GIS BASED ATES MAPPING IN NORWAY, A TOOL FOR EXPERT GUIDED MAPPING

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ABSTRACT: Manual classification of terrain using the Avalanche Terrain Exposure Scale (ATES) is time consuming. To increase the efficiency of expert terrain mapping, this study proposes a fully automated algorithm within GIS software to be used as a base layer to guide expert mapping. Our new algorithm is based on the technical model for ATES zoning. This model has specific terrain based thresholds that can be applied for automated terrain based modelling. Our algorithm expands on prior work by including the Potential Release Area (PRA) model to calculate the likelihood of an avalanche releasing from a start zone. We also use the raster based, TauDEM model to determine the avalanche runout length based on a specified alpha angle from the identified start zones. The start zone and avalanche runout data are then merged with the slope incline thresholds according to the model for ATES zoning. The final product is a 10 m resolution ATES map accounting for slope incline, start zone density, avalanche runout and slope shape. As a base layer for expert guided mapping, this product could provide the necessary quantitative input to ensure robust and consistent classification across different regions in Norway, or globally. We demonstrate the utility of our methods by comparing expert guided ATES maps to those generated solely by our new algorithm.

KEYWORDS: ATES, GIS, algorithm, zoning, avalanche, terrain

1. INTRODUCTION

The Avalanche terrain exposure scale (ATES) is a terrain classification system developed by Parks Canada to better communicate the complexities and risks of traveling in avalanche prone terrain (Statham et al., 2006). In 2012, the Norwegian Water Resources and Energy Directorate (NVE) conducted a pilot study to determine whether the Canadian ATES classification could be adapted for Norway. A Norwegian version was proposed and several locations across the country were manually classified by experts (NVE, 2014). This paper presents an algorithm to derive high spatial resolution ATES maps based on the practical model proposed by Campbell and Gould (2014). The approach could be used as a base layer for expert guided mapping to ensure quantitative rigidity and consistent classification across different regions in Norway, or globally.

1.1 Study Area

We used a case-study approach to examine the performance of the automated ATES algorithm. Our three case study regions are located in the 26,000 km^2 county Troms, Norway, a popular area for backcountry skiing. Fagerfjellet, Gabrielfjellet and Skitntinden are three popular mountains in the proximity of the county capital Tromsø (Figure 1). The mountains proximal to Tromsø rise from a sea level to an elevation of roughly 1200 m a.s.l. The approximate tree line elevation for the region ranges from 300-350 m a.s.l. The area is known as a mountainous fjord landscape with steep mountains and u-shaped valleys as a result of glacial erosion. The area around Tromsø has an Arctic transitional climate due to the low insolation in the polar regions and conflicting weather systems as a result of warm ocean currents in the West and cold continental areas in the East (Velsand, 2017).

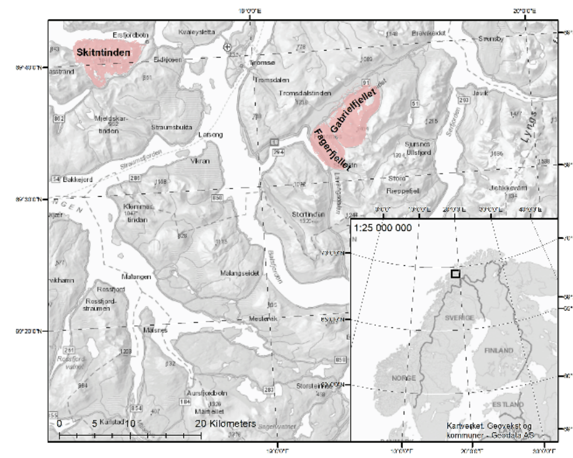

Figure 1: The three study areas near Tromsø.

