HIGH-ARCTIC SNOWPACK MODELING FORCED BY NUMERICAL WEATHER PREDICTIONS AND MANUALLY OBSERVED SNOW PROFILES

Kristin Lyche[1,2,*], Holt Hancock[3,4], Siiri Wickström[3,2], Oddbjørn Bruland[1]

[1]*Norwegian University of Science and Technology, Department of Hydraulic and Environmental Engineering, Trondheim, Norway*
[2]*Skred AS, Tromsø, Norway*
[3]*University Centre in Svalbard, Department of Arctic Technology, Arctic Safety Centre, Longyearbyen, Svalbard*
[4]*Norwegian Geotechnical Institute, Oslo, Norway*

ABSTRACT: Snow avalanches are significant natural hazards in mountain areas with a seasonal snow cover, putting people and infrastructure at risk. Snow avalanche forecasting aims to mitigate this risk, and detailed numerical modeling of snow stratigraphy is increasingly relied upon. Our work addresses the potential to improve avalanche forecasting in the high-Arctic by utilizing numerical snowpack modeling forced by numerical weather predictions and observed snow profiles. The Arctic environment presents challenges, both in terms of data collection and the expected quality of the numerical weather predictions. In this study, we validated the performance and usefulness of a model chain consisting of AROME-Arctic, manually observed snow profiles, and SNOWPACK for a site in Longyearbyen, Svalbard.

We found that shortwave radiation significantly influenced the modeled snow temperature and, thereby, the metamorphism of the snowpack. Shortwave radiation showed great variability within the gridded AROME-Arctic output, making the method of linking AROME-Arctic and SNOWPACK critical. The model chain's inability to capture wind deposition and the resulting wind slabs has practical implications for operational avalanche forecasting.

Our research suggests that numerical snowpack modeling forced by numerical weather predictions and manually observed snow profiles can effectively aid avalanche forecasting in the high-Arctic region. Based on the promising results, we encourage further exploration of the model chain, both for site-specific avalanche forecasting and to include the developed model in regional forecasting. As the potential of machine learning and the utilization of neural networks increases, we see possibilities in expanding the model chain to incorporate automated conclusions based on the predicted snow profile.

Keywords: snowpack simulations, snow profiles, numerical weather predictions, avalanche forecasting

1. INTRODUCTION

Svalbard has an extensive snow avalanche problem, posing a threat to infrastructure and houses in Longyearbyen (Engeset et al., 2020). In response to the severe snow avalanche accident in December 2015, claiming two lives while in their home in Longyearbyen, site-specific avalanche warnings for several avalanche paths were launched. Snow profiles are a key element in this operational avalanche forecasting, and currently this information is provided through snow observations around the city of Longyearbyen. However, physically-based models relying on meteorological data are increasingly utilized to provide reliable information about the snowpack in operational avalanche forecasting world wide (Morin et al., 2020).

*Corresponding author address:
Kristin Lyche
9102 Tromsø, Norway;
tel: +47 412 28 541
email: kristin.b.lyche@gmail.com

As numerical weather predictions (NWP) continue to improve alongside advancements in computer science and technology (Aguado and Burt, 2015), we anticipate that model chains combining NWP and snow cover models will become even more accurate. Progress in computer science is not only enhancing the accuracy of these models, but recent research in both the Canadian and Swiss scientific communities are exploring the potential of expanding the model chain (e.g., Mayer et al., 2023; Herla et al., 2024).

In this study, we validated the performance and usefulness of a model chain consisting of AROME-Arctic, manually observed snow profiles, and SNOWPACK for a site in Longyearbyen, Svalbard. The findings provide a foundation for discussing and evaluating the possibilities and challenges of utilizing this model chain in a high-Arctic region, as well as guiding further developments in avalanche forecasting in the high-Arctic conditions around Longyearbyen.

2. STUDY AREA

The archipelago of Svalbard is situated in the Arctic Ocean, between 74°and 81°north. Svalbard is significantly milder and wetter than other locations at similar latitudes (Hanssen-Bauer et al., 2019). The typical winter weather pattern is dominated by high-pressure systems, which bring stable, cold, and clear periods, punctuated by warm, wet low-pressure systems that bring heat and moisture from the south (Isaksen et al., 2016).

The distinct climate of Svalbard gives rise to snowpack features classified as the high-Arctic maritime snow climate (Eckerstorfer and Christiansen, 2011). This is caused by low air temperatures and dry conditions, culminating in a thin and cold snowpack. Depth hoar usually appears during the early season and represents a structural weakness throughout the season (Hancock, 2021) and due to strong winds and limited vegetation, wind slabs are usually a leading stratigraphic aspect in the snowpack (Hancock, 2021; Jaedicke and Sandvik, 2002). Additionally, warm winter storms, often accompanied by rain, also result in widespread ice layering. The continuous permafrost results in a basal snowpack temperature well below zero (Humlum et al., 2003).

