A SENSITIVITY ANALYSIS TO QUANTIFY HOW ERRORS IN FOREST DATA AFFECT AVALANCHE HAZARD MAPS IN NORWAY

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ABSTRACT: Forests play a major role in the mitigation of avalanche risk in Norway, but the regulations surrounding the management of "protection forests" are still being worked out. To promote protection forest management, avalanche hazard indication maps for Norway have been produced with the automated mapping tool NAKSIN in a way that makes it possible to quantity the effects of the current forests in a spatially explicit way. NAKSIN makes use of published relations for forest effects on snow properties and uses national models of forest characteristics to estimate the effects on release probability and runout given local climate and topography. The forest properties contain parameters that are directly measured (canopy cover), and properties that are predicted (tree diameter, number of trees) with approximately 70% precision according to ground truth data. NAKSIN uses these forest properties in long chains of models, comprising of both mechanistic and empirical elements, some of which are iterated over timesteps during avalanche flow. This means that errors could be propagated throughout those model chains in unexpected ways. The aim of this study was to conduct a sensitivity analysis to examine the effects of errors in the forest data for hazard mapping in a relevant case study region in fjordic western Norway. We examined hazard maps produced using 95% prediction errors for tree diameter and the number of trees per hectare to determine if these would dramatically affect the hazard zones. These hazard maps focused on runout properties as common release areas were implied for avalanches through a common forest canopy cover percentage applied across the two extreme scenarios. Across the entire region, the hazard zones were generally stable with respect to potential errors in the forest data, suggesting the approach is robust and the braking effect of forest is not overstated. There was one exception, where the prediction errors could reduce the forest braking function to negligible. This exception was easy to identify from the difference in hazard zones and the process allows us to consider where more precise measurements of forests could be required in areas with high consequences. The implications of various approaches to estimate forest leaf area index, and how this might impact on release probability are illustrated to further consider this in the next steps of this research.

KEYWORDS: Protection forest, uncertainty, avalanche, risk analysis

1. INTRODUCTION

Norway is a fjordic country, the steepest slopes are often found at sea level, and the northern latitude means winter snow accumulates even at low altitudes. An examination of the national avalanche database, subset for events where the precise location was known, suggests that approximately 95% of avalanches in Norway south of the Arctic Circle (i.e. <66° 34'N), occur below the treeline (Figure 1). This does not discern that there were forests present in the avalanche zone, rather that low altitude avalanches are a significant hazard and that forests should be considered in avalanche dynamics. Furthermore, due to the natural topography, a large fraction of the population live at the base of steep slopes, often with dwellings or transport infrastructure directly in risk zones. At the same time, people and infrastructure in the risk zones are for the most part not protected by supporting structures due to the low

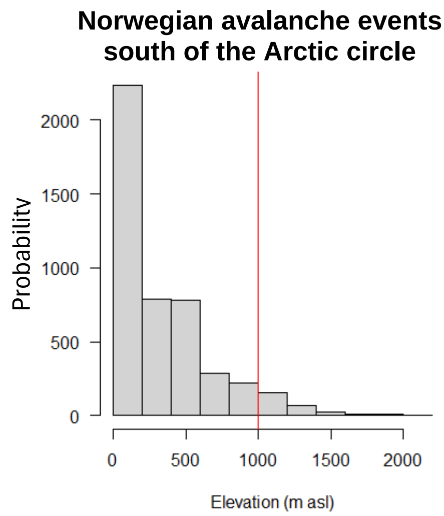

Figure 1: Histogram of historical avalanche event elevation south of the Arctic Circle. The figure counts only events with precise geolocation and the red line indicates the typical treeline altitude.

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population density and high cost of such protection measures. For these people, the forest is their protection, and it is therefore important to understand the degree of risk reduction provided by different forest areas.

The mechanisms by which forests provide protection has been detailed in several studies (refs to add), but generally it can be stated that they (i) alter snowpack properties, by delaying or even preventing snow accumulation on the ground through interception in the branches during snowfall (ref), (ii) provide mechanical support to anchor the snow in place (refs) and (iii) modify avalanche flow providing a braking effect (e.g. Védrine et al 2022). In general, all these effects are dependent on the number, size and type of trees in a given area. These parameters are typically available at low spatial resolution in national forest inventories; for example Norway's traditional national forest inventory is predominantly a 1 km grid. These measurements are conducted with a high degree of precision, but they are not sufficient to be used at the slope scale relevant for avalanche models. In the last two decades, significant advances in so called remote-sensing technology (mainly airborne LIDAR and RGB imagery) coupled with empirical modelling and/or machine learning have enabled high resolution measurements of forests with complete national coverage in some countries, including Norway. This means that national maps of forest cover contain information at sufficient spatial resolution to be used in regional to national avalanche risk analyses. However, these national maps of forest attributes contain errors because some of the important attributes for avalanche models are predicted, not measured. There is consequentially the potential for error propagation throughout the model chain. These errors could affect national regulations on forest management and regional planning, and in the worst case underestimate the risk to human life. It is important to investigate and quantify the potential implications.

