source. Regarding hypotheses 2 and 3 (differences in TSS, AUC and Boyce due to SMOD source), we implemented a linear mixed effect model (LMM) of the form $TSS_{absolute} \sim \text{SMOD source} + (1|\text{species})$ (likewise for $AUC_{absolute}$, $Boyce_{absolute}$) followed by a pairwise post-hoc test for differences among SMOD sources. In this test, we set the absolute and proportional difference to zero for insignificant models, but kept them in the dataset. The LMM and post-hoc tests were implemented in R version 4.4.2 (R Core Team, 2024) using the packages "lme4" (Bates et al., 2015) and "emmeans".

3. Results

3.1. Inter-agreement of SMOD products

Spearman rank correlations between the SMOD products varied from a minimum of 0.42 (between logger and snow model at 20 m resolution) to a maximum of 0.85 (between satellite and webcam, both at 20 m resolution, Fig. 2). Assuming perfect, i.e., error-free SMOD products, at least variables at the same spatial resolution should show perfect agreement. Here, only webcam- (20 m) and satellite SMOD show a high correlation, pointing to substantial differences between the other datasets. Snow model and webcam SMOD show high correlation between their respective 1 and 20 m versions, too, suggesting that the nature of the data source rather than the resolution is responsible for lack of correlation between the SMOD values. Low correlation of the logger SMOD with the other datasets are due to the many plots that show no snow at all or a short snow cover according to the logger data (Fig. 2).

3.2. Performance of SMOD products in SDMs

The number of significantly improved SDMs when adding SMOD was highest for 1 m webcam-based SMOD when considering TSS (27 improved models out of 74, Table 1) and 20 m satellite-based SMOD when considering AUC (44 improved models out of 74, Table 1). Boyce index generally indicated an improvement only for up to 7 out of 74 SDMs. Webcam-based SMOD at 20 m resolution provided the least amount of improved models for TSS and AUC (21 and 31 models, respectively). Despite the high correlation between satellite-based and webcam-based SMOD at 20 m (Fig. 2) these two products differ considerably in terms of the number of species for which they improve SDMs. In terms of the number of significantly improved SDMs, satellite-based SMOD at 20 m resolution and webcam-based SMOD at 1 m resolution consistently ranked among the top-3 SMOD products, even if this number varied across the evaluation metrics.

The magnitude of model improvement was moderate, on average across species, with $TSS_{absolute}$ and TSS_{prop} ranging from 0.08 and 17 % for webcam-based SMOD at 20 m (greatest improvement among all SMOD variables) to 0.07 and 14 % for snow model-based SMOD at 1 m resolution (lowest improvement). However, for both TSS and AUC, the magnitude of improvement did not vary considerably between the SMOD products. $AUC_{absolute}$ and AUC_{prop} were generally quite low, however, it has to be noted that mean $AUC_{baseline}$ is already > 0.8. Values for $Boyce_{absolute}$ and $Boyce_{prop}$ varied more strongly than TSS and AUC, but should only be carefully interpreted, as the number of significantly improved SDMs they are based on is rather low (Table 1). The LMM used to test for statistical differences between $TSS_{absolute}$ ($AUC_{absolute}$, $Boyce_{absolute}$) of any two SMOD SDMs paired showed that, on average across species, there are almost no significant differences (supplementary, Table S.1., S.2, S.3).

SMOD products also varied considerably with respect to which species' model they were able to improve. Considering TSS and AUC, only 4 and 11 out of 74 species were consistently improved, respectively, by adding any of the six SMOD products to the SDMs (Fig. 3, supplementary, Fig. S.4, S.5). Considering TSS, AUC and Boyce index, SDMs of 18, 13 and 53 species, respectively, were not significantly improved by any of the SMOD products. On the flipside, SDMs of about a third and more than half of the species (considering TSS and AUC, respectively) were significantly improved by at least one or more SMOD products (supplementary, Fig. S.4, S.5, S.6) and >80 % of the SDMs were improved by at least one of the SMOD data sets (considering AUC, Fig. S.5). The magnitude of improvement for a specific species showed considerable variation between SMOD products, for TSS, AUC and Boyce index (Fig. 3, supplementary, S.2, S.3).