Several factors make avalanche forecasting the high-Arctic and Longyearbyen challenging. These include the short history of observations and, consequently, a lack of historical data and recordings. Additionally, weather forecasts based on AROME-Arctic are less accurate than those in the mid-latitudes (Randriamampianina et al., 2021). The Arctic polar night, stretching from December to February, also makes visual observation difficult and increases the risk for observers in the field (Engeset et al., 2020). On top of these challenges, the ongoing climate shift and its consequences for the snow cover influence the snow avalanche regime. In the forthcoming decades, climate change is expected to affect the occurrence of all kinds of snow avalanches in Svalbard, particularly due to the predicted rise in extreme events involving intense snowfall or heavy rain on snow. This could lead to a possible escalation in wet snow avalanches as well as slush flows (Hanssen-Bauer et al., 2019; Engeset et al., 2020).

For this study, we selected a study site close to Longyearbyen to collect the manual snow observations. The study site was chosen due to limited associated risks, and a snowpack thickness of approximately one meter. The location of the study site is shown in Figure 1.

3. METHODS

3.1 Research design

We established a workflow in which we forced 3.6.0 SNOWPACK from a manually-observed initiation snow profile with 2.5 km resolution, gridded AROME-Arctic model meteorological data. This resulted in a visualization of the snowpack development, which in turn was qualitatively compared with a validation snow profile using an objective snow profile comparison method as validation criteria. This resulted in an objective agreement score. Lastly, we conducted sensitivity analyses looking into the coupling between AROME- Arctic and SNOWPACK.

3.2 AROME- Arctic data collections

We used the MET AROME-Arctic archive data[1] to access the AROME-Arctic data in a NetCDF format. The extraction of data was done by modifying the AROME-Arctic extraction program developed by Frank (2023).

The model runs we used were based on the time of the observed initiation snow profile, making the starting time as similar as possible. All 66 hours of the four model runs we chose were included, despite the risk of spin-up errors in the early hours of the data set.

We took careful consideration when transferring the gridded data from the AROME-Arctic model to the point data SNOWPACK model. Based on location, elevation, and local knowledge of the weather patterns we selected grid points A, B, C, and D (Figure 1 as the four most relevant points for performance evaluation. This was done by using the lowest Root Mean Square Error (RMSE) (Eq. 1a) and the scaled RMSE (Eq. 1b) as evaluation criteria, comparing the modeled weather data with measurements from Svalbard Airport and Adventdalen Weather Station.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=n}^{n}(y_i - \hat{y})^2} \tag{1a}$$

$$RMSE_{scaled} = \frac{RMSE - RMSE_{min}}{RMSE_{max} - RMSE_{min}} \tag{1b}$$

$RMSE$ = Root Mean Squared Error
y_i = Observed value
$\hat{y}$ = AROME-Arctic model prediction of y_i
n = number of samples
$RMSE_{scaled}$ = Scaled Root Mean Squared Error
$RMSE_{max}$ = Maximum RMSE for the specific parameter
$RMSE_{min}$ = Minimum RMSE for the specific parameter

[1] Link to the MET AROME-Arctic archive

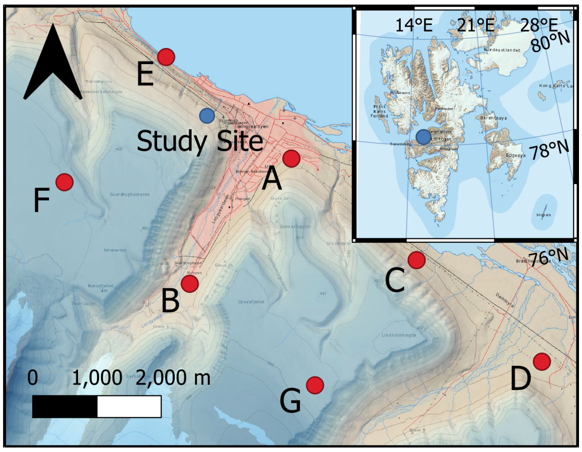

Figure 1: The map displays the AROME-Arctic grid points in the area around the field site as red dots. The location of the study site is marked with a blue dot. The overall location of Longyearbyen is displayed in the overview map. The background map is provided from the Norwegian Polar Institute.

Point A and B were chosen as they were the closest points at representative heights above sea level. Additionally, Points C and D were examined as they were both land-based, had a matching aspect, and had comparable topographic characteristics to the study site. Points E, F, and G were excluded due to their locations in water or at substantially higher elevations.