The aim of this study is to assess how errors in forest attribute maps will impact avalanche runout behaviour at the slope scale. Some consideration is also given to release probability.

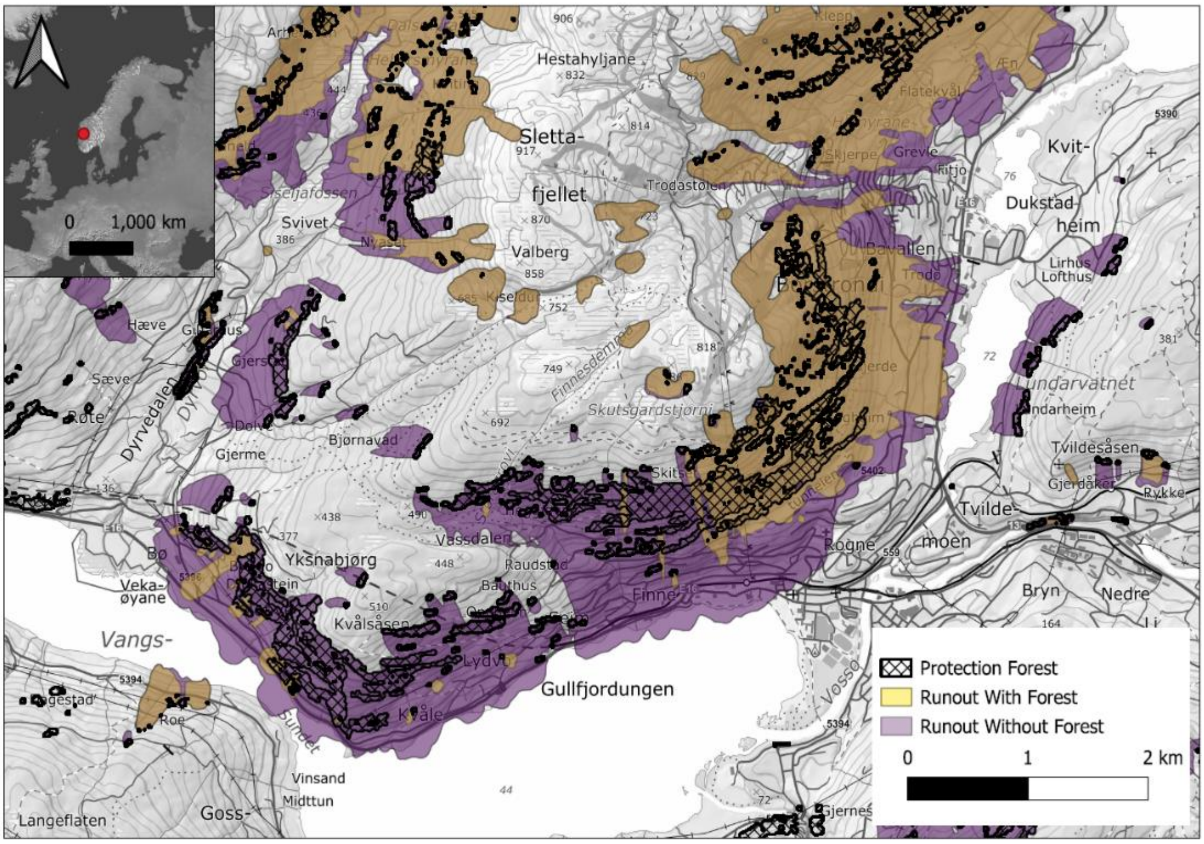

Figure 2 – Voss is in a typical fjordic landscape of western Norway. The avalanche hazard is significant here. Voss is home to approximately 7000 inhabitants and frequented by many tourists. Comparing the avalanche hazard zones with and without the current forest cover produced using NAKSIN (hosted at https://temakart.nve.no/tema/snoskredaktsomhet) shows the important protection provided here. The runout without forest includes the residences of 2800 people and about four km of railway line. Forests cover about 42% (2847 ha) of the region of interest, with about 9% of this total forest area that can be designated as protection forests. The base maps are provided by the Norwegian Mapping Authority under CC BY 4.0. © Kartverket

