The utility of forest attribute maps for automated Avalanche Terrain Exposure Scale (ATES) modelling

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Abstract

Fatalities associated with recreational activities occur every year as a result of snow avalanches. Terrain classification systems, such as the Avalanche Terrain Exposure Scale (ATES) are designed to provide guidance for safe route finding and this system has been automated (AutoATES). ATES classifies terrain into the three classes simple, challenging, and complex. Forests can provide some protection from avalanches, and these can be incorporated into avalanche hazard models. The objective of this study was to map relevant forest attributes (stem density and canopy cover) based on National Forest Inventory and remote sensing data and, subsequently, use these forest attributes as input to the AutoATES model to improve avalanche hazard maps. We predicted stem density with species-specific mixed-effects models and directly calculated canopy cover using airborne laser scanning data in a 20 Mha study area ranging from the arctic circle to southern Norway. We mapped these forest attributes for 16 m x 16 m pixels, which were used as input for the AutoATES model. The uncertainty of the stem number and canopy cover maps were 30% and 32%, respectively. The overall classification accuracy of 52 ski touring routes in Western Norway with a total length of 282 km increased by up to 12% when utilizing the mapped forest attributes, compared to the model without forest information. The F1 score for the three predicted ATES classes improved by up to 31%, 9%, and 6% for the three classes, respectively, when including a forest attribute in the AutoATES model. We conclude that large-scale fine-resolution forest attribute maps are valuable data in the modelling of avalanche hazards.

Keywords: Avalanches, Airborne laser scanning, remote sensing, National Forest Inventory, SR16

1 Introduction

Snow avalanches cause on average six fatalities per year in Norway (NGI 2022; Varsom 2022), these deaths and other injuries are primarily associated with recreation. Considerable resources have therefore been invested to reduce the number of casualties and hazard maps to assist route-finding are believed to be an important tool. Forest cover can alter avalanche behavior primarily by modifying the snowpack through canopy interception (Bebi et al. 2001), but also to a lesser extent by increasing friction on prone slopes though the mechanism of the physical barriers of tree stems (Teich et al. 2014). On the other hand, large avalanches that release above the tree line are not affected by forests (Teich et al. 2012), these are more often a source of significant forest disturbance. Snow interception is largely dependent on tree species, because of the different morphology of tree crowns (i.e. branch structure, leaves or needles) and the size and number of trees in a given area, which are the factors that will collectively determine canopy cover and gaps. These parameters can potentially be derived from remote sensing in a way that is ideally suited to avalanche simulation (Brožová et al. 2020), the data are superior to traditional ground based inventory in this respect because they are spatially explicit. Maps of such forest attributes allow for monitoring of forest development and, subsequently, for adequate and effective forest management towards an optimized avalanche protection function to reduce avalanche hazards (Brang et al. 2006). This is especially crucial under the challenge of climate change that requires us to adapt forests to changing growing conditions to maintain healthy and resilient forests that can fulfil their functions.

Worldwide, various hazard maps have been developed for recreationalists using different avalanche classification schemes (Barbolini et al. 2011; Schmudlach and Köhler 2016; Harvey et al. 2018; Larsen et al. 2020b). In Norway, the most used classification of avalanche terrain is the Avalanche Terrain Exposure Scale (ATES, Statham et al. 2006). The classification scheme divides avalanche terrain into simple (class 1), challenging (class 2 and complex (class 3) terrain (Table 1).

Table 1: ATES Public Communication Model (v1.04) (Statham et al. 2006).

Description	Class	Terrain Criteria
Simple	1	Exposure to low angle or primarily forested terrain. Some forest openings may involve the runout zones of infrequent avalanches. Many options to reduce or eliminate exposure. No glacier travel.
Challenging	2	Exposure to well defined avalanche paths, starting zones or terrain traps; options exist to reduce or eliminate exposure with careful route finding. Glacier travel is straightforward, but crevasse hazards may exist.
Complex	3	Exposure to multiple overlapping avalanche paths or large expanses of steep, open terrain; multiple avalanche starting zones and terrain traps below; minimal options to reduce exposure. Complicated glacier travel with extensive crevasse bands or icefalls.

Originally, the ATES classification scheme was developed to provide an overall classification of an entire route based on the overall exposure likely to be encountered. Recent advances including modern cartographic techniques have made it more common to develop spatial maps. Making ATES maps, Delparte (2008) found that slope angle and forest density (number of trees per ha or stem density) were the two most important factors when classifying avalanche terrain with the ATES model. Campbell and Gould (2013) developed a specific model for spatial ATES including specific thresholds for slope angle and forest density. Building on the proposed model for spatial ATES mapping, (Larsen et al. 2020b, a) developed an automated ATES algorithm (AutoATES) for nationwide maps in Norway. However, due to limits in the spatial resolution and area-coverage of forest data the first version of the algorithm was only developed for non-forested terrain. The classification accuracy is consequentially most likely to be inaccurate below the treeline. While many recreational accidents associated with avalanches happen above the treeline, Norway is not a country with particularly high mountains and the fjordic landscape means that a considerable amount of avalanche prone terrain is found below the treeline. Therefore, the inclusion of forest attributes in terrain exposure classification is important. Consequentially, in this study we aim to integrate high spatial resolution data on forests into the spatially explicit classification of avalanche exposure.

Forest attributes can be mapped using remote sensing data when a relationship between remotely-sensed variables and the forest attribute of interest exists. This relationship can be quantified via regression models, where the response (a forest attribute) is explained by predictors (remote-sensing variables). Such models are usually established using ground reference data from field plots with known locations and remote-sensing data extracted for the same locations. This is commonly known as the area-based approach (Næsset 2002). In Norway, the National Forest Inventory (NFI) collects extensive information about forest properties in sample plots with a size of 250 m^2 (Breidenbach et al. 2020a), which can serve as ground reference for remote-sensing data to establish regression models predicting these forest attributes. Once established, these models can be extrapolated to areas beyond field-inventory plots, to obtain prediction maps for the attribute or attributes of interest. These predictions are particularly useful to support operational forest management (reviewed by Brosofske et al. 2014). To achieve this mapping of forest attributes, the entire area is gridded into aerial units of the same size as used for model fitting on NFI plots (250 m^2), and the same remote sensing variables are extracted for each unit. Following this approach, various forest attributes were modelled and mapped for the Norwegian forest resource map SR16 (Astrup et al. 2019; Hauglin et al. 2021), which is a national map at spatial resolution of 16 m x 16 m.