1.2 ATES

Campbell and Gould (2014) identified that the technical ATES v1.04 (Statham et al., 2006) has several limitations and proposed a more deterministic model. Their model is derived from a Canadian study where 2,000 km^2 of expert zoned terrain were analyzed, resulting in a set of

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thresholds (Table 1). So far over 8,000 km^2 of zoned terrain has been classified at the basin scale of 100 m to 1 km using this method. At this scale, it can be useful for recreational trip planning, but not for route finding in complex terrain were a spatial scale of at least 20-30 m is needed (Schweizer, 2003). Larger scale (i.e. higher resolution) maps are therefore needed to open up the possibility for more detailed route decision-making (Thumlert and Haegeli, 2017). Several different approaches have been attempted (Gavaldà et al., 2013; NVE, 2014; Schmudlach and Köhler, 2016; Thumlert and Haegeli, 2017). However, for a spatial ATES classification to be efficient, a fully automated algorithm would need to be developed (Schmudlach and Köhler, 2016).

Table 1: Proposed model for zoning with the Avalanche Terrain Exposure Scale. Thresholds listed in bold-type are required for that particular zone classification. (From: Campbell and Gould, 2014).

		Class 0 (optional)	Class 1 (Simple)	Class 2 (Challenging)	Class 3 (Complex)
Slope incline[1] and forest density[2]	**Open**	99 % ≤ 20°	90 % ≤ 20° 99 % ≤ 25°	90 % ≤ 30° 99 % ≤ 45°	< 20 % ≤ 25° 45 % > 35°
	Mixed	99 % ≤ 25°	90 % ≤ 25° 99 % ≤ 35°	90 % ≤ 35° 99 % ≤ 45°	
	Forest	99 % ≤ 30°	90 % ≤ 35°	99 % ≤ 45°	
Starting zone density		No start zones.	No start zones with ≥ Size 2 potential. Isolated start zones with < Size 2 potential.	No start zones with > Size 3 potential. Isolated start zones with ≤ Size 3 potential. or several start zones with ≤ Size 2 potential.	Numerous and overlapping paths of any size. Any position within path
Interaction with avalanche paths[3]		No exposure to avalanche paths.	Beyond 10-year runout extent for paths with ≥ Size 2 potential.	Single path or paths with separation. Beyond annual runout extent for paths with > Size 3 potential.	Potential for complete burial and fatal injury.
Terrain traps[4]		No potential for partial burial or any injury	No potential for complete burial or fatal injury.	Potential for complete burial but not fatal injury.	Potential for complete burial and fatal injury.
Slope shape		Uniform or concave.	Uniform	Convex	Convoluted

[1]Slope inclines are averaged over a fall-line distance of 20-30 m.
[2]Open: < 100 stems/ha or > 10.0 m tree spacing on average. Mixed: 100-1000 stems/ha or 3.2-10.0 m tree spacing on average. Forest: > 1000 stems/ha or < 3.2 m tree spacing on average.
[3]Position within paths based on the runout extent for avalanches with a specified return period.
[4]Terrain traps are features in tracks or runouts that increase the consequences of being caught in an avalanche. Thresholds are based on the potential increased consequences they would add to an otherwise harmless avalanche. For this purpose, terrain traps can be thought of as either trauma-type (e.g. cliffs, trees, boulders, etc.) or burial-type (e.g., depressions, abrupt transitions, open water, gullies, ravines, etc.). Degrees of burial used in this model are based on Canadian standard avalanche involvement definitions (CAA, 2014).

2. METHODS

2.1 Digital elevation model

A digital elevation model (DEM) for Troms county was downloaded from the Norwegian Mapping Authority in the nationwide 10x10 meter USGS raster model (Kartverket, 2013). The coordinate system EUREF89 Universal Transverse Mercator Zone 33, 2d + NN54, one of Norway's official coordinate systems were chosen. The vertical standard deviation of the DEM is $\pm$ 4 to 6 m and the scale is 1:10,000.

2.2 Slope

A slope raster was delineated after the thresholds proposed by Campbell and Gould (2014) in ESRI ArcMap 10.6. All slope inclines above 40° were assigned class 3, values between 40° – 25° were assigned class 2. Slope inclines below 25° were assigned class 1 and the optional class 0 threshold was put at 15°. The delineated classes were then exported as a shapefile for each class (Figure 2).