2. METHODS

2.1 The case study region

Voss is a town and popular ski resort in Vestland county (Western Norway) (Figure 2). The resort is at low altitude (54 m asl, summit about 800 m asl) and winter snow is common to the sea level. The main railway line between Oslo and Bergen (Norway's two largest cities) passes through Voss. The forest in the area is dominated by spruce forests planted in the 1960s and 1970s to create a timber resource in the region and is predominantly privately owned. Today this forest is at harvesting maturity and there is a conflict of interest between timber production and societal protection, which is becoming typical throughout Norway.

2.2 Forest data

Forest data was obtained from the Norwegian Forest Resource (SR16) map (Hauglin et al., 2021). The map is produced by using remote sensing (both RGB imagery and aerial laser scanning) to predict forest attributes at a resolution of 16×16 m^2 primarily based on empirical correlations (Astrup et al., 2019; Hauglin et al., 2021; Rahlf et al., 2017), but also machine learning approaches (Breidenbach et al., 2016, Breidenbach et al., 2021). Thus (i) the data are not necessarily observations and (ii) there are errors associated with the predictions. The parameters that are important for avalanches are canopy cover, the number of trees per hectare, tree species and trunk diameter at breast height (Issler et al 2023). Within the parameters produced in the SR16 model suite, only canopy cover can be considered a direct measurement, whereby the number of ground returns can be compared directly to the number of returns. In fact, airborne laser scanning is currently the most reliable way to measure canopy cover on a meaningful scale. Dominant height (i.e. the height of the tallest trees in each pixel) is also quite reliable because the view of the forest canopy from the air is unrestricted, whereas this is not always true for traditional ground-based assessments using inclinometers. Dominant height is not currently used in NAKSIN, but it is used in the production of other forest parameters and to discern if forests are tall enough to support the snowpack. The parameters describing forest attributes typically assessed below the canopy (e.g tree diameter, number of trees), are less reliable because the low-resolution lidar (~5 points m^{-2}) used in regional mapping does not penetrate the canopy. Quantitatively this translates as approximately a 10% error for height, and a 30% error for other measurements (Hauglin *et al.*, 2021). Nonetheless, as the corresponding errors have been quantified, this allows the production of 95% prediction intervals which should reasonably estimate the range of possible forest properties. In this study, we make use of the upper and lower prediction intervals on a 16 m^2 grid to represent the largest probable errors in the forest data.

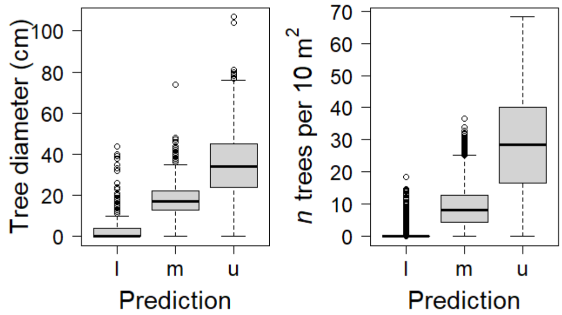

Figure 3: Boxplots showing the distribution of forest metrics used in avalanche modelling in this study. These are according to lower (l), expected or mean (m), and upper (u) values of 95% prediction intervals. The boxes represent the 25th, median and 75th percentile of the data, while the whiskers represent the 2.5th and 95th percentiles.

2.3 The mapping tool NAKSIN

We use the same automated hazard mapping tool, NAKSIN (Issler et al., 2023) as was used for the production of the current national hazard indication maps for snow avalanches in Norway. It is a Python 3 code that implements the following computational steps:

1. Set up the calculation (mapping area, data sources, model parameters) from the user-supplied configuration file.
2. Find potential release areas (PRAs) according to a set of topographic criteria (slope angle, planform curvature, PRA size and altitude span, boundary shape and watersheds),
3. For each PRA, estimate the annual release probability and fracture depth by evaluating a simple stability criterion for several million synthetic "winter days".
4. If the estimated annual release probability exceeds the user-selected threshold (0.001 a^{-1} in our study), simulate the run-out area corresponding to an event of that frequency.
5. Superpose the run-out areas from all avalanche paths to obtain the final map.