To assess the quality of the AROME-Arctic performance, we collected observed weather parameters from Svalbard Airport as a reference. This station was selected due to its proximity to the research site and its known representativeness of the area. Parameters unavailable from this weather station were supplemented with values from the Adventdalen weather station. Snow surface temperature was not observed at either of these weather stations or at any other stations in the area, and was therefore excluded from the performance analysis.

3.3 Manually observed snow profiles

When collecting the manually observed snow profiles, we followed the recommendations of the Norwegian Water Resources and Energy Directorate (NVE) for snow profiles related to avalanche forecasting, as detailed in Haslestad and Larsen (2022). We collected data on stratigraphy, hand hardness, grain shape, grain size, moisture content, and bulk density. Additionally, for stability assessment, the Extended Column Test (ECT) was performed according to the methodology described by Simenhois and Birkeland (2006). Our dataset consisted of five manual snow profiles, all collected with a three-day interval, starting on April 12, 2024, and ending on April 24, 2024. The profiles were gathered at a consistent location, with movement limited to finding undisturbed snow.

3.4 SNOWPACK setup

The SNOWPACK output time step was set to 60 minutes to match the hourly resolution of the AROME-Arctic input data. The atmospheric conditions were assumed to be neutral for all four model periods. The energy exchange at the surface was governed by a shifting boundary condition, switching between the Dirichlet and Neumann boundary conditions depending on the surface temperature. The water transport model was set to Bucket, and the SNOWPACK stability evaluation was not utilized. We used the program's default parameters for all other parameters.

3.5 Model chain validation

We qualitatively assessed the performance of the model output using an objective snow profile comparison algorithm. The algorithm involved manual layer mapping according to the principles outlined in Herla et al. (2021), where the mapping was performed between the simulated snow profile at the final time step and the validation snow profile. Based on the layer mapping, we applied the goodness-of-fit criteria presented in Herla et al. (2021), while also incorporating additional elements from Lehning et al. (2001) to achieve an objective agreement score for the parameters of stratigraphy, snow temperature, grain size, and grain shape. These were combined into a total agreement score. The comparison scheme is described in detail in Lyche et al. (2023). The total representativeness is expressed as a number between zero and one, where one represents a perfect replication and zero indicates no resemblance.

3.6 Sensitivity analysis

To assess the model's sensitivity to the chosen AROME-Arctic grid point, we ran SNOWPACK separately on the output of all four relevant AROME-Arctic grid points identified. All other parameters, including the model period, input snow profiles, and settings in SNOWPACK, were kept constant. We qualitatively evaluated the results of these sensitivity analyses.

4. RESULTS

4.1 AROME-Arctic model performance

Divergent data outputs were observed from the four selected AROME-Arctic grid points. An overview of air temperature, precipitation, wind speed, and net shortwave radiation from all four model periods, along with observed data from the Svalbard Airport and Adventdalen weather stations, is presented in Figure 2. Notably, the net shortwave radiation parameter exhibits the most substantial variance, with significant differences between the grid points. Overall, no signs of model spin-up errors were detected. However, it is important to note that all four grid points from AROME-Arctic predicted surface temperatures above 0 °C in periods with positive air temperatures, which is a non-physical result (Dingman, 2015).