2.3 Potential Release Area

To calculate the start zone density (Table 1) the potential release area (PRA) algorithm is used (Veitinger et al., 2016). The algorithm uses three criterions; slope, wind shelter and roughness, calculated from the input parameters which is a DEM, average snow depth and main wind direction (optional, not used). Using a 10 m DEM, the roughness criteria is neglected due to the coarse scale. The script is optimized for a 2 m DEM, but both a finer and coarser scale DEM could be applied (Veitinger et al., 2016). The PRA algorithm is written in the programming language R (V. 3.4.4, https://www.r-project.org/). Important functions are accessed by the RSAGA package (Brenning, 2008), connecting to the open source SAGA GIS software (V. 2.2.2, http://www.saga-gis.org/). The PRA output is an ASCII raster file assigning values between 0 – 1 for each cell. Higher value means an increased likelihood of avalanches to release. In this paper, values below 0.05 are not considered to be a starting zone. The values between 0.05 – 1 was exported as a shapefile and assigned class 3 (Figure 2).

2.3.1 Slope

Slope inclines between 28 and 60° are considered to be possible release areas. Slope inclines between 35° and 45° are assigned the largest membership value. On each side, the membership values decrease and slope inclines below 30° and above 50° are assigned low membership values.

2.3.2 Wind shelter

The wind shelter index is used instead of a curvature measure. Wind exposed terrain have negative values and are assigned low membership values, wind sheltered terrain have positive values and are assigned high membership values. Studies show that wind-shelter parameters based on a DEM can reflect the accumulated snow patterns to an outstanding extent (e.g. Schirmer et al., 2011; Winstral et al., 2002)

2.3.3 Roughness

The roughness factor is derived from the neighboring tiles in the raster in a 3x3 window. The scale of the roughness factor is therefore averaged over a line of 30 m. Planar and smooth terrain are assigned low roughness values and high membership values because these are more prone to avalanche. Rough surfaces are assigned high roughness values and are less likely to avalanche (Veitinger and Sovilla, 2016).

2.4 Avalanche runout

To estimate the avalanche runout, the hydrologic terrain analysis software TauDEM and TauDEM toolbox for ESRI ArcMap was used to derive interaction with avalanche paths from the DEM (Table 1) (version 5.1, http://hydrology.usu.edu/taudem/). This is a suite of tools that can compute the avalanche runout length. The D-Infinity Avalanche tool detects all locations downslope of a given starting cell until a given alpha angle from the starting cell is reached (Tarboton, 2013). In the algorithm, avalanche runouts were calculated for using the tools from TauDEM and alpha angle. Runouts where exported as shapefiles where an 18° alpha angle runout were assigned class 1, while a 23° alpha angle runout were assigned class 2 (Figure 2). These runout angles were based on studies of avalanche runouts in Norway (Lied and Bakkehøi, 1980).

2.5 Merging and generalization

Finally, all the shapefiles for each class where merged together. All clusters smaller than 10,000 m^2 within a class were bumped up to the higher class it's surrounded by. All areas that have multiple class values are assigned the highest class. At the end, all polygons are smoothed out using generalization tools in ESRI ArcMap 10.6.

2.6 Simplified flowchart

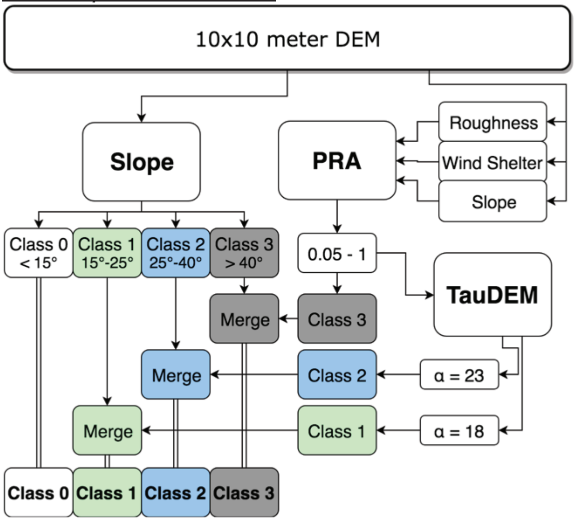

Figure 2: The main steps of the algorithm.