The sample "winter days" are generated by randomly picking values for old-snow depth and snow water equivalent (SWE), three-days precipitation and snowfall following the distribution in the seNorge 2 data set, a more than 65 years long time series of gridded daily data (Lussana et al., 2018; Saloranta, 2016). These data, referring to the average altitude of a 1 km^2 grid cell, are extrapolated to the altitude of the PRA and corrected for rain-on-snow events. The mean snow density derives from the ratio of snow height and SWE.

For each "winter day", the position of a weak layer in the snowpack is randomly drawn and its shear strength estimated based on field data (Jamieson and Johnston, 2001), multiplied with a random factor typically in the range [0.5, 2]. NAKSIN presently uses a simple infinite-slope stability criterion, i.e., the ratio of weak-layer strength to the gravitational traction of the overburden. The stabilizing forces across the snow slab are neglected, thus overestimating the release probability.

Where forest is present, the old-snow and new-snow heights are reduced and the snow densities increased, which leads to increased strength of the weak layer. The modification depends on the canopy coverage (i.e. crown size and number of trees) and winter-time leaf-area index. The latter, in turn, depends on the local dominant tree species, snow interception being strongest for spruce, somewhat less for pine and much less for deciduous trees like birch. Another important effect is the supporting effect of the tree trunks, which depends on the number of trees per unit area and their average diameter. In the search for PRAs (step 2 above), NAKSIN anticipates these effects by eliminating cells with very dense forest, the threshold depending on tree species and local slope angle.

In principle, many different run-out models could be used in NAKSIN. We use MoT-Voellmy, a 2-D depth-averaged flow model of the Voellmy type. The two friction parameters, μ and $k = g/\xi$, are spatially varying and chosen according to the calibration proposed in (SLF, 2017). However, the altitude dependence suitable for the Swiss Alps is replaced by a dependence on the local average winter temperature from the seNorge 2 data set, adjusted for altitude (Issler et al., 2023) so that it can be used universally.

MoT-Voellmy accounts for the braking effect of trees on flowing avalanches by incrementing μ and k by local values $\Delta\mu$, Δk that depend on the Froude number of the flow and $n \cdot \phi$, the product of the stand density (i.e. the number of trees per unit surface area or n) and average tree diameter ϕ:

$$\Delta\mu = 1.25n \cdot \phi \cdot h \cdot \cos\theta \quad (1)$$

$$\Delta k = 0.5n \cdot \phi \cdot h.\cdot \cos\theta \quad (2)$$

where h is the flow depth perpendicular to the slope. Detrainment effects (Teich et al., 2014; Védrine et al., 2022) are presently neglected. However, to avoid overestimating the braking effect, MoT-Voellmy removes the forest cover in a cell if and when the avalanche exerts a moment that exceeds the individual tree i strength, i.e. a critical moment CM_i which breaks the tree i. This critical moment is calculated based on the tree diameter and the wood material modulus of rupture MOR, which varies by tree species:

$$\mathrm{CM}_i = \frac{\pi}{32}\mathrm{MOR} \cdot \phi_i^3 \quad (3)$$

with the moment exerted on the tree by the avalanche with density ρ , velocity ν and height h being represented by:

$$\mathrm{M}_i = (0.5\nu^2 + 2.5g\_\perp \cdot H)\rho \cdot \phi \cdot H\left(H + \frac{h}{2}\right) \quad (4)$$

where H is the height of snow that the avalanche flows over and$g_\perp$ the gravitational acceleration perpendicular to the slope. It then follows that if M_i exceeds CM_i then tree i will break. In large avalanches, the lengthening of run-out due to forest destruction may exceed 200 m.

3. RESULTS AND DISCUSSION

3.1 Risk area mapping

Table 1: Release areas and corresponding runout areas predicted by NAKSIN for the different forest scenarios in the study. "Upper" and "lower" correspond to the prediction intervals for forest properties described in the text.

Scenario	No. of release zones	Total release area (ha)	Total runout area (ha)
No forest	298	425	1941
Mean forest	161	143	927
Lower forest	161	143	946
Upper forest	161	143	901

The summary results from using NAKSIN to produce hazard indication maps for the region of interest are shown in Table 1. In general, the largest difference is seen between the "no forest" and any of the "with forest" scenarios, this difference is already evident in the map shown in Figure 2. When it comes to differences between the forest scenarios, the release areas can be seen to be almost identical. This is explained because canopy cover and tree species are common between all scenarios as NAKSIN was run in a custom setup for this study. When it comes to runout, the effects of varying forest structure due to prediction errors are more pronounced. Based on how the braking effects of forest are implemented within NAKSIN, we see the logical consequences of fewer and smaller trees (lower scenario) having correspondingly longer runouts than more and larger trees (upper scenario). The differences between the forest scenarios appear almost negligible when observed across the case study region (Figure 4), with the one noticeable exception to the northeast of the area, which will be examined in further detail below.