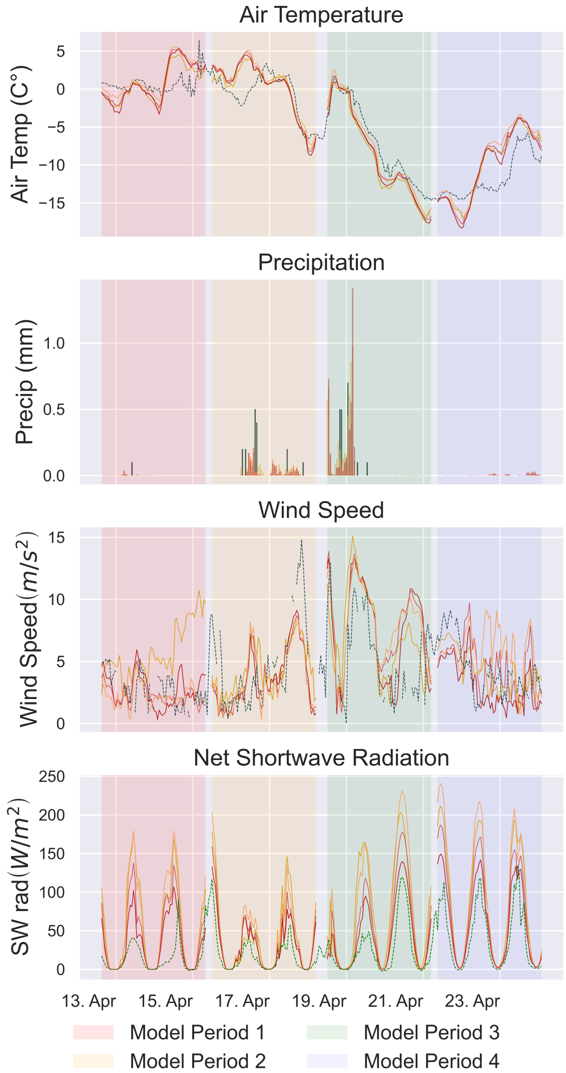

Figure 2: The figure presents a general impression of the variance and order of scale for hourly measured air temperature, precipitation, wind speed, and net shortwave radiation from all four grid point as well as Svalbard Airport and Adventdalen.

The numerical assessment of performance (Figure 3) revealed a similar output across all four grid points for the parameters of air temperature and longwave radiation. Greater discrepancies were observed for wind speed, relative humidity, and precipitation. The greatest divergence was evident in the net shortwave radiation parameter. Point D displayed the lowest RMSE value for six out of five parameters, with relative humidity being the exception. Based on the selection criteria, point D was utilized for further modeling.

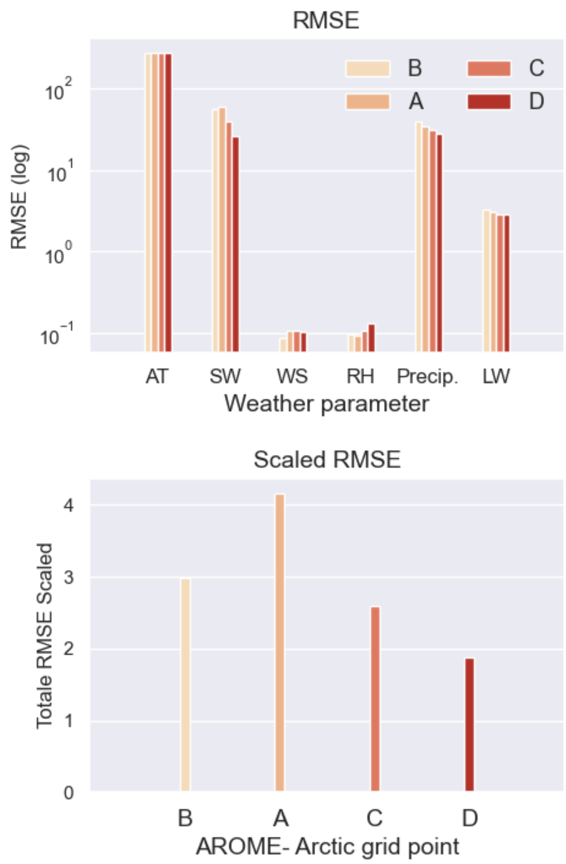

Figure 3: RMSE and scaled RMSE for each AROME-Arctic parameter across all four grid points. A lower score denotes a more accurate replication of observed events

4.2 The manually observed snowpack

The initial state of the snowpack exhibited characteristics typical of a high-Arctic maritime environment, with 12 distinct stratigraphic layers identified within a snow depth of 100 cm. Throughout the study period, the snow cover underwent several types of metamorphosis. On April 12, 2024, we detected a melt/freeze crust at the surface, which experienced both melting and refreezing during the first half of the field period. Additionally, the layer of decomposing and fragmented precipitation particles beneath the ice layer transformed into faceted crystals. Between April 18 and April 21, a new layer of wind-affected snow developed at the surface.

4.3 SNOWPACK simulations

Figure 4 illustrates the SNOWPACK model's temporal tracking of grain shape across all four model periods. Over the four model periods, the forecast predicted melt/refreeze, development of faceted crystals, precipitation, rounding, and faceting. The model chain forecasts periods of rapid warming and cooling of the snow temperature.

4.4 Sensitivity

When studying the conducted sensitivity analysis, it is apparent that the model chain's output varies significantly depending on the grid point used. The differences are most pronounced for grid point A, which forecasts a warmer snowpack, leading to increased melt and different metamorphic processes. This aligns with the notable deviations observed in four grid points modeled shortwave radiation.

4.5 Model chain validation

Based on the validation criteria, our results yielded total agreement scores across the four model periods ranging between 0.85 and 0.91, where 1 represents a perfect replication. The total agreement score averages a value of 0.88. The results are given in Table 1.

Table 1: The results of the model validation. The agreement score for each property and the total score for each model run are provided.