The necessary forest attributes for the AutoATES avalanche hazard model in Norway are canopy cover or stem density. Canopy cover is defined as the proportion of the forest floor that is obscured by tree crowns. Consequentially, airborne laser scanning (ALS) is almost the ideal way in which to assess this because it can be directly obtained from discrete return laser scanner data as the proportion of first returns above a specified height threshold, even though this method is slightly biased in areas that are off the azimuth of the ALS scanner (Korhonen et al. 2011). On the other hand, stem density is more challenging to obtain from wide-area coverage ALS because the lasers do not penetrate the canopy with sufficient spatial-resolution to directly observe the stems. Therefore, the aforementioned relationships need to be quantified. Previous studies have attempted to do this in comparable forest types (Næsset and Bjerknes 2001; Lindberg et al. 2010; Lindberg and Hollaus 2012; Ene et al. 2012; Eysn et al. 2015). In general, the relative errors (based on RMSE) are quite high and these increase with increasing complexity of the forest in terms of species and age structure. As none of the currently available models are extrapolatable to the national level in Norway, this was an important facilitating aim in the current study.

Our objectives were twofold: (I) to describe empirical models linking stem density (number of trees per ha) by tree species observed at NFI sample plots to ALS metrics that are used to map these forest attributes in a fine resolution of 16 m × 16 m; to map canopy cover obtained directly from ALS data; and (II) to demonstrate and assess the inclusion of these in avalanche hazard classification models for recreational activities. For the latter, we use the case studies of existing ski-touring routes in Western Norway.

2 Material and methods

2.1 Study areas

In this study we referred to two different areas for the different analysis levels: modelling forest attributes (large part of Norway), and modelling avalanche hazard for recreational activities (mountainous hiking and skiing area).

For modelling forest attributes with field reference data and auxiliary remote sensing data, we used NFI data from a large part of the country covering 21.5 Mha (66% of the Norwegian mainland), located in Norway between latitudes 58° and 69.5° N. This spatial extent was determined by the availability of ALS data (Figure 1). Within the study area, forest growing conditions vary considerably with latitude and elevation. The natural tree line is at around 1100 m asl in southern Norway and around 130 m asl in the north. Depending on these factors, climate zones range roughly from subarctic in the north and east, oceanic at the west coast, and continental in the south-east. The tree species are primarily Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*). These make up the majority of above ground biomass and standing volume. Birch (*Betula pendula* and *B. pubescens*) is the most abundant species in terms of surface area and mainly occurs as early succession following disturbance (including timber harvests) or in high elevation and/or latitude forests (Breidenbach et al. 2020a). In this study the term broadleaves is used to represent what are mostly birch forests.

For assessing the effect of forest towards improved avalanche hazard models for recreational activities we used the area of Romsdalen (Figure 2). This region is a popular destination for ski-touring attracting national and international visitors. Within this area we focused on forested areas on slopes that were relevant for avalanche hazard mapping along 52 documented ski-touring routes (Table 2). The study area has an area of 3200 km^2 and the mountains reaches from sea level and up to 1784 m above sea level.

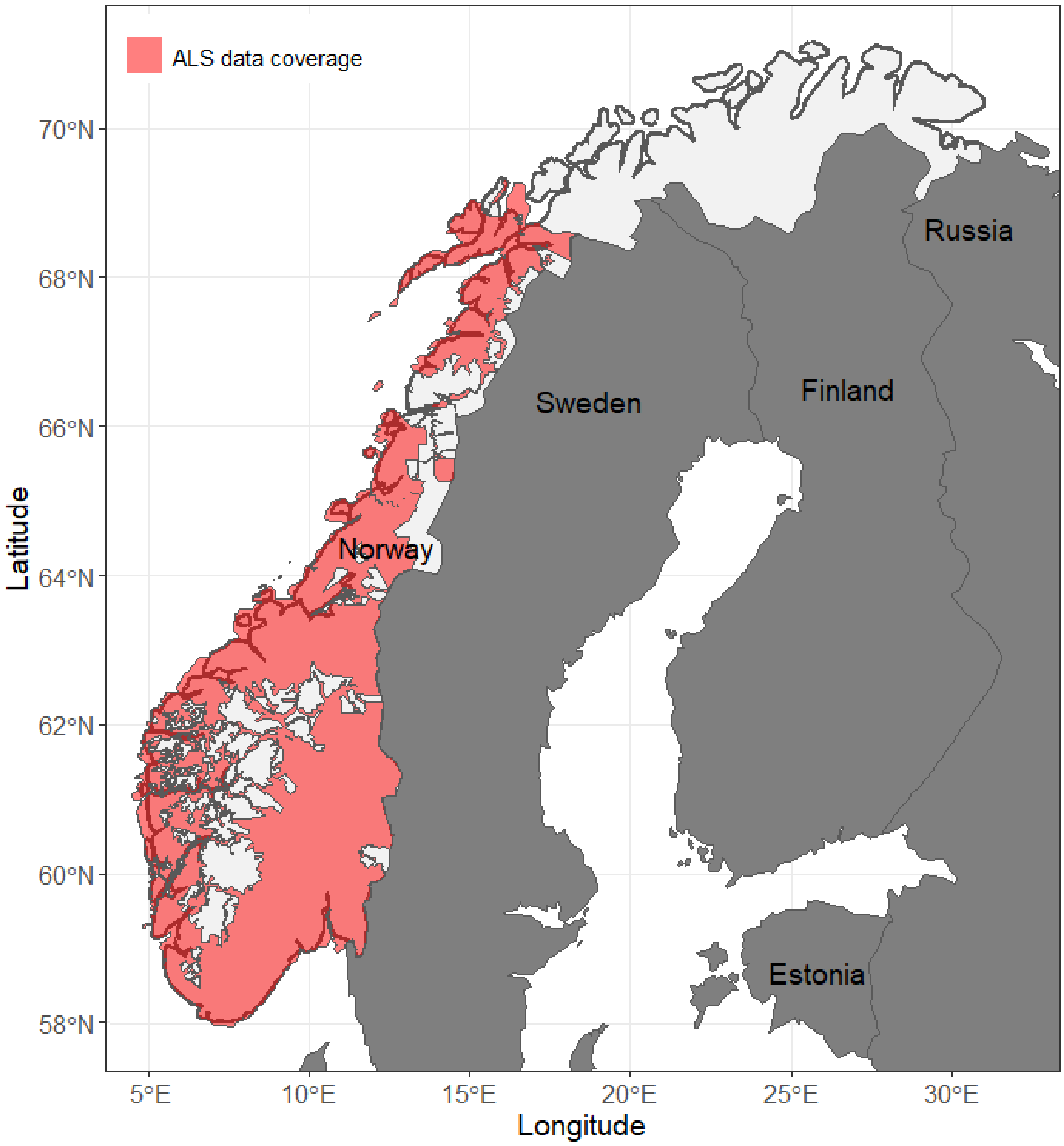


Figure 1: Study area with airborne laser scanner (ALS) data coverage used for modelling forest characteristics.