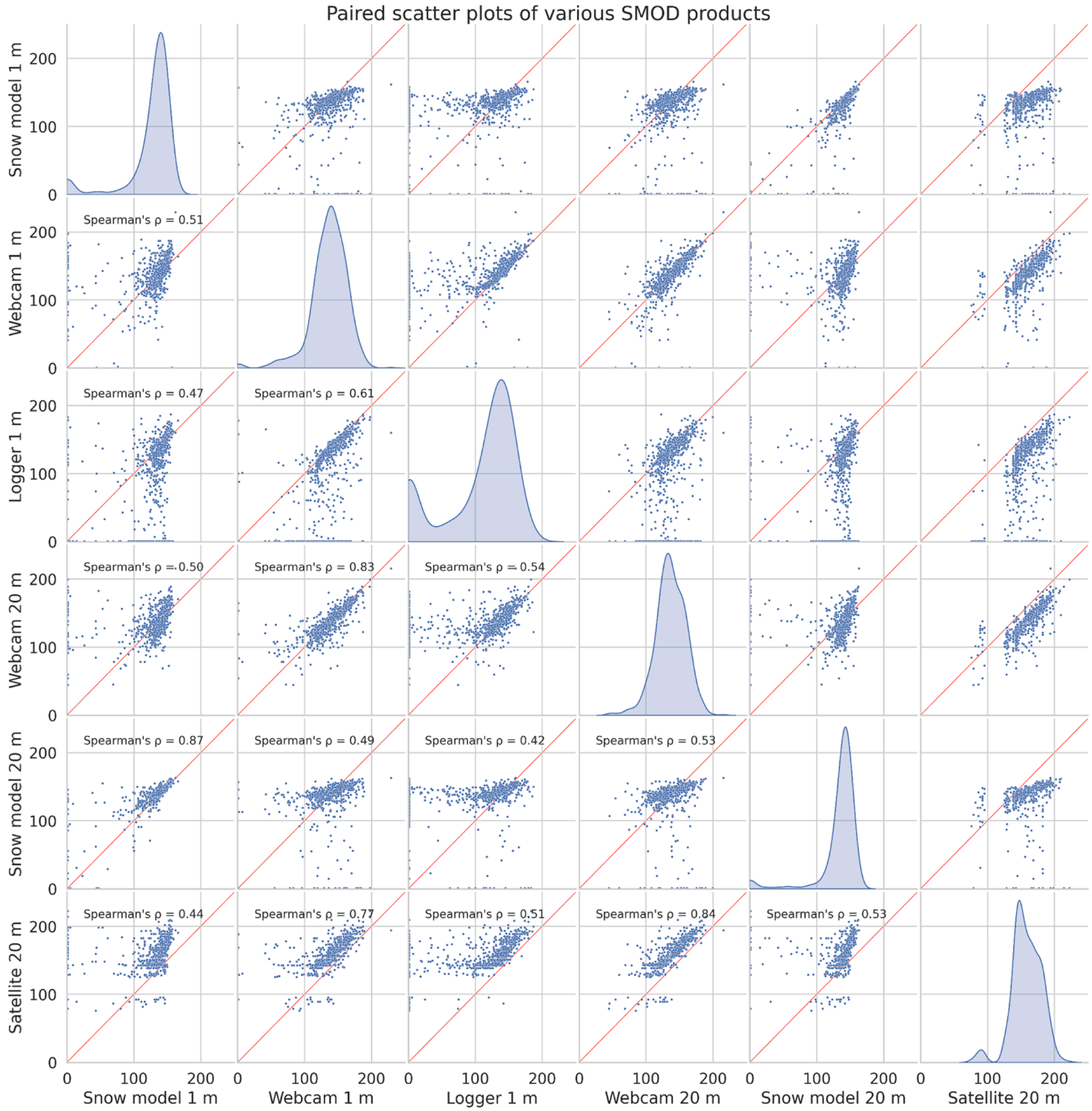

Fig. 2. Pairwise scatter plots of melt-out dates (Julian day) derived from the six SMOD data sets, as well as a kernel density estimate of dates in each data set. The red line indicates a perfect agreement between any two data sets.