Model Period	K_{strat}	K_{temp}	K_{size}	K_{shape}	K_{tot}
1	0.56	0.96	0.90	1	**0.85**
2	0.83	0.68	0.91	1	**0.86**
3	0.92	0.88	0.96	0.89	**0.91**
4	0.85	0.74	0.98	1	**0.89**
Mean value	**0.79**	**0.82**	**0.94**	**0.97**	**0.88**

5. DISCUSSION

5.1 AROME-Arctic as data source for SNOWPACK

We argue that the similarity between the forecasted and observed weather, coupled with the high agreement score shown in Table 1, suggests that AROME-Arctic can produce robust results for SNOWPACK modeling. This finding is consistent with the results of Myhre (2018); Zweigel et al. (2021). However, despite AROME-Arctic's high resolution in the NWP context, a grid resolution of 2.5 km is coarse for site-specific avalanche forecasting. This mesh size makes AROME-Arctic likely to miss small-scale local phenomena, indicating that incorporating it into the model chain requires careful consideration. Our evaluation criteria identified a surprising AROME-Arctic grid point as the best-performing data source, despite it being the grid point located farthest from the study site (Figure 1). Further, when comparing the four grid points in Figure 3, it is clear that the performance is highly variable. Whereas the variance in wind speed can be explained by different topographic channeling effects from the valley systems around Longyearbyen, the strong variability in bias for the net shortwave parameter is unexpected. There are local features, such as cloud coverage, that would influence this parameter and further result in differences between the four simulations. However, the consistent biases over the model period for all four grid points contradict the theory of differences in simulated local cloud coverage, as this phenomenon occurs over a shorter temporal scale. Due to the consistency in outgoing longwave radiation, drastic differences in AROME-Arctic interpreted surface properties are not likely. We find that explaining the shortwave radiation dynamics in AROME-Arctic is nontrivial due to the complex interactions between cloud coverage, reflection, and incoming solar radiation. Furthermore, short-wave radiation is known to be a challenging parameter for NWP to model (Gregow et al., 2020), and a model error can therefore not be ruled out.

Additionally, the AROME-Arctic model predicted snow surface temperatures above 0°C during model periods 1 and 2, when the air temperature rose above 0°C. We expect this to indicate that AROME-Arctic does not recognize that the surface is snow-covered. However, the effects of this error were limited due to the shifting boundary conditions in SNOWPACK. As we used shifting boundary conditions, Neumann boundary conditions were applied when surface temperatures exceeded -1°C. Nevertheless, this represents a weakness, as it increases uncertainty regarding the quality of the simulated surface temperature.

5.2 From grid to point value

Our findings demonstrate that in the maritime Arctic climate, characterized by highly localized and complex terrain features such as valleys, glaciers, and mountains, the selection of a grid point for snowpack modeling requires thorough investigation. Therefore, further exploration of various approaches will be highly interesting and essential in future studies. We recommend validating the AROME-Arctic model output before integrating it with the SNOWPACK model, as this could enhance the likelihood of high performance and improve the credibility of the snowpack predictions."

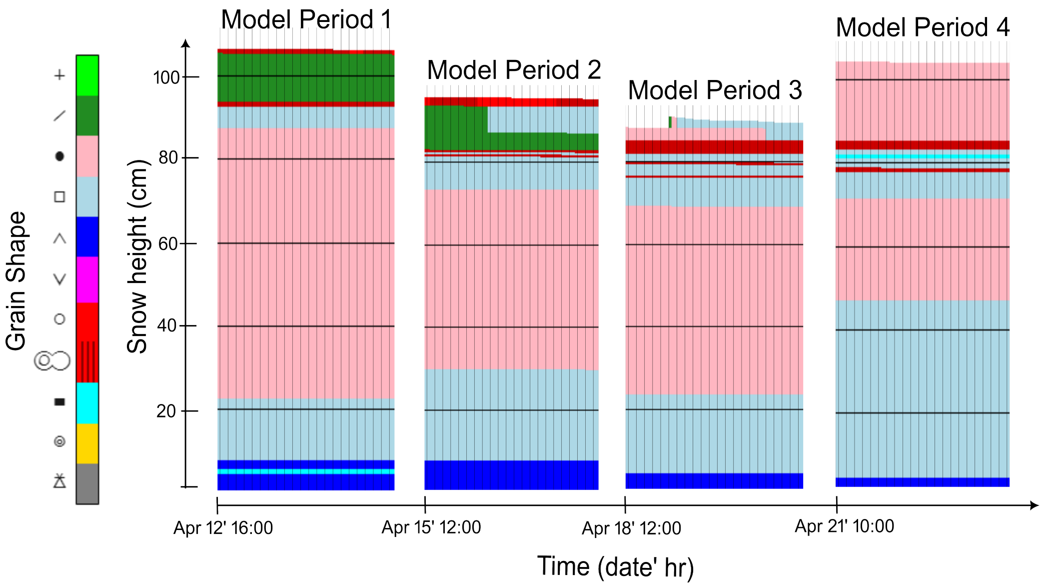

Figure 4: The simulated grain shape evolution over four model periods. The horizontal black lines indicate snow depth, with vertical lines positioned at every three-hour intervals within the model periods. The start time of each simulation is denoted by the date and time at the beginning of the model period.