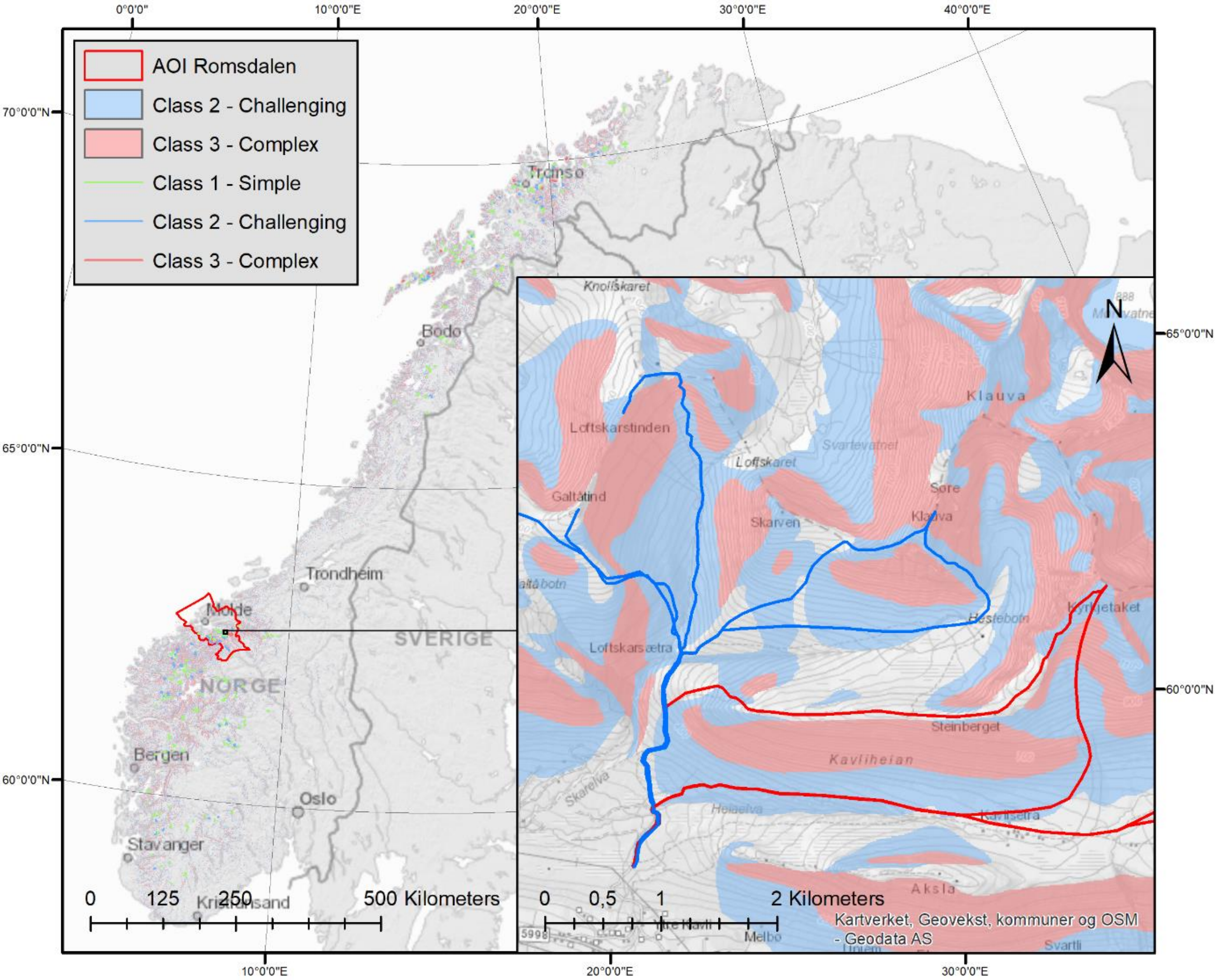


Figure 2: Romsdalen including ski-touring routes through mountainous terrain. The terrain and touring routes is classified according to the ATES classification scheme.

Table 2: Summary of the 52 documented ski-touring routes used in this study.

Manual ATES class	N routes	Total length (km)
1	12	43
2	26	131
3	14	108

2.2 Mapping forest attributes

To map the forest attribute stem density, we developed a mixed-modelling regression between this attribute (our response variable) and independent predictor variables calculated from remote sensing data. We used field measured stem density and visually interpreted canopy cover from the Norwegian National Forest Inventory (NFI, Breidenbach et al. 2020) as response variables, and remote sensing data from airborne laser scanning (ALS) and Sentinel-2 satellite images (S2) as independent predictor variables (sections 2.2.2 and 2.2.3). The attribute canopy cover could be obtained from the ALS data directly. More details on this process can be found in Hauglin et al. (2021).

2.2.1 Data

National Forest Inventory data

We used the permanent sample plots of the Norwegian NFI as reference data (Breidenbach et al. 2020a). In the study area, the NFI is based on a systematic grid of 3 km x 3 km in the lowland region and 3 km x 9 km in the low-productive, birch-dominated mountain region. For trees with a diameter at breast height >= 5 cm (dbh, 1.3 m above ground), parameters are measured on circular plots with a size of 250 m^2.

We used NFI plots located in stands dominated by spruce, pine, and birch (defined as plots with >= 75% timber volume of each tree species, respectively). From these plots, we only selected NFI plots in productive forest (yearly volume increment > 0.1 m^3 / ha), and in one-layered forests, resulting in 1,351 spruce, 1,064 pine, and 535 birch dominated plots that were used for modelling (Table 3).

Table 3: Summary statistics of the Norwegian national forest inventory (NFI) data used for modelling in this study.

	Height (m)	Volume* (m^3)	Stem density**	Canopy cover (%)
		overall		
Min	4.9	5.2	40	0
Max	34.1	1144.7	2840	99.0
Mean	15.2	208.9	860	68.5
STD	4.4	152.2	463	23.3
		Spruce		
Min	5.7	7.6	40	3.0
Max	34.1	1144.7	2840	99.0
Mean	17.0	277.1	1030	75.8
STD	4.4	172.2	451	19.5
		Pine		
Min	7.2	12.7	40	5.0
Max	28.3	693.7	2560	99.0
Mean	14.8	176.2	652	64.4
STD	3.5	106.2	370	22.0
		Broadleaved trees		
Min	4.9	5.2	40	0.0
Max	26.4	400.7	2760	99.0
Mean	11.3	101.7	845	60.2
STD	3.5	70.9	485	28.1

*Volume with bark; **number of trees >= 8 cm diameter at breast height (dbh) per ha.