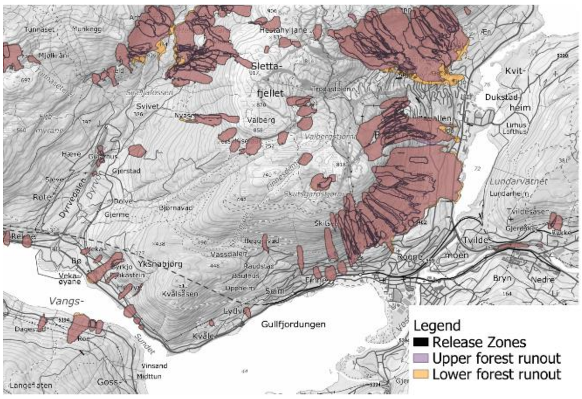

Figure 4: Release zones and avalanche runouts predicted by NAKSIN for the "upper" and "lower" forest scenarios. The base maps are provided by the Norwegian Mapping Authority under CC BY 4.0. © Kartverket

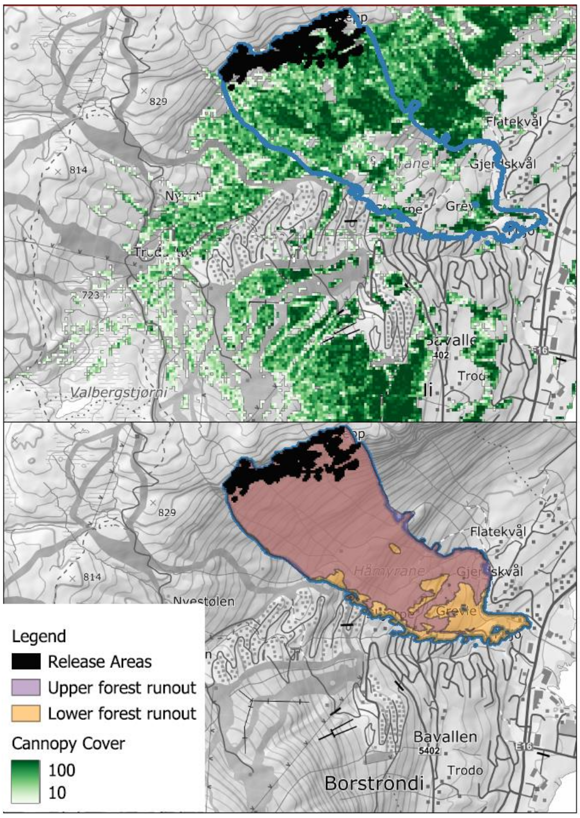

Figure 5: An avalanche path where the errors of predicted forest structure led to a noticeable difference in runout distance. The largest area is outlined in both maps. The access road to the ski resort and some residences are affected by these differences. The base maps are provided by the Norwegian Mapping Authority under CC BY 4.0. © Kartverket

3.2 The effect of forest structure on a specific avalanche runout

In one predicted avalanche the errors in forest structure had a more significant effect on runout (Figure 5). As the risk zone is extended or retracted it affects residences and critical winter infrastructure (here the only road to and from the ski resort). The predicted release occurs on a convex section of the slope at, or just above, the treeline. The runout passes through a mixed forest structure consisting of dense patches and open patches, before passing through fields used for grazing. In principle therefore, this forest should provide a braking effect near the treeline and the absence of this forest should lead to increased runout. Indeed, the accumulations of snow can be seen from the height profiles just below the forest in the upper scenario (Figure 6). However, the lower prediction interval for tree diameter and the number of trees almost removes the forest in this area (figure 7) rendering it ineffective in avalanche braking.

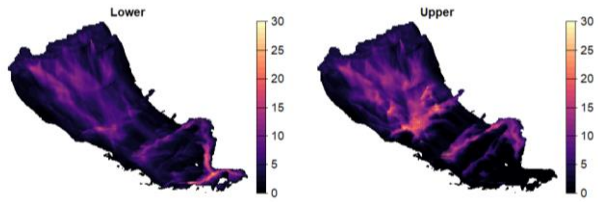

Figure 6 – Height profiles of the simulated avalanche depth (i.e the total of flowing and deposited snow) in the lower and upper forest scenarios showing the braking effect of a dense forest in the runout path.