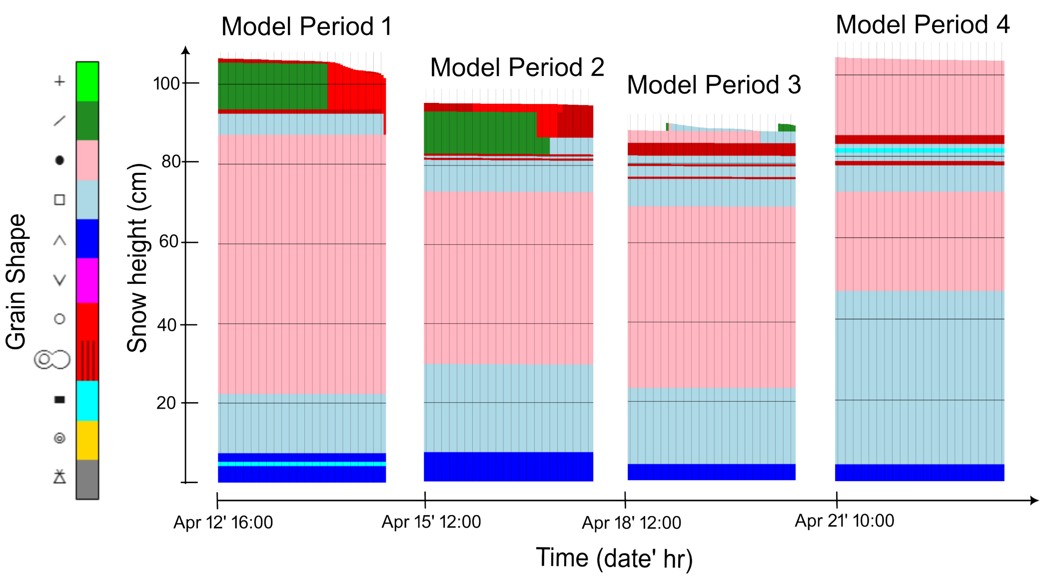

Figure 5: Simulated grain shape development over the four model periods when SNOWPACK was forced by AROME-Arctic output from point A.

5.3 Predicting the development of the snowpack

AROME-Arctic and SNOWPACK model chain forced by manual snow observations demonstrated considerable success in predicting the snowpack's development throughout all four modeling periods. The average agreement score of 0.88 suggests a strong correspondence between modeled and observed results (Table 1), signaling a high level of accuracy in all four conducted simulations. The agreement score of 0.97 for grain shape strengthens this claim, as grain type, according to Herla et al. (2021), constitutes one of the most crucial parameters in such simulations. It's noteworthy that the stratigraphic parameter indicated the lowest performance, with especially weak performance for the first modeling period. However, the interpretation of these findings must take into account the conditions and context of the observed snow profiles that served as the basis for the initiation and validation of model parameters.

Further, we found that this model chain showed sensitivity towards shortwave radiation, as this parameter both varied between the grid points, as well as significantly influencing the modelled snow temperature and metamorphism of the snowpack.

5.4 Implications for avalanche forecasting

For site-specific avalanche forecasting in Longyearbyen, the model chain has provided an accurate forecast of the snow cover development in different snow development scenarios. The model output is both a visualization, as well as an independent opinion on the snow cover development. This can be compared with the human forecasters' evaluations and therefore might strengthen the performance of avalanche forecasting.

This claim is strengthened by the model chain's ability to accurately reproduce the observed weak layers during the field period. Additionally, the observed snow profiles included stability tests. All layers that yielded results in these tests were captured by the model chain's output, indicating that the avalanche forecaster would be provided with precise information on the most critical layering during these model periods. This strongly supports the model chain's usefulness in a forecasting scenario.

However, as SNOWPACK is a one-dimensional model, it has the inherent limitations of this type of modeling, and topographic effects as snowdrift are not captured. Although both model periods 2 and 3 yielded high agreement scores, a visual inspection reveals that these simulations might be problematic for avalanche forecasting. Both periods ended with an observed wind slab, which was not captured in the simulations. Wind slabs are a common avalanche problem in Longyearbyen, and while the stability tests conducted indicate that this was not the primary avalanche problem or concern during these periods, the inability to capture this process is a significant drawback.