Table 1
Statistics on the performance of SMOD products in SDMs of 74 species on Schrankogel, Austrian Alps. Parentheses indicate ± 1 standard deviation. Mean AUC, TSS and Boyce metrics shown here were computed among significant SDMs only.

	Satellite 20 m	Logger 1 m	Snow model 20 m	Snow model 1 m	Webcam 1 m	Webcam 20 m
Nr. of species with significantly improved SDMs (TSS)	25	23	25	22	27	21
Nr. of species with significantly improved SDMs (AUC)	44	37	36	28	38	31
Nr. of species with significantly improved SDMs (Boyce index)	6	7	2	3	6	4
Mean $TSS_{absolute}$	0.081 (± 0.049)	0.073 (± 0.039)	0.077 (± 0.045)	0.068 (± 0.027)	0.078 (± 0.036)	0.082 (± 0.042)
Mean $AUC_{absolute}$	0.04 (± 0.022)	0.039 (± 0.023)	0.037 (± 0.024)	0.037 (± 0.022)	0.039 (± 0.023)	0.042 (± 0.022)
Mean $Boyce_{absolute}$	0.294 (± 0.329)	0.385 (± 0.261)	0.255 (± 0.103)	0.552 (± 0.332)	0.562 (± 0.263)	0.258 (± 0.291)
Mean TSS_{prop}	0.159 (± 0.101)	0.143 (± 0.088)	0.163 (± 0.106)	0.14 (± 0.058)	0.157 (± 0.084)	0.166 (± 0.095)
Mean AUC_{prop}	0.05 (± 0.029)	0.049 (± 0.03)	0.047 (± 0.031)	0.046 (± 0.028)	0.049 (± 0.03)	0.052 (± 0.028)
Mean $Boyce_{prop}$	1.022 (± 1.477)	1.006 (± 0.991)	0.373 (± 0.202)	48.779 (± 82.9)	2.298 (± 1.796)	0.611 (± 0.848)

Fig. 3. $TSS_{absolute}$ for all species (i.e., SDMs), including those where SMOD did not lead to a significant improvement. Results for $AUC_{absolute}$ and $Boyce_{absolute}$ can be found in the supplementary, Fig. S.2 and S.3, respectively.

4. Discussion

4.1. General findings

Our results are generally in line with previous findings (Dedieu et al., 2013; Carlson et al., 2015; Dedieu et al., 2016; Niittynen and Luoto, 2018; Rissanen et al., 2021; Panchard et al., 2023) which showed, based on different datasets at medium to coarse resolution for alpine and arctic environments, that snow data can improve SDMs, but that the improvement also varies by species. Our results thus confirm the importance of snow for vegetation modeling from studies (i.e., not restricted to SDMs) around the whole of Scandinavia (Niittynen and Luoto, 2018; Rissanen et al., 2021; Panchard et al., 2023), sites in Switzerland (Panchard et al., 2023) and the French Alps (Dedieu et al., 2016). However, the improvement of model accuracy we achieved in terms of TSS and AUC was only moderate for most of the alpine plant species. At first glance, this appears at odds with the well-known impact that snow cover has on alpine plant distribution in temperate and boreal mountains (Billings and Mooney 1968; Ellenberg 2009). However, snow cover is closely related to topography (Körner, 2021), and part of its explanatory power is hence already covered by the topographical variables in our models. Put differently, our data suggest that despite a strong imprint of topography on snow cover dynamics (Randin et al., 2009), distribution models of alpine species do still profit from an explicit inclusion of snow products. Most likely, this is the case because snow dynamics are not exclusively predictable from topography (Niittynen and Luoto, 2018), and even less from the selected set of topographical descriptors that we used. Niittynen & Luoto (2018) also showed that SDMs for lichens benefit more from inclusion of SMOD than vascular plants. We also did not find significant differences in the magnitude of improvement between generalist and snowbed species (Fig. S.7). While the fact of model improvement by snow products hence matches prior expectations and the moderate magnitude of improvement is plausibly explained by topography partly accounting for snow cover, the variation in the strength of improvement by the different products was surprising: in contrast to our hypotheses, higher resolution and *in-situ* products neither led to higher predictive power (in terms of TSS and AUC magnitude) nor to a higher number of significantly increased SDMs.