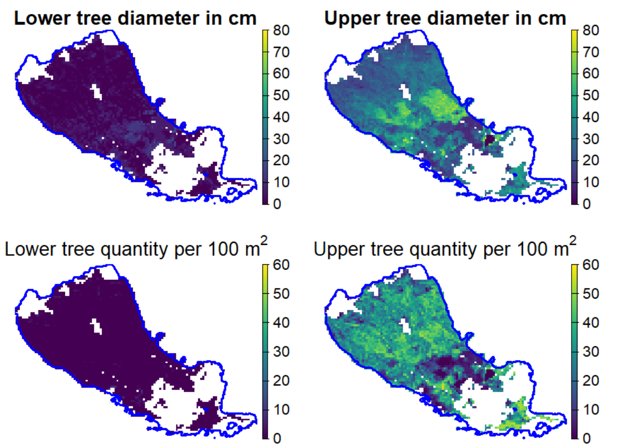

Figure 7: Forest properties within the examined runout zone shown in Figure 5. These properties are based on 95% prediction intervals. In this area there is a high degree of uncertainty in the forest and the number of trees is almost negligible at the lower range of the prediction

Due to the way in which the forest effect is included in the runout simulations (Equations 1-4), it follows that any reduction in tree diameter will have a considerable influence on the braking effect, which is clearly demonstrated on a 2D transect through the profile (Figure 8). This transect shows that the largest accumulation of snow occurs at the toe when the forest braking effect is negligible, whereas the forest has stopped most of the snow when the trees are large and dense. As these scenarios represent the upper and lower prediction intervals for tree diameter, the uncertainly about the protection from this particular forest is high.

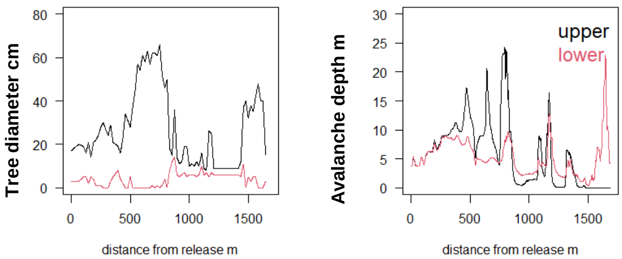

Figure 8 – Tree diameters and simulated avalanche depth (flow and deposit) illustrated along a transect of the avalanche depicted in Figure 5. The braking effect of the forest is observed in the upper forest scenario. Trees in the lower scenario have negligible diameters. Tree diameter is difficult to assess with low resolution airborne laser scanning and the errors are therefore large.

This result requires further investigation in more case study areas, however here there are two important practical outcomes. First, this process has identified a forest with an extremely important braking effect. More precise measurements of this forest could be acquired, for example with higher spatial resolution instrumentation, to improve quantification and assist the appropriate management. The cost should be justified based on the risk. Secondly, this could indicate an area where additional engineered protection in the release areas could be prioritised. Considering the simulations of avalanches using the forest resource map, we need to accept that tree diameter has relatively large prediction errors in the current forest resource map. From the point of view of avalanche hazards, improvements in how it is predicted should be a priority, although predicting tree diameters with low resolution airborne LiDAR measurements used in national mapping does not offer much scope for substantial improvements due to the inherent technical limitations. Alternatively, and perhaps more relevantly to avalanche hazard mapping incorporating the braking effect through an alternative approach such as the use of forest basal area, a common composite metric of tree diameter and the number of trees per unit of surface area, could prove to be less sensitive to such errors (Figure 9). Using basal area instead of diameter and the number of trees could be tested through a direction incorporation in the modification of the MoT-Vollemy friction components in Equations 1 & 2, as these already contain the product of tree diameter and the number of trees in per unit surface area, which is in effect the definition of basal area.

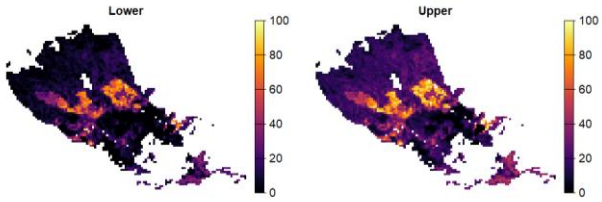

Figure 9 – The prediction intervals for forest basal area (in m^2 ha^{-1}) are narrower than for tree diameter and could be more reliable for avalanche hazard mapping.