3. RESULTS

To assess the new automated ATES algorithm, expert guided maps classified by NVE (2014) for three areas are compared against the results from our algorithm. We focus our analysis here on one of our three case study areas for the sake of brevity. The classification undertaken by NVE in 2012 was a manual classification and could account for land cover, something which the current version of our algorithm doesn't. Future work will address this deficiency. As such, areas below 300-350 m a.s.l. (lower third) may be incorrectly classified in some locations as a result of the lack of forest cover consideration. A visual comparison of the maps is shown in Figure 3 and 4 with the NVE expert guided classification in figure 3, and the new algorithm results in figure 4.

3.1 Algorithm performance

To measure the performance of the algorithm compared to the expert guided NVE maps, we used the model performance metrics, true skill score (TSS) and the probability of detection (POD) as calculated from a 2x2 contingency plot (e.g. Hendrikx et al., 2014; Table 2).

Table 2: The algorithm model performance scores compared to the expert guided maps.

	TSS	POD
Class 1	0.15	0.57
Class 2	-0.02	0.57
Class 3	0.21	0.69

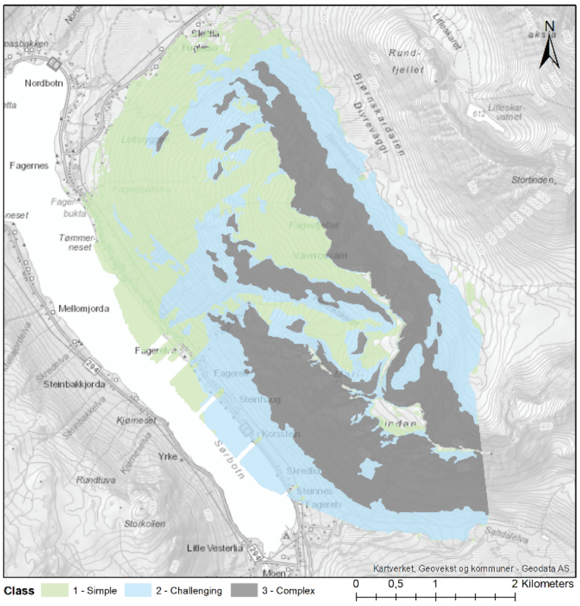

Figure 3: Map of Fagerfjellet showing the output map from the algorithm, where green, blue and black is class 1, 2 and 3 terrain respectively.

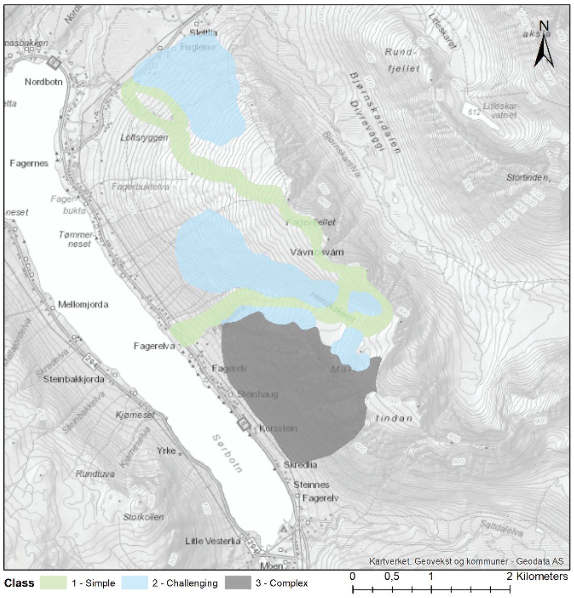

Figure 4: Map of Fagerfjellet showing the expert guided classification done by NVE.

A beta version of the ATES mapping for all of Norway can be found at https://temakart.nve.no/link/?link=autokast.