Remote sensing data

ALS data were acquired during several measurement campaigns for the study area between 2010 and 2019 with a density of 2 to 5 pulses per m^2. A high-resolution digital terrain model (DTM, 1 m x 1 m pixel size) was produced from the last-return data by the Norwegian Mapping Authority

(Kartverket 2019). The ALS point cloud was height-normalized by subtracting the DTM elevation from corresponding point cloud elevation using bi-directional interpolation. The height-normalized point cloud was used to calculate various descriptive metrics for each NFI plot based on first returns, first returns above 2 m height above ground, and last returns. The metrics included mean, variance, coefficients of variation, kurtosis and skewness of ALS return heights, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}, and 95^{th} height percentiles, and ALS return density metrics for 10 height slices (d0 – d9). A canopy coverage metric was calculated as percentage of first returns above 2 m (pctab2f). The DTM was resampled to 16 m x 16 m, such that the cell size corresponded approximately to the area covered by an NFI plot (250 m^2). From the DTM, terrain slope was computed as a raster with a cell size of 16 m x 16 m. S2 bottom of atmosphere reflectance images acquired between 30 June and 31 July 2018 were mosaiced using the bands B2, B3, B4, B5, B6, B7, B8, B8A, B11, and B12, measuring reflectance in the visible, NIR and SWIR spectrum (Drusch et al. 2012). The normalized difference vegetation index (NDVI) was calculated as band 8 minus band 4 divided by band 8 plus band 4 and tested as predictor in the prediction models.

2.2.2 Modelling and mapping tree density

In the Norwegian forest resource mapping project SR16 (Astrup et al. 2019; Hauglin et al. 2021) linear mixed regression models were developed estimating various forest properties. These models have the structure:

$$y = \mathbf{X}\beta + \boldsymbol{Z}u + \epsilon, \text{with } u \sim \mathrm{N}(0, \mathbf{G}) \text{ and } \epsilon \sim \mathrm{N}(0, \mathbf{R}), \qquad \text{(Equation 1)}$$

where y is the dependent response variable, $\mathbf{X}$ and $\mathbf{Z}$ are the design matrices for fixed and random effects, respectively, β are the fixed effects parameters, u is a vector of random effects, and $\mathbf{G}$ and $\mathbf{R}$ are the covariance matrices for random effects and residual errors, respectively. We used the nlme package (Pinheiro et al. 2020) in the statistics software R (R Core Team 2020) to estimate the model parameters. A starting model was stepwise reduced by forward and backward selection of predictors based on Akaike Information Criterion as stopping rule (stepAIC function in R (Venables and Ripley 2002)) and was further reduced by backward selection based on p-values ($p<0.05$). We used the information on ALS project acquisition as random effect on slope in the models to account for differences in ALS data collection between the different projects.

We used the approach described above and the model structure in equation 1 to fit linear-mixed effects models predicting stem density (for trees >= 8 cm dbh) for three tree species of interest. Area wide predictions of the forest attributes were made by applying the developed models to 16 m x 16 m pixels, which is similar to the area of the NFI plots used during model fitting. A tree species map (Breidenbach et al. 2020b) was used to apply the corresponding tree species specific model.

2.2.3 Mapping canopy cover

Canopy cover was calculated from the ALS data directly by analyzing the spatial distribution of laser echoes with above-ground heights >= 5 m. The normalized laser point cloud of each 16 m × 16 m pixel was divided into 64 voxels of size 2 × 2 × h m^3, where h is the vertical distance from 5 m above ground to the maximum above-ground echo height. Each voxel was thus defined by a 2 × 2 m^2 base at 5 m above ground and extended upwards to the height of the highest echo, i.e., h. Note that this means that the shape of the voxels where in most cases not cubical, but typically was higher than the 2 m sides of the base. The proportion of non-empty voxels were used as a representation for canopy cover in the 16 m × 16 m pixel, with non-empty voxels being voxels containing at least one laser echo. Canopy cover was then compared to field-based estimates of canopy cover at NFI plots.

2.3 Avalanche hazard maps for recreational activities

To investigate the effect of forest data on recreational avalanche maps, we ran AutoATES using both canopy cover and stem density and compared it to AutoATES with no forest data as input (Larsen et al. 2020b, a). AutoATES is an automated algorithm that is made to create spatial ATES maps using only a DEM and forest data (optional) as input. The first step of the algorithm is to calculate the potential release areas (PRA) using the algorithm developed by Veitinger et al. (2016) and later modified by Sharp (2018). Using a fuzzy operator, they combine the slope angle, terrain roughness, win d shelter and forest data into a raster layer ranging from 0 to 1, where 1 is a very likely release area, and 0 is not likely (Veitinger et al. 2016; Sharp 2018). When the PRA layer is completed, a runout model is used to calculate areas downslope of the PRAs that could be affected by an avalanche. In Larsen et al. (2020b) the TauDEM model is being used (Tarboton 2004), but recent advances show that the new FlowPy model (D'Amboise et al. 2021) is much better suited (Larsen et al. 2020a). Both models use a flow model that is limited by the angle of reach, which is the angle from the PRA to the lowermost point in the flow model. In this paper, we only use the best performing algorithm utilizing FlowPy. The improved algorithm can be tuned using different thresholds for slope angle (SAT), cell count (CC), angle of reach (AAT), PRA threshold (PRA THD) and forest density. To test whether the forest input data improves the result of the AutoATES model, we used a fixed set of thresholds except for forest data (Table 4).

Table 4: The input parameters used for AutoATES. The parameters were held constant between the models that included no forest data, stem density and canopy cover data.

Parameter:	AAT1	AAT2	AAT3	CC1	CC2	SAT01	SAT12	SAR23	SAT34	PRA THD
Value:	20°	25°	31°	50	250	15°	25°	31°	37°	0.15

A fuzzy membership value also has to be set for each forest density type used in the PRA calculation. The value is defined using a Cauchy membership value given by the function μ(x) (Jang et al. 1997).

$$\mu(x) = \frac{1}{1+\left(\frac{x-c}{a}\right)^{2b}} \quad \text{(Equation 2)}$$

where x is the weighting of the forest attribute vs. slope angle, roughness and wind shelter in the fuzzy operator (Veitinger et al. 2016; Sharp 2018). The remaining parameters are described in Table 5. Sharp (2018) defined the membership values for stem density, while we suggest new preliminary membership values for canopy cover (Table 5).

Table 5: The parameters used to calculate the fuzzy membership of forest input in the PRA model.

Parameter:	a	b	c
Stem density (Sharp et al., 2018)	350	2.5	-150
Canopy cover	240	25	-200

As a basis for comparison in the case study area we considered the classification of routes by local avalanche experts. The dataset consists of a set of 52 routes with a total length of 282 km that were manually mapped by local avalanche experts working for NVE (Larsen et al. 2020b) in 2018. The work was done using the ATES v1.04 defined by Statham et al. (2006). Methods used included: a GIS web tool, visual interpretation of aerial imagery, local expertise, and field surveys. Each route is classified according to eleven different avalanche terrain factors and classified as either simple, challenging, or complex terrain. If the route is within the challenging or complex definition of slope angle for a short section of the trip, the whole trip will be classified as challenging or complex. Therefore, it is important to note that there is a difference between the manual ATES classification of linear routes and the spatial AutoATES classification of 10 m x 10 m pixels (Larsen et al. 2020a). The manual ATES classification considers the trajectory of the whole route, while the AutoATES algorithm outputs a classification value for each pixel. To compare the manual ATES classification with the AutoATES classification, the AutoATES map was sampled every 10 m along the length of the route. The 95th percentile of the extracted AutoATES predictions was used to assign one predicted class per route. We calculated weighted accuracies using lengths of classified routes.