3.3 *Leaf Area Index and Release Probability*

Within NAKSIN, the forest partly influences release probability through Leaf Area Index or LAI. LAI is a metric that is used to describe how porous the canopy is in a way that can be related to both snow interception and solar radiation, thereafter new snow mass and snow density (Issler *et al*. 2023). LAI is directly proportional to snow stability as less porous canopies (i.e. higher LAI) have increased interception and increased shading properties.

In the documented default setup, NAKSIN uses tree diameter and number of trees to calculate crown radius, canopy cover and then converts this to LAI based on a sequence of North American relationships (Figure 10). In the custom setup used in this study, canopy cover was a direct measurement and therefore there are no prediction errors. While there will certainly be measurement errors, these are not easy to quantify within the confines of this study because of the variety of instruments, settings (resolution), carrier vehicle and so on. Moreover, measuring canopy cover over large surface areas is prohibitive, and in any case not guaranteed to produce better results to be used as a comparative standard. Tree species is likely to have bigger errors, but as this is produced using a machine-learning approach (Breidenbach et al., 2021), empirical prediction errors are nor readily available. Nonetheless, it is expected that this will be correct about 60% of the time, and that it is reasonable to assume that it should be quite reliable when distinguishing between coniferous and

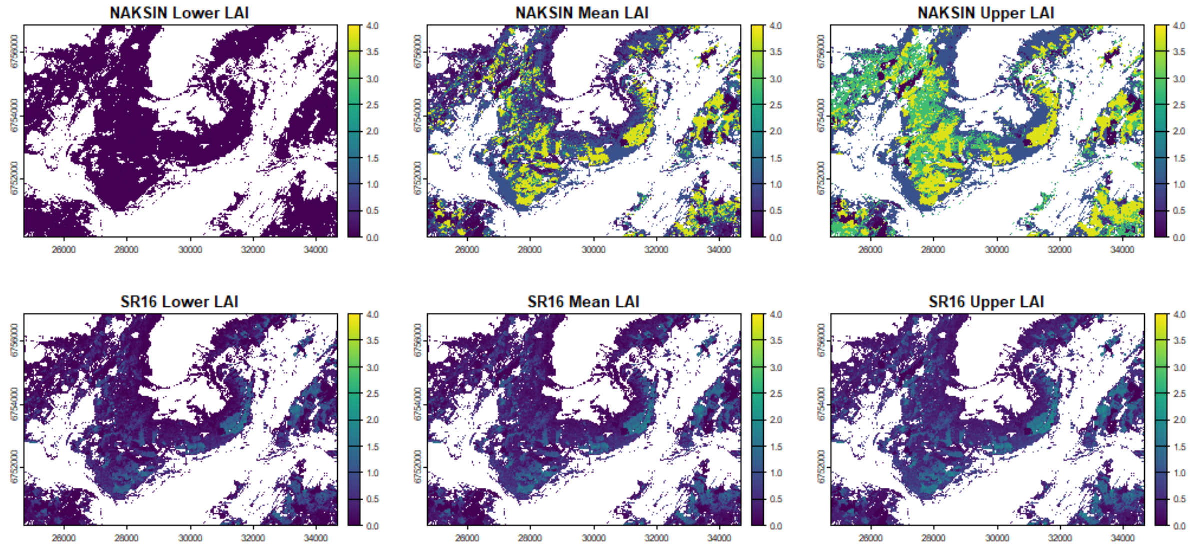

Figure 10 – LAI produced from a variety of methods, “indirectly” through a chain of models in the current default setup of NAKSIN, or “quasi-directly” through remote sensing of forests. This includes prediction intervals and the mean expected value.

broadleaved species, which is arguably the most relevant for the purposes of considering snowfall interception.

Recent developments in forest remote sensing in Norway have now allowed us to consider predicting LAI directly in Norwegian conditions (Figure 10). Further, these predictions have been produced with prediction intervals. At the time of writing, it has not been possible to investigate these effects in scenario modelling due to time constraints, but the investigation of the range of LAI values into the probability within this case study region is ongoing and the full results will be presented in due course. Nonetheless, it is apparent that the values that are directly produced for Norwegian conditions are lower (on average by a factor of 0.85) than those derived indirectly from tree diameter and number of trees, which have already appeared to be problematic in at least one case for avalanche runout modelling, moreover the prediction interval is noticeably smaller for the direct approach. Applying a conservative approach would already suggest that the direct measure will be the most appropriate for the purposes of hazard mapping, however the error should be quantified *in situ*, meaning there is more sensitivity testing to be conducted on the NAKSIN simulator.