4.2. Why could fine-scale SMOD not improve SDMs more than coarse-scale SMOD?

The number of significantly increased SDMs was highest for 20 m resolution satellite-based SMOD and 1 m webcam-based SMOD while the average magnitude of improvement was similar across the various snow products. This was in line with the results of the statistical tests that mostly confirmed the absence of significant statistical differences in this improvement between any two pairs of SDMs based on different SMOD products. As a corollary, the additional effort taken for on-site measurements and finer-resolution data did not result in better models as compared to the more readily available satellite data characterized by a comparably coarse resolution. Our data hence show - against expectations - that deca-meter resolution snow variables, represented by satellite-, snow model- and webcam-based SMOD, may adequately represent the snow conditions relevant to alpine plants' distributions and that characterization of very fine-scale conditions does not generally benefit species distribution modeling (Kemppinen et al., 2024; Panchard et al., 2023, Pradervand et al., 2014), although this may be true for some species (Fig. 3). For the average alpine plant species, satellite-based SMOD at deca-meter resolution, which is commonly included in SDMs (Niittynen and Luoto, 2018; Rissanen et al., 2021, 2023; Panchard et al., 2023), is hence a sensible choice for snow data according to our comparison. These results support findings by Chytrý et al. (2024) who showed that intermediate-scale topographic information is superior to a very fine-scale one in predicting alpine species' distributions, probably because of the impact that neutral processes have on species distribution. Since snow distribution is strongly linked to topography in alpine environments, we assume those conclusions are also relevant for our findings. Put differently, our results suggest that species which require an early or late melt-out will occur in both higher density and diversity in larger ridge or snowbed habitats, respectively, but may often lack in smaller and more isolated ones, which makes coarser-scale data predictors similarly reliable in distinguishing species' presence and absence.

4.3. Potential sources of inconsistent improvement across species and SMOD products - uncertainty in SMOD products

Our findings did not show a consistent pattern across all 74 investigated species when relating the change in TSS (AUC, Boyce index) to the choice of SMOD data source and resolution (cf. Fig. 3, supplementary, Fig. S.2, S.3). We hypothesize that the absence of such a consistent pattern regarding the predictive power of the different SMOD data sources in SDMs can be attributed to both ecological factors, uncertainty of the SMOD product itself and processing details of SMOD products. While in theory the different SMOD products - at least for the same spatial resolution - should be highly correlated, the intercomparison (section 3.1, Fig. 2) already indicates that they vary substantially, hence it is expected that this variation carries over to a certain degree into the SDM's prediction.

With respect to ecological factors, snow model-, logger- and satellite- (or webcam-) based SMOD likely differ, for example, with respect to the information they carry on temperature insulation, which is important to protect sensible plants against deep frost (Körner 2021). While shallow snow on windblown areas has little insulating effect and is hence ecologically different from deeply covered snow beds with respect to frost risk, it might be indistinguishable from the latter by satellite or webcam imagery. Soil temperature loggers, by contrast, are useful to detect these differences in insulation and hence potentially provide a more accurate description of this particular ecological feature. Vice versa, imagery might better indicate light interception effects which co-determine snow effects on growth period length, as even shallow snow cover reduces light levels considerably. Despite these apparent differences in the information they carry, logger-based and satellite-based SMOD both led to a similar number of improved SDMs and a similar magnitude (Table 1), indicating that the role of this effect might not dominate the predictive power of SMOD variables in our SDMs.