During model period 3, the model chain simulated a layer of surface faceted crystals instead of the wind slab. If surface faceted crystals are subsequently buried by wind-deposited snow or new precipitation, they could quickly become a significant avalanche problem. This error could potentially mislead avalanche forecasters. However, the relatively frequent updates using observed profiles help to limit the extent and consequences of these misinterpretations. In light of these findings, we recommend revisiting the model chain setup. Currently, the model chain is run for a full 66-hour lead time based on one complete model run of AROME-Arctic. By adjusting the criteria for updating the model state with observed snow profiles to be linked to specific weather events, the model chain could improve both its capacity and accuracy. Based on SNOWPACK documentation and the observed weaknesses over the four model periods, high wind speeds and precipitation could be used as triggering mechanisms for updates. For periods with calmer conditions, less frequent manual snow profiles would be necessary.

6. CONCLUSION AND OUTLOOK

Our overall goal for this study was to evaluate the performance and usefulness of a model chain consisting of AROME-Arctic, manually observed snow profiles, and SNOWPACK for a site in Longyearbyen, Svalbard. To conclude, we found that:

- During the fourteen-day test period, the model chain accurately forecasted the development of the snow stratigraphy, as well as correctly predicted the applicable avalanche problems.
- Great caution should be exercised when linking the gridded AROME-Arctic model output to SNOWPACK, as the accuracy of the NWP weather output has been shown to vary significantly even between adjacent grid points.
- Both AROME-Arctic and SNOWPACK demonstrated sensitivity to short-wave radiation, which should be given special consideration when setting up an operational model chain.
- Updating the model chain with manually observed snow profiles based on weather events, rather than on a fixed schedule, would mitigate the limitations of SNOWPACK being a one-dimensional model.
- The overall strong performance of the model chain indicates that it could be a highly effective tool for operational avalanche warning in the High-Arctic region, given availability of sufficient observations.

Our findings suggest that, despite the challenges of data availability in the Arctic region, snowpack modeling based on local NWP provides promising results as an operational tool. These results support investing resources into exploring its incorporation into operational forecasts, as well as further developing and automating the process.

Highly inspired by the work conducted in the Canadian snow science community e.g. Herla et al. (2021, 2023), we encourage exploring the use of the model chain to support the regional forecast around Longyearbyen as well. In a time when the potential of machine learning and neural networks is growing, high-quality data is desirable and powerful. Based on our validation study, we find the data output to be of high quality and see opportunities to expand the model chain by incorporating automated conclusions derived from these models' predictions of snowpack development. We strongly recommend further investigation of these possibilities.

ACKNOWLEDGEMENT

Thank you to the ARCT-RISK project, Research Council of Norway grant number 315260, for making this research possible.

References

Aguado, E. and Burt, J. E.: Chapter 13: Weather Forecasting and Analysis, in: Understanding Weather and Climate, Pearson, 7th edn., 2015.

Dingman, S. L.: Physical Hydrology: Third Edition, Waveland Press, 2015.

Eckerstorfer, M. and Christiansen, H. H.: The High Arctic Maritime Snow Climate in Central Svalbard, Arctic, Antarctic, and Alpine Research, 43, 11–21, doi:10.1657/1938-4246-43.1.11, 2011.

Engeset, R. V., Landrø, M., Indreiten, M., Müller, K., Mikkelsen, O. A., and Hoseth, K. I. A.: Avalanche Warning in Svalbard, Tech. Rep. 35/2020, Norwegian Water Resources and Energy Directorate, 2020.

Frank, L.: MET-model_download, URL https://github.com/UNISvalbard/unisacsi, 2023.

Gregow, E., Lindfors, A. V., van der Veen, S. H., Schoenach, D., de Haan, S., and Lindskog, M.: The use of satellite and surface observations for initializing clouds in the HARMONIE NWP model, Meteorological Applications, 27, e1965, doi:10.1002/met.1965, 2020.

Hancock, H.: Snow Avalanche Controls, Monitoring Strategies, and Hazard Management in Svalbard, Ph.d. thesis, University of Oslo, 2021.

Hanssen-Bauer, I., Førland, E. J., Hisdal, H., Mayer, S., Sandø, A. B., and Sorteberg, A.: Climate in Svalbard 2100: A Knowledge Base for Climate Adaptation, Tech. Rep. 1/2019, The Norwegian CCS Research Centre, 2019.