4. CONCLUSION

In the context of regional hazard mapping, simulations of avalanche runout appear relatively stable with the range of possible errors present in the forest data. However, there are some concerns with the uncertainty in tree diameter measurements that could lead to important differences in runout predictions. In some cases, it may be possible to use these errors to identify forests with an important braking effect, which could justify more precise measurements of these forests or prioritise additional engineered infrastructure for release prevention. Further simulations over a wider area are required, and the consideration of alternatives to individual tree diameter predictions within the current forest maps of Norway should be investigated.

ACKNOWLEDGEMENTS

NAKSIN was produced primarily through funds provided by the Norwegian Water Resources and Energy Directorate (NVE) through the NGI project 20150457 “Nye aktsomhetskart for snoskred i Norge”. The SR16 forest map was produced by NIBIO as part of its commitment and public responsibility to provide official forest statistics and maps of natural resources. The background topographic map data used is made available through creative commons from the Norwegian mapping authority (Kartverket), who also provide the digital terrain models used in the simulations.

REFERENCES

Astrup, R., Rahlf, J., Bjørkelo, K., Debella-Gilo, M., Gjertsen, A.-K., Breidenbach, J.. Forest information at multiple scales: development, evaluation and application of the Norwegian forest resources map SR16. 2019 Scand. J. For. Res. 34, 484–496. https://doi.org/10.1080/02827581.2019.1588989

Bartelt, P.; Bühler, Y.; Christen, M.; Deubelbeiss, Y.; Salz, M.; Schneider, M. & Schumacher, L. RAMMS::AVALANCHE User Manual WSL Institut für Schnee- und Lawinenforschung SLF, 2017. https://ramms.slf.ch/fileadmin/user_upload/WSL/Microsite/RAMMS/Downloads/RAMMS_AVAL_Manual.pdf

Breidenbach, J., McRoberts, R.E., Astrup, R. Empirical coverage of model-based variance estimators for remote sensing assisted estimation of stand-level timber volume. 2016 Remote Sens. Environ. 173, 274–281. https://doi.org/10.1016/j.rse.2015.07.026

Breidenbach, J., Waser, L.T., Debella-Gilo, M., Schumacher, J., Rahlf, J., Hauglin, M., Puliti, S., Astrup, R. National mapping and estimation of forest area by dominant tree species using Sentinel-2 data. 2021 Can. J. For. Res. 51, 365–379. https://doi.org/10.1139/cjfr-2020-0170

Hauglin, M., Rahlf, J., Schumacher, J., Astrup, R., Breidenbach, J. Large scale mapping of forest attributes using heterogeneous sets of airborne laser scanning and National Forest Inventory data. 2021. For. Ecosyst. 8, 65. https://doi.org/10.1186/s40663-021-00338-4

Issler, D.; Gisnås, K. G.; Gauer, P.; Glimsdal, S.; Domaas, U. & Sverdrup-Thygeson, K. NAKSIN -– a New Approach to Snow Avalanche Hazard Indication Mapping in Norway, 2023, DOI 10.2139/ssrn.4530311

Jamieson, B. & Johnston, C. D. Evaluation of the shear frame test for weak snowpack layers Annals Glaciol, 2001, 32, 59–69, DOI 10.3189/172756401781819472

Lussana, C.; Saloranta, T.; Skaugen, T.; Magnusson, J.; Tveito, O. E. & Andersen, J. SeNorge2 daily precipitation, an observational gridded dataset over Norway from 1957 to the present day, Earth Syst. Sci. Data, 2018, 10, 235–249, DOI 10.5194/essd-10-235-2018.

Rahlf, J., Breidenbach, J., Solberg, S., Næsset, E., Astrup, R. Digital aerial photogrammetry can efficiently support large-area forest inventories in Norway. 2017 For. Int. J. For. Res. 90, 710–718. https://doi.org/10.1093/forestry/cpx027

Saloranta, T. M. Operational snow mapping with simplified data assimilation using the seNorge snow model. 2016 J. Hydrol. 538, 314-325. https://doi.org/10.1016/j.jhydrol.2016.03.061

Teich, M.; Fischer, J.-T.; Feistl, T.; Bebi, P.; Christen, M. & Grêt-Regamey, A. Computational snow avalanche simulation in forested terrain NHESS, 2014, 14, 2233–224, DOI 10.5194/nhess-14-2233-201.

Védrine, L.; Li, X. & Gaume, J. Detrainment and braking of snow avalanches interacting with forests #NHESS#, 2022, 22, 1015–1028, DOI 10.5194/nhess-22-1015-2022