Relevant technical aspects that contribute to the uncertainty of the SMOD products in our study can be broadly classified into misclassification errors of snow cover (relevant for the image-based satellite- and webcam datasets and logger-based SMOD), geometric inaccuracies, introduced during monoplotting of the webcam images and georegistration of satellite products and uncertainty inherent to the interpolated meteorological data used to force the snow model.

Snow detection in satellite- and webcam images carries uncertainty and is known to be less accurate on shaded slopes during wintertime (Gascoin et al., 2019; Portenier et al., 2020). Furthermore, despite being projected onto a 1 m DEM, the effective ground resolution of the webcam data (i.e., the size of an image pixel projected onto the land surface), locally also varies with respect to viewing angle and distance to camera. For snow models, accurate meteorological forcing data is needed (Strasser et al., 2024), which, while being a state-of-the-art method, the spatial interpolation based on a few stations can probably not always deliver. Interpreting the influence of these sources of uncertainty is hindered by the fact that the magnitude of uncertainty is likely to vary spatially, but this variation is not known. It is the uncertainty inherent to each SMOD dataset itself that likely accounts for the differences in number of significantly improved SDMs in general, and the spatial variation of uncertainty in each SMOD dataset that likely explains the difference in magnitude of change in TSS between different SMOD products when considering a single species. Given the known stability of snow (melt-) out patterns (Tappeiner et al., 2001; Sturm and Wagner, 2010), capturing relative spatial SMOD patterns correctly (i.e., not the absolute dates) is more important than a small mean SMOD error anyway (Heegaard, 2002). The observation that the correlations among SMOD products do not directly carry over to the number of improved SDMs might seem odd at first glance, but could also suggest that the spatial variation of uncertainty and error in SMOD products also interact with the location of presences and absences of the species in the study site.

A way to quantify the uncertainty and its spatial patterns in the SMOD datasets themselves could be the acquisition of multi-temporal point clouds by laser scanning which would enable spatially-comprehensive quantification of snow depth and SMOD (Deems et al., 2013) or very high resolution satellite imagery. If improved quantification of SMOD is the sole interest in the context of species distribution modeling, data assimilation (e.g., assimilation of logger- and webcam-based snow cover into the snow model) has recently been shown to be promising (Alonso-González et al., 2023), however, it would prevent the quantification of the predictive power of individual SMOD products, which has been the aim of our study.

Lastly, the pre-computed satellite-based SMOD is defined as the last day of the longest period of continuous snow cover in a hydrological year (last-snow-day method, Barrou Dumont et al., 2025), while the other SMOD products are derived by fitting a GLM to the binary snow cover values, which is the method widely used for computing SMOD in the context of an explanatory variable in SDMs (Niittynen and Luoto, 2018; Rissanen et al., 2021, 2023; Panchard et al., 2023). In a comprehensive study for the French Alps and Pyrenees covering the hydrological years 1986 to 2022, Barrou Dumont et al. (2025) showed that the median absolute and median error of the last-snow-day method is 8 and −1 days, respectively, with respect to point measurements of meteorological stations. Data by Panchard et al. (2023, in the supplementary material) indicates a median absolute and median error of the GLM method of 13 and −6 days. The methodological difference in computation of SMOD could partly explain the different predictive power among SMOD variables. Yet, only a thorough evaluation of the different methods under a common framework can help answering this question.

Despite efforts in this study to follow Good modelling practice (GMP, Jakeman et al., 2024) by providing multiple evaluation metrics, employing ensemble models and basing the results on a comparably conservative permutation approach, a specific analysis of uncertainty of the individual SMOD products (computation of melt-out date, uncertainty inherent to specific data sources) would be a valuable contribution in terms of GMP.