3 Results

3.1 Forest attribute maps

We successfully modelled the stem density using linear mixed effects models, and directly calculated canopy cover from ALS data for the spruce, pine, and birch forests (Figure 3). The fit statistics associated with the linear-mixed models for stem density showed the results for spruce were the most accurate in terms of RMSE (Table 6). The significant predictors were similar for the spruce and pine models. Both models contained the 75th percentile of first ALS returns, (h75f) and its squared version (h75fsq), the percentage of first ALS returns above 2 m height, (pctab2f) and its squared version (pctab2fsq), the interactions between h75f and pctab2f, and between h75fsq and pctab2fsq, the normalized difference vegetation index (NDVI), and terrain slope. For the spruce model one additional first return density metric d6f was included, and for the pine model the first return density metric d4f was included. The model for birch forests only included the predictors h75fsq, pctab2fsq, and d6f. The model details can be found in Table 9 in the appendix.

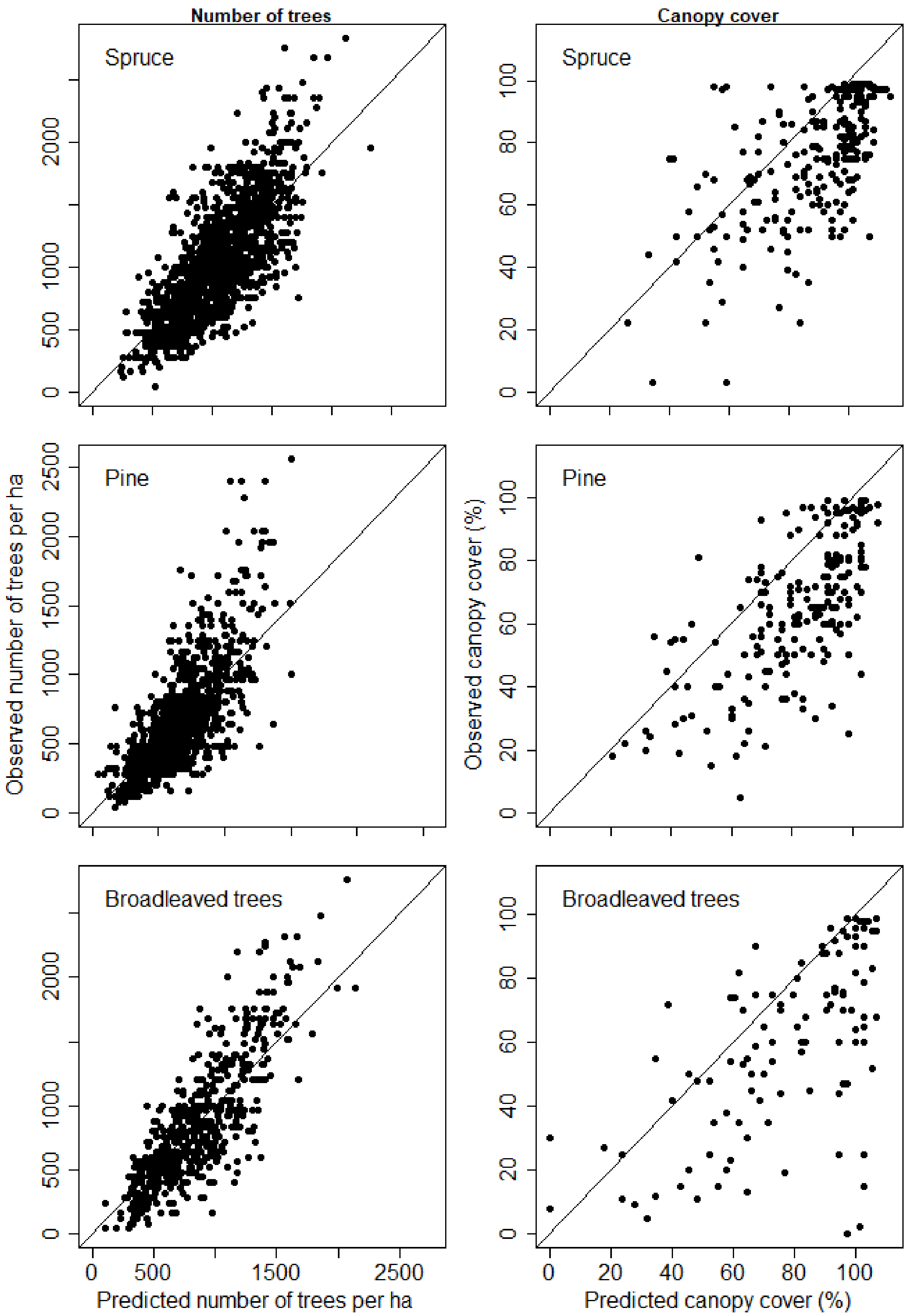


Figure 3: Results of models for stem density (number of trees per ha, left column), and canopy cover directly from laser scanner data (right column); all attributes were stratified into three tree species groups: spruce (top row), pine (middle row), and broadleaved trees (bottom row).

Canopy cover directly obtained from the ALS data as described in the Methods section showed a good fit with canopy cover values from the NFI data (Figure 3, Table 6). We also compared canopy cover calculated as proposed by Korhonen et al. (2011) with canopy cover from the NFI. However, this relationship was worse and therefore not further considered in this study.

Table 6: Characteristics of the fitted models and canopy cover relationship

	Stem density	Canopy cover
Norway spruce		
Pseudo R^2	0.59	-
$RMSE_{cv}$	307.9	21.0
$RMSE_{cv}$%	29.9	31.5
Variance components %		
Fixed effects	50.91	-
Random effect	5.59	-
Residual	43.50	-
Scots pine		
Pseudo R^2	0.56	-
$RMSE_{cv}$	277.4	23.9
$RMSE_{cv}$%	42.5	37.1
Variance components %		
Fixed effects	40.72	-
Random effect	10.81	-
Residual	48.47	-
Broadleaved trees		
Pseudo R^2	0.68	-
$RMSE_{cv}$	330.7	29.2
$RMSE_{cv}$%	39.1	39.6
Variance components %		
Fixed effects	48.08	-
Random effect	13.99	-
Residual	37.93	-

3.2 Assessment of hazard maps for recreational activities

Due to the inherent differences in scale between the route-level reference and the pixel-level predictions we can only make a meaningful comparison for reference classes 1 and 2 and predicted classes 2 and 3 (see methods description in section 2.3). For comparison of all classes, we made additional analyses on route-level by summarizing pixel-level predictions for each route.