Haslestad, A. and Larsen, H. T.: Snøprofil, Tech. Rep. 01/2022, Norwegian Water Resources and Energy Directorate, 2022.

Herla, F., Horton, S., Mair, P., and Haegeli, P.: Snow profile alignment and similarity assessment for aggregating, clustering, and evaluating snowpack model output for avalanche forecasting, Geoscientific Model Development, 14, 239–258, doi:10.5194/gmd-14-239-2021, 2021.

Herla, F., Haegeli, P., Horton, S., and Mair, P.: How many snow profiles can you process? Making the wealth of information included in large-scale snowpack simulations more accessible for operational avalanche forecasting, in: Proceedings of the International Snow Science Workshop, Bend, Oregon, 2023.

Herla, F., Haegeli, P., Horton, S., and Mair, P.: A large-scale validation of snowpack simulations in support of avalanche forecasting focusing on critical layers, Natural Hazards and Earth System Sciences, 24, 2727–2756, doi:10.5194/nhess-24-2727-2024, URL https://nhess.copernicus.org/articles/24/2727/2024/, 2024.

Humlum, O., Instanes, A., and Sollid, J. L.: Permafrost in Svalbard: a review of research history, climatic background and engineering challenges, Polar Research, 22, 191–215, doi:10.3402/polar.v22i2.6455, URL https://doi.org/10.3402/polar.v22i2.6455, 2003.

Isaksen, K., Nordli, , Førland, E. J., Łupikasza, E., Eastwood, S., and Niedźwiedź, T.: Recent Warming on Spitsbergen—Influence of Atmospheric Circulation and Sea Ice Cover, Journal of Geophysical Research: Atmospheres, 121, 11,913–11,931, doi:10.1002/2016JD025606, 2016.

Jaedicke, C. and Sandvik, A. D.: High resolution snow distribution data from complex Arctic terrain: a tool for model validation, Natural Hazards and Earth System Sciences, 2, 147–155, doi:10.5194/nhess-2-147-2002, 2002.

Lehning, M., Fierz, C., and Lundy, C.: An objective snow profile comparison method and its application to SNOWPACK, Cold Regions Science and Technology, 33, 253–261, doi:10.1016/S0165-232X(01)00044-1, URL https://www.sciencedirect.com/science/article/pii/S0165232X01000441, 2001.

Lyche, K., Hancock, H., Bruland, O., and Wickstöm, S.: Snowpack Modeling Forced by Numerical Weather Predictions and Manually Observed Snow Profiles, Master's thesis, Norwegian University of Science and Technology, 2023.

Mayer, S., Techel, F., Schweizer, J., and van Herwijnen, A.: Prediction of natural dry-snow avalanche activity using physics-based snowpack simulations, Natural Hazards and Earth System Sciences, 23, 3445–3465, doi:10.5194/nhess-23-3445-2023, URL https://nhess.copernicus.org/articles/23/3445/2023/, 2023.

Morin, S., Horton, S., Techel, F., Bavay, M., Coléou, C., Fierz, C., Gobiet, A., Hagenmuller, P., Lafaysse, M., Ližar, M., Mitterer, C., Monti, F., Müller, K., Olefs, M., Snook, J. S., van Herwijnen, A., and Vionnet, V.: Application of physical snowpack models in support of operational avalanche hazard forecasting: A status report on current implementations and prospects for the future, Cold Regions Science and Technology, 170, 102 910, doi:10.1016/j.coldregions.2019.102910, URL https://www.sciencedirect.com/science/article/pii/S0165232X19302071, 2020.

Myhre, M.: Model Based Snow Cover Analysis Regarding the Avalanches in Longyearbyen 2015 and 2017, Master's thesis, University of Oslo, 2018.

Randriamampianina, R., Bormann, N., Køltzow, M. A. , Lawrence, H., Sandu, I., and Wang, Z. Q.: Relative impact of observations on a regional Arctic numerical weather prediction system, Quarterly Journal of the Royal Meteorological Society, 147, 2212–2232, doi:10.1002/qj.4018, 2021.

Simenhois, R. and Birkeland, K.: The extended column test: a field test for fracture initiation and propagation, in: Proceedings of the International Snow Science Workshop, Telluride, Colorado, 2006.

Zweigel, R. B., Westermann, S., Nitzbon, J., Langer, M., Boike, J., Etzelmüller, B., and Vikhamar Schuler, T.: Simulating Snow Redistribution and its Effect on Ground Surface Temperature at a High-Arctic Site on Svalbard, Journal of Geophysical Research: Earth Surface, 126, e2020JF005 673, doi:10.1029/2020JF005673, URL https://onlinelibrary.wiley.com/doi/abs/10.1029/2020JF005673, 2021.