4.4. Practical implications for the choice of SMOD dataset

Several works have highlighted the decisive role for capturing the (micro-)climate and fine-scale environmental characteristics that are relevant to plants (Kemppinen et al., 2024; Zellweger et al., 2019). Some studies have found fine-scale, *in-situ* temperature data to be superior to coarse-scale climate data sets in SDMs (Lembrechts et al., 2019) and that predictions of SDMs based on finer resolution data can differ markedly from results based on coarse-scale predictors (Stark and Fridley, 2022). The question of scale of predictors hence is frequently addressed by searching across multiple scales (e.g., Chytrý et al., 2024) or by choosing a hierarchical modeling framework (e.g., Simon et al., 2023). Our approach differs in that we employ multiple data sources at different resolutions, rather than only searching the same data source across different resolutions and hence offers the advantage to allow an intercomparison of SMOD derived from distinct data sources that come with different levels of effort in terms of obtaining the data set itself. However, in many cases, dataset choice will be guided by availability which largely follows pragmatic aspects summarized in Table 2. We note that the aspects summarized in the table could change with technological advancements, but should be qualitatively accurate when comparing the data sources.

Table 2
Practical considerations for choosing the data source to derive SMOD from.

	Computational requirements	Complexity of processing	Instrument cost	Field work required
Satellite	low-medium	low	Not applicable	no
Snow model	medium-high	medium	Not applicable	no
Webcam	medium-high	medium-high	-**/ medium-high*	yes*/no**
Temperature logger	low	low	low	yes

[*] assumes installation of a new, dedicated webcam instead of using publicly available imagery.

[**] assumes usage of publicly available imagery.

5. Conclusions

Our findings show that snow melt-out date derived from any of the sources we used are able to significantly improve distribution models of >80 % of species in typical temperate alpine landscapes. In terms of predictive power, the average improvement is moderate, suggesting that topographical variables partly explain snow melt-out but cannot fully substitute direct information on snow melt-out date (SMOD). Contrary to our main hypothesis, we did not find that higher spatial resolution (1 m, point measurement) melt-out products increase the predictive power of distribution models more than lower resolution (20 m) snow products. By contrast, we found that 20 m resolution satellite products led to similarly high numbers of improved distribution models. In particular, the S2 Theia SMOD, which, to the best of our knowledge, has not been used in SDMs of alpine plants before, turned out to be equally well suited as a predictor when compared to other SMOD products at the same or finer spatial resolution. However, as different SMOD products benefit species to different degrees, a general recommendation of one of them at the cost of the others is not warranted. In fact, the recent rise in the collection of microclimatic datasets (Zellweger et al., 2019; Kemppinen et al., 2024) and the widespread availability of webcams in alpine regions (Portenier et al., 2020) will likely put researchers in a situation, where they indeed can choose between the ubiquitously available satellite-based SMOD products (Barrou Dumont et al., 2025; Theia, 2024) and other datasets - explicit comparisons might hence not only be recommendable, but may also become increasingly possible. This might also allow researchers to use ensemble modeling strategies by combining models that use different SMOD sources. Finally, the comparatively strong performance of snow-modeling products is promising because it enables consistent integration of future snow conditions in alpine and arctic biodiversity modeling.

CRediT authorship contribution statement

Andreas Kollert: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kryštof Chytrý:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Norbert Helm:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Karl Hülber:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Dietmar Moser:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Johannes Wessely:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Stef Lhermitte:** Conceptualization. **Simon Gascoin:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Andreas Mayr:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Patrick Saccone:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Johannes Hausharter:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Michael Warscher:** Writing – review & editing, Methodology. **Ulrich Strasser:** Writing – review & editing, Methodology. **Stefan Dullinger:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Martin Rutzinger:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2025.111366.

Data availability

Code for the SDMs is available under https://doi.org/10.5281/zenodo.17226152.

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