Overall, including forest attributes in the AutoATES model improved terrain and, thereby, route classifications with regard to avalanche hazard. Using the 95th percentile of predicted values to assign one class per route, AutoATES-Forest classifications showed a considerable improvement compared to AutoATES without forest attribute (Table 7).

Table 7: Confusion matrices for 282 km manually classified routes (ATES) in Romsdalen and the automated ATES algorithms AutoATES, AutoATES-Forest (canopy cover) and AutoATES-Forest (stem density) on entire-route

level. Routes were classified according to the 95th percentile of AutoATES and AutoATES-Forest predictions. Values represent km of routes (route count is given in brackets).

No forest parameters included				
		AutoATES		
		Class 1	Class 2	Class 3
Manually mapped (ATES)	Class 1 simple	10.5 (3)	21.8 (7)	10.6 (2)
	Class 2 challenging	0 (0)	59.9 (12)	71.2 (14)
	Class 3 complex	0 (0)	23.1 (3)	84.7 (11)
Including canopy cover				
		AutoATES-Forest		
		Class 1	Class 2	Class 3
Manually mapped (ATES)	Class 1 simple	23.1 (6)	13.8 (5)	6.0 (1)
	Class 2 challenging	0 (0)	90.1 (16)	41.0 (10)
	Class 3 complex	0 (0)	31.9 (4)	75.8 (10)
Including stem density				
		AutoATES-Forest		
		Class 1	Class 2	Class 3
Manually mapped (ATES)	Class 1 simple	29.2 (8)	13.7 (4)	0 (0)
	Class 2 challenging	24.7 (3)	78.9 (16)	27.5 (7)
	Class 3 complex	0 (0)	38.7 (5)	69.0 (9)

Overall accuracies weighted by route lengths increased from 0.55 for AutoATES to 0.67 for AutoATES-Forest using canopy cover and to 0.63 for AutoATES-Forest using stem density. Similarly, also the other accuracy statistics F1 score, Sensitivity, and Precision improved (Table 8). Only sensitivity of class 3 decreased when using forest properties in the model since more routes that were marked as class 3 in the reference were predicted as class 2.

Table 8: accuracies for routes assigned to one class; routes were assigned one predicted value using the 95th percentile of predicted pixel values within a route; OA = Overall accuracy, PA = Producer's accuracy, UA = User's accuracy, PPV = positive predictive value.

	OA	F1 score			Sensitivity/Recall (PA)			Precision/PPV (UA)		
		Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
AutoATES No forest	0.55	0.39	0.51	0.62	0.25	0.46	0.79	1.00	0.57	0.51
AutoATES Canopy cover	0.67	0.70	0.58	0.66	0.54	0.69	0.70	1.00	0.66	0.62
AutoATES Stem density	0.63	0.60	0.60	0.68	0.68	0.60	0.64	0.54	0.60	0.72

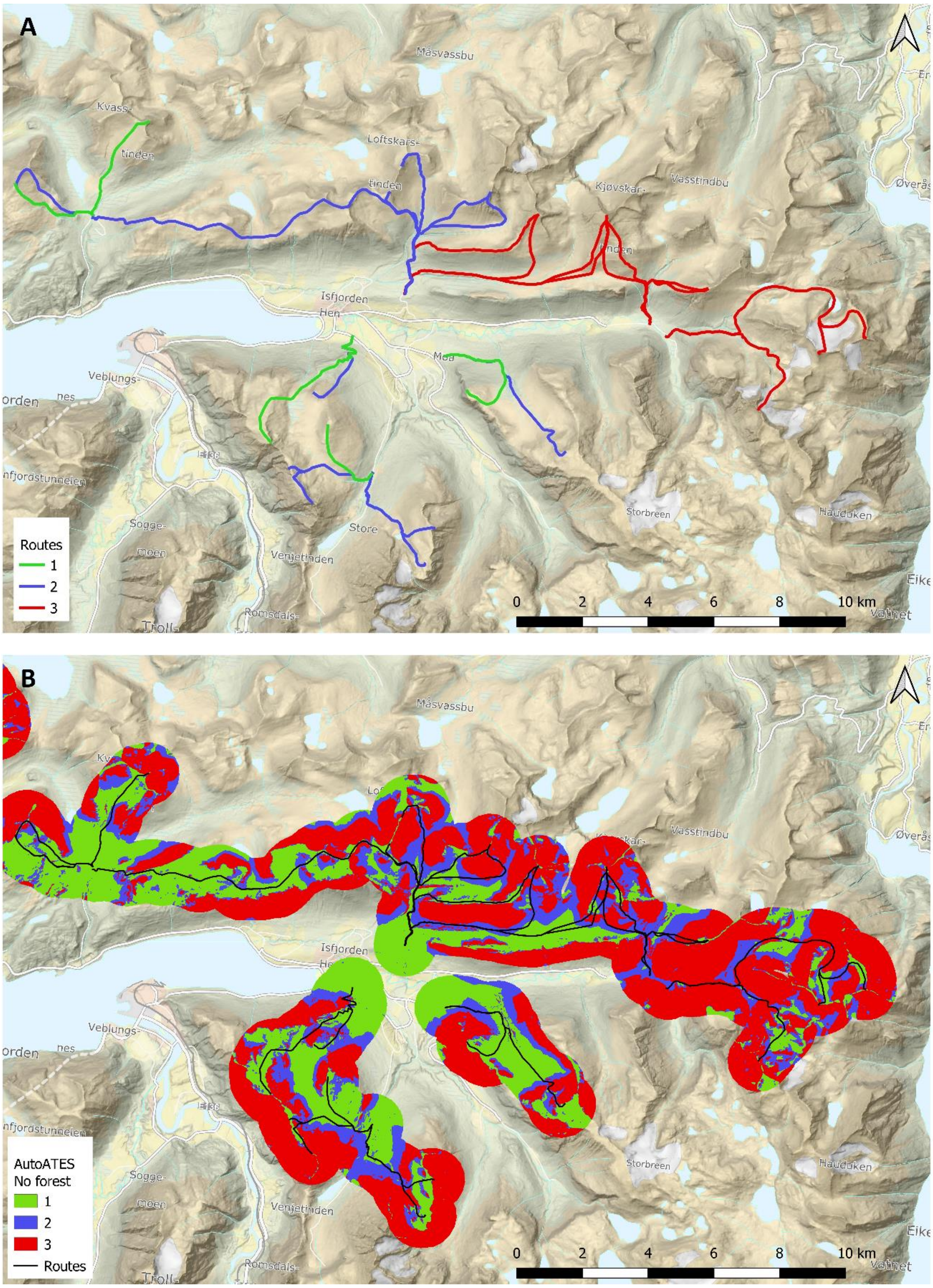
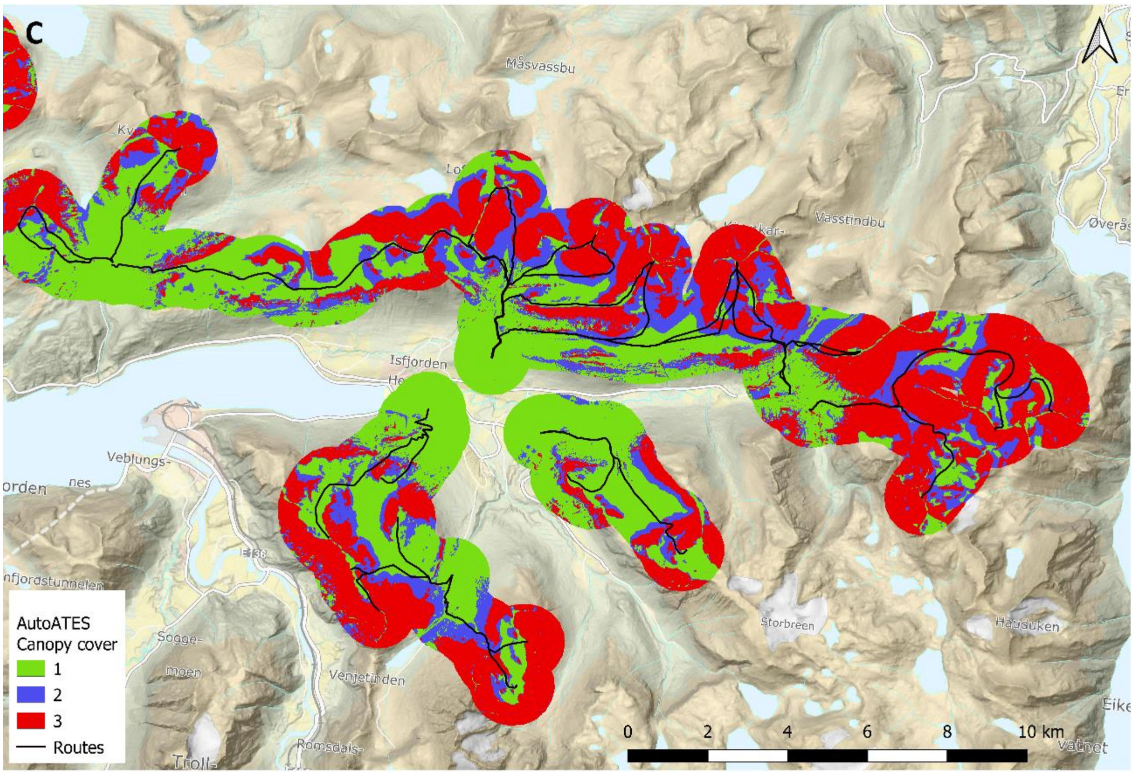