4. DISCUSSION

4.1 Methods

To create an automated algorithm for ATES terrain classification, it's challenging to use the qualitative classification (v1.04) as proposed by Statham (2006). Therefore, the quantitative model proposed by Campbell and Gould (2014) is used. Its primarily derived from slope incline and land cover, but the model additionally emphasizes start zone density, interaction with avalanche paths, terrain traps and curvature are emphasized (Table 1). To avoid simple terrain being neglected, the non-avalanche class threshold was changed to 15°

The second most important factor is the land cover. Implementing a land cover in the algorithm should be straight forward based on the given thresholds dividing the land cover into open, mixed and forest. At this stage, it has not been implemented in the algorithm due to the lack of reliable land cover data for Norway at the relevant spatial scale. If in the future, robust landcover data were to become available at the appropriate scale, then this could be easily implemented into the algorithm.

The avalanche runout is estimated using the raster based TauDEM model (Tarboton, 2013) to determine the avalanche runout length based on the alpha angle from the identified start zone. The advantage of using the alpha angle to estimate the runout length is that it's a powerful input variable to fine tune the algorithm runout estimations for different regions and climates. Lied and Bakkehøi (1980) undertook empirical studies on 423 well known maximum extents of avalanche events in Norway. They found that 100% of avalanches stop within an alpha angle of 18° and 95% stop within 23°. Due to this, all runouts within an 18° alpha angle would be classified as simple terrain. Avalanches don't normally run that far, so a 23° runout angle was set as the threshold for challenging terrain, having more frequent avalanches.

4.2 Results

The algorithm is on average within the thresholds proposed by Campbell and Gould (2014), except for in simple terrain where 15% of the terrain is between 20-25°, 5% more than allowed (Table 1). This value is dependent on the total amount of simple terrain and the valley floor has not been classified. Including these, would increase the number of data points below 20°, resulting in a lower percentage of terrain between 20-25°. At this stage, the algorithm works well for open terrain, but not able to account for land cover data, something the expert guided maps does. Due to these limitations, the maps should not be compared directly, with only consideration given to the POD and TSS scores.

Furthermore, the survey area classified by the algorithm is larger than the NVE classification. However, only the area mapped by NVE is used for the contingency plots. Looking at the figure 3 and 4, the algorithm produces a similar spatial pattern as the NVE classification. The long narrow corridor in the lower middle is identified in both maps. Some small areas of this corridor is determined as challenging by the algorithm, but its located below the tree line and would possibly be classified down if a land cover mask was included. Above this corridor, NVE has classified the area as simple and challenging terrain. The algorithm identified this as a potential start zone, and therefore been classified as complex.

Looking at the POD and TSS (Table 2), the NVE classification results in a more generous classification. This is especially shown in challenging terrain with a TSS of -0.02.

Various other automated models have been proposed to create ATES maps. Schmudlach and Köhler (2016) developed an algorithm that computes a 10 m continuous ATES map based on the statistical likelihood of human triggered avalanches. A drawback with this method is that validation is based on expert judgement making it difficult to validate. The latest model proposed is the one from Thumlert and Haegeli (2017) which developed a mapping algorithm from the movement of professional ski guides. They developed an ATES map with a spatial resolution of 20 m and proved that it's possible to make an ATES map based on observed terrain use from professional ski guides. However, they acknowledge that the method has several limitations including having to decide whether the skied terrain was a wise decision or not to determine whether to include it in the dataset or not. The method is also computationally expensive and only derived from one climate over two seasons, making it vulnerable if applied for different climates. The advantage with the GIS algorithm proposed in this paper is that it can be fully automated and only needs a digital elevation model as input. This makes it possible to map large areas.

5. FUTURE WORK

The next logical step would be to include land cover data if the resolution and data would become reliable. Also, the alpha angles could be adjusted according to the ones that can be calculated from automatic avalanche occurrence data (e.g. Eckerstorfer et al., 2017).

6. CONCLUSION

The goal of this work was to develop a fully automated algorithm that would be able to produce a high resolution ATES map from a DEM. Comparing the algorithm towards the expert guided ATES maps made by NVE, the spatial trends are similar, but NVE does not map strictly according to the proposed thresholds making a direct comparison difficult. Despite this, the preliminary results look promising, but more work is needed to make a fully automated algorithm that accounts for all parameters. A large percentage of the Norwegian backcountry terrain is above tree line, for such a region, the current algorithm could already be a helpful tool for expert guided mapping. Using the automated algorithm could increase the quantitative rigidity and the consistency between different experts.

6. REFERENCES

Brenning, A., 2008, Statistical geocomputing combining R and SAGA: The example of landslide susceptibility analysis with generalized additive models: Hamburger Beiträge zur Physischen Geographie und Landschaftsökologie, v. 19, p. 23–32.

Campell, C., and Gould, B., 2014, An ATES Zoning Model: The Avalanche Journal, p. 26–29.

Eckerstorfer, M., Malnes, E., Müller, K., 2017, A complete snow avalanche activity record from a Norwegian forecasting region using Sentinel-1 satellite-radar data. Cold Reg. Sci. Technol. v. 144, 39–51.

Gavaldà, J., Moner, I., and Bacardit, M., 2013, Integrating the ATES into the Avalanche Information in Aran Valley (Central Pyrenees): Proceedings, International Snow Science Workshop 2013, p. 381–384.

Gould, B., 2014, Modern Snow Avalanche Terrain Mapping for Industrial Projects: Geohazards 6, p. 8.

Hendrikx, J., Murphy, M., and Onslow, T., 2014, Classification trees as a tool for operational avalanche forecasting on the Seward Highway, Alaska: Cold Reg. Sci. and Technol. v. 97, 113–120.

Kartverket, 2013, Height DTM 10:, https://kartkatalog.geonorge.no/metadata/kartverket/dtm-10-terrengmodell-utm33/dddbb667-1303-4ac5-8640-7ec04c0e3918 (accessed January 2018).

Lied, K., and Bakkehøi, S., 1980, Empirical calculations of snow avalanche run-out distances based on topographic parameters: Journal of Glaciology, v. 26, p. 165–177.

NVE, 2014, Snøskredfarekartlegging med ATES (Avalanche Terrain Exposure Scale): The Norwegian Water Resources and Energy Directorate.

Schirmer, M., Wirz, V., Clifton, A., and Lehning, M., 2011, Persistence in intra-annual snow depth distribution: 1.Measurements and topographic control: Water Resources Research, v. 47, p. 1–16.

Schmudlach, G., and Köhler, J., 2016, Method for an automatized avalanche terrain classification: Proceedings, International Snow Science Workshop 2016, p. 729–736.

Schweizer, J., 2003, Snow avalanche formation: Reviews of Geophysics, v. 41, p. 1016.

Statham, G., McMahon, B., and Tomm, I., 2006, The avalanche terrain exposure scale: Proceedings, International Snow Science Workshop 2006, p. 491–497.

Tarboton, D.G., 2013, TauDEM 5.1 - Guide To Using The TauDEM Command Line Functions.:

Thumlert, S., and Haegeli, P., 2017, Describing the severity of avalanche terrain numerically using the observed terrain selection practices of professional guides: Natural Hazards, p. 1–27.

Veitinger, J., Sovilla, B., and Purves, R.S., 2016, Model code of release area algorithm:, https://github.com/jocha81/Avalanche-release (accessed January 2018).

Veitinger, J., and Sovilla, B., 2016, Linking snow depth to avalanche release area size: Measurements from the Vallée de la Sionne field site: Natural Hazards and Earth System Sciences, v. 16, p. 1953–1965.

Velsand, P., 2017, Comparison and classification of an Arctic Transitional snow climate in Tromsø , Norway: 1-135 p.

Winstral, A., Elder, K., and Davis, R.E., 2002, Spatial Snow Modeling of Wind-Redistributed Snow Using Terrain-Based Parameters: Journal of Hydrometeorology, v. 3, p. 524–538.