Modelling the spatial variability of maximum mountain snow depth in Northern Norway

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Abstract: Snow depth is highly variant in wind-dominant mountain environments. The variation is especially high at local scales. Winter maximum snow depth influences the ground temperatures and the beginning of the growing season. Statistical modelling provides a feasible and cost-effective method for the analysis and prediction of local-scale snow depth variations. The focus of this study is to analyse the spatial variability of near-maximum snow depth at local scale. Moreover, a statistical model for estimating the near-maximum snow depth distribution is provided.
The study area in Northern Norway, Tana municipality, is characterized with a mountain landscape. The elevation range of the area is 500 m and the study sites are located on the slopes of the Rásttigáisá and Geaidnogáisá mountains. The lowest parts consist of mountain birch forest and most of the area does not have vegetation above the snow surface.
Snow depth observations were collected in mid-April 2015 in a one-week measurement campaign. Modelling was conducted with Generalized Additive Model (GAM) using GIS-based terrain and vegetation surrogates.
Upwind exposure to westerly winds and horizontal (plan) curvature measure were the most important explanatory variables in the analyses. The interaction of wind and topography defines the winter maximum snow depth in the study area. Terrain sheltering from westerly winds and concave topography show increases in snow depth. The impact of vegetation was only visible in the mountain birch forests which had relatively even snow depth. In open areas above the forest, snow depth was highly variable. Elevation and solar radiation, which have been commonly used in mountain snow depth models, did not indicate impact in this study area.
The GAMs calibrated in this study approximate the near-average snow depth quite well. Most of the sites with shallow or thick snow cover could not be predicted with the resolution, sample size and variables used in this research.

Key words: Snow depth, mountain, Norway, statistical modelling, GAM, upwind exposure, curvature

Introduction

Seasonal snow cover is an elementary part of the annual and diurnal water and energy cycles (Groisman & Davies 2001; Pomeroy & Brun 2001). For instance, the snow depth influences the ground temperatures and the beginning and duration of the growing season (Anderton *et al.* 2004; Wang *et al.* 2015). High economic interest focuses at mountain snow because it provides drinking and irrigation water and propulsion for the hydropower (Stepphun 1981; McClung & Schaerer 2006; Schirmer *et al.* 2011; Saloranta 2014; Buckingham *et al.* 2015). Global warming is changing the depth, duration and characteristics of snow cover (Callaghan *et al.* 2011). Large uncertainties lie even in measuring the snow depth or water equivalent especially in remote mountain areas (Sexstone & Fassnacht 2014; Sturm 2015).

In large scale, the snow depth depends on latitude, elevation and air mass movements (Pomeroy & Brun 2001; Mott *et al.* 2014). The local scale variation is dependent on winds and solar radiation (Kind 1981; McKay & Gray 1981; Pomeroy & Brun 2001). Wind velocity and direction may change markedly over small distances according to topography and vegetation (McClung & Schaerer 2006; Mott *et al.* 2010; Dvornikov *et al.* 2014). Large variation within small distances is descriptive in open mountain snow cover (Dadic *et al.* 2010; Mott *et al.* 2010; Schirmer *et al.* 2011; Shirmer & Lehning 2011). Mountain snow depth is often modelled due to lack of small-scale snow data (Grünewald *et al.* 2013; Buckingham *et al.* 2015; Magnusson *et al.* 2015; Sturm 2015). Statistical modelling provides a feasible and cost-effective method for the analysis and prediction of local-scale snow depth variations (Erickson *et al.* 2005; Sturm & Wagner 2010).

The focus of this study was to analyse the spatial variability of near-maximum snow depth at local scale in one year. Moreover, a statistical model and prediction for estimating the near-maximum snow-depth distribution is provided.

Description of the research

The 35 km^2 study area is located in Northern Norway, Tana municipality. It lies on the slopes of the Rásttigáisá and Geaidnogáisá mountains. The elevation range of the area is 500 m with highest site at 660 m above sea level. The lowest parts are covered with mountain birch forest, most of the area does not have vegetation reaching above the snow surface.

Snow depth observations from 63 sites were collected manually in mid-April 2015 in a one-week measurement campaign. One observation is a mean of five snow probe measurements. Mean snow depth for the study area was 42 cm. There were five distinctly deeper sites, deepest drift was 172 cm.

A set of terrain and vegetation surrogates was implemented as explanatory variables. Upwind exposure (Sx) is defined as the angle of the horizon within given searching distance (Winstral *et al.* 2002). The upwind direction was selected according to correlation comparison with the snow distribution as wind observations were not available in the study area (Revuelto *et al.* 2014). Plan curvature was selected after comparison of different curvature measures. It is defined as the curvature perpendicular to the steepest gradient (Gallant & Wilson 2000). Maximum theoretical solar radiation and heatload were also compared and latter chosen (McCune & Keon 2002). Also slope angle, aspect and topographic wetness index (Beven & Kirkby 1979) were in the full model. Normalized Difference Vegetation Index (NDVI) represented the vegetation impact (Rouse *et al.* 1974 in Wang *et al* 2015: 61). Elevation could not be used in the same models with the NDVI due to strong mutual correlation. The Digital Elevation Model resolution was 10 m (Kartverket.no 2016).

Modelling was conducted with Generalized Additive Model (GAM) (Hastie & Tibshirani 