Figure 4: Area around the town Isforden; A) manually ATES classification of touring routes according to the part with the greatest hazard used as reference; B) output of AutoATES model without forest; C) output of AutoATES-Forest model with forest canopy cover as model input; D) output of AutoATES-Forest model with forest stem density as model input.



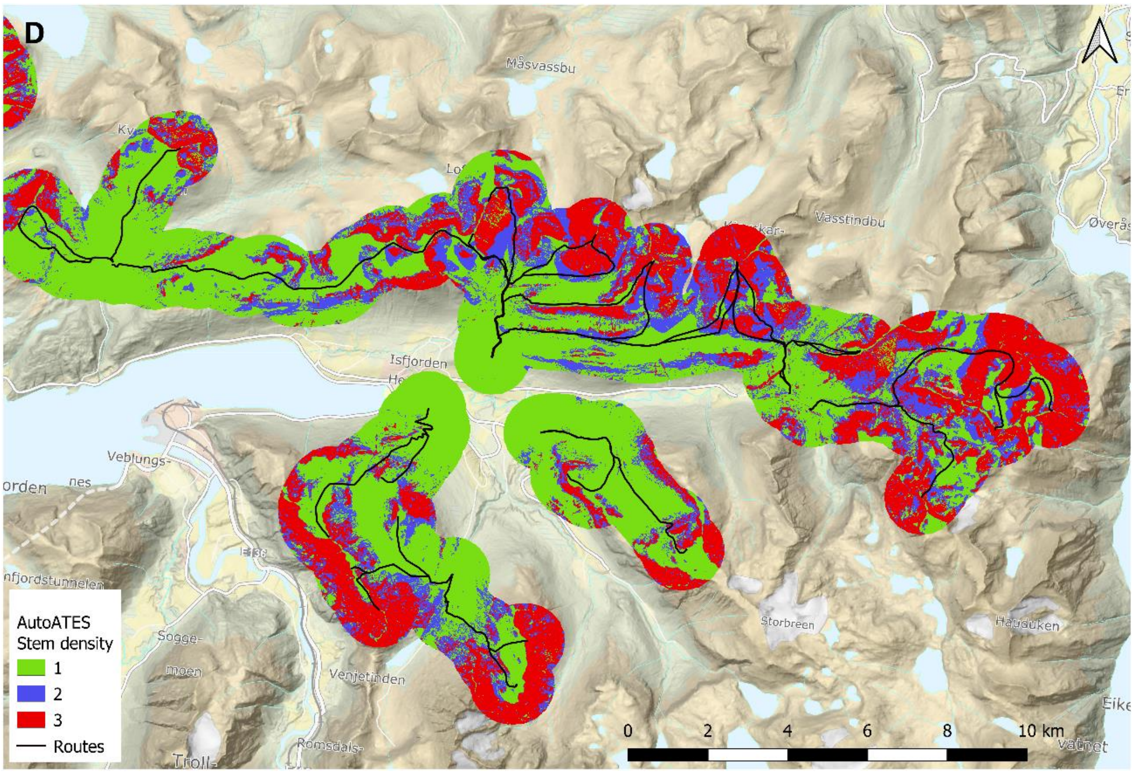


Figure 4 continued.

4 Discussion and Conclusion

In this study we successfully modelled and estimated the forest attributes of stem density and canopy cover respectively using NFI and remote sensing data collected over a large area in Norway encompassing various growing conditions. We could produce maps of these attribute and include them as inputs in the spatially explicit avalanche hazard model AutoATES-Forest in order to improve avalanche hazard maps for recreational activities.

We found that the forest attribute stem density could be modeled with relatively high accuracy using remote sensing data and observed coefficient of determination (pseudo R^2) values of 0.59, 0.56, and 0.68 for Norway spruce, Scots pine, and broadleaved trees, respectively. Cross-validated RMSEs were 308 (30%), 277 (43%), and 331 (39%) for Norway spruce, Scots pine, and broadleaved trees, respectively. Tompalski et al. (2019) found similar results with R^2 and RMSE of 0.37 and 293 (42%), respectively, for modelling stem density in Canada. Lindberg and Hollaus (2012) compared area-based and single tree-based approaches for estimating the number of trees and found RMSE of 53% (area-based) and 63-92% (single tree based). Ene et al. (2012) used the single tree-based approach and reported 46-50% detection rate for stem number estimates in heterogenous boreal forests. Eysn et al. (2015) reported 47% overall tree detection rate in heterogenous alpine forest. Stem density is difficult to predict using the type of remote sensing data used in this study and the area-based approach. While using very high-resolution ALS or drone data would allow for analyses on single tree level that might result in higher accuracies, collecting such high-resolution data for the single tree approach on such a large spatial scale used in this study is practically not feasible. In additional to the area that needs to be covered, forests are dynamic ecosystems and their structure changes from year to year, therefore it is not a matter of once off acquisition but rather regular monitoring. We have therefore tried to consider approaches that can make use of data collected in regular surveys, but for areas of particular concern, higher-resolution data might still be appropriate to guide forest management.

We estimated canopy cover in a slightly different way as proposed by Korhonen et al. (2011). Our voxel-based approach with a height threshold of 5 m showed a better correlation with canopy cover obtained by the NFI than canopy cover calculated according to Korhonen et al. (2011). The relation between predicted and observed canopy cover was not as good as for the other forest attribute stem density. This can partially be attributed to the fact that canopy cover in the NFI is not measured, but visually estimated by the NFI crew in five percent steps. Therefore, the ground-truth could be argued to be less reliable than the aerial measurement.

Using the forest attributes stem density or canopy cover in the AutoATES-Forest models improved the terrain and route hazard classification compared to the AutoATES model without forest attributes. The percentage of class 1 (simple terrain) wrongly classified as class 2 (challenging) or 3 (complex) was reduced. When classifying ski-touring routes linearly using manual ATES, the overall class is decided by the most hazardous area on a given route. This means that if the route is located in mostly simple terrain (class 1), the whole route could be classified as complex terrain (class 3) if there is a short section of this type of terrain along the given route. This is a deliberate design feature that errs on the side of safety. A result of this is that even though the algorithm, which works on the pixel level, defines a large percentage of a given route as less hazardous than the manual classification class rating, it is not necessarily wrong. When assigning one hazard class to each route according to the 95th percentile of pixel values from the AutoATES predictions, the overall accuracy increased from 55% (AutoATES) to 67% (AutoATES-Forest canopy cover) and to 63% (AutoATES-Forest stem density). Using the forest attribute canopy cover appeared to result in slightly better classifications, but the difference between the two forest metrics was not as great as the difference between the use of forest metrics and the lack of forest metrics. These results indicate that adding spatially explicit information on forest attributes are beneficial for terrain evaluation. Other forest properties such as diameter distributions can be estimated and mapped from laser scanner data (Räty et al. 2021) and should be considered as in put to avalanche hazard models. Furthermore, avalanche hazard models can be further developed to use forest properties are used as continuous values as input.

Brožová et al. (2020) evaluated variables extracted from ALS and photogrammetric point clouds towards their influence on simulation results of avalanche runout. Remote sensing based tree heights, canopy coverage, and DTM roughness were used for avalanche simulation. They concluded that remote sensing data with a fine resolution of about 1 m x 1 m were generally suitable to model relevant forest attributes used as input for avalanche simulation. The simulation results using the two data sources - ALS and photogrammetric point clouds – were both sufficiently accurate for numerical modelling and for real-world applications in snow avalanche hazard mapping. Bühler et al. (2022) described automated avalanche hazard mapping using the RAMMS model in one Canton in Switzerland. Terrain slope and the forest properties percentage of crown cover and gap width were used to predict an avalanche release probability for each forested raster cell of 5 m x 5 m. This was used as input into the avalanche model. Similar to the present study the authors deduced threshold values for forest properties that entered the model.

A wider implication of these findings is that the value of ecosystem services, such as the protection function of forests, is often difficult to assess. In this respect, our study showed the positive effect of forest in avalanche hazard prediction, and this is something that can be quantified, at least spatially. The authors jointly consider that no price should be put on human lives and therefore we will not enter into discussion of the monetary value of such protection here, though examples exist (e.g Grilli et al. 2020) and it is no doubt an important subject for forest owners whose primary interests are timber revenues. In this respect however, we feel that protection should influence forest management decisions, but that significantly more research is required to investigate optimal forest management of protective forests in a Norwegian context. Finally, models and maps based on those models are only predictions. Predicting and mapping the probability of avalanche releases is meant as an additional planning aid for route choice, much like a weather forecast, and they can be wrong. Avalanche conditions change dramatically depending on snow conditions and these are not in any way included in the ATES system. While we strive to improve the decision-making tools, these are no substitute local evaluation of the current conditions on the ground, and this requires specific training and experience. Even then, avalanches pose a significant threat and safety is solely the responsibility of the individual. Nonetheless, we can conclude that the inclusion of forest attributes in avalanche hazard models can considerably improve their predictive performance.

5 Acknowledgements

6 Appendix

Table 9: stem density models; coefficients, their standard errors, and p-values for the tree species specific linear regression models for spruce, pine, and broadleaved trees.

Variable	Estimate	Std. Error	p-value
Stem density model for spruce			
Intercept	-73.85	130.87	0.573
h75f	37.52	23.48	0.110
h75fsq	-1.37	0.65	0.034
pctab2f	-175.99	406.92	0.665
pctab2fsq	1862.63	421.25	< 0.001
d6f	1122.08	103.12	< 0.001
NDVI	414.73	113.61	< 0.001
slope	-1.94	0.57	< 0.001
h75f_x_pctab2f	-89.52	35	0.011
h75fsq_x_pctab2fsq	1.57	0.74	0.033
Stem density model for pine			
Intercept	-171.32	109.02	0.116
h75f	16.39	15.27	0.283
h75fsq	0.60	0.65	0.361
pctab2f	364.46	421.98	0.388
pctab2fsq	1491.58	375.16	< 0.001
d4f	986.33	140.30	< 0.001
NDVI	240.69	110.80	0.03
Slope	-1.84	0.54	0.001
h75f x pctab2f	-126.86	32.79	< 0.001
h75fsq x pctab2fsq	2.37	0.84	0.005
Stem density model for broadleaved trees			
Intercept	191.58	41.93	< 0.001
h75fsq	-2.07	0.25	< 0.001
pctab2fsq	1255.46	91.02	< 0.001
d6f	993.70	180.47	< 0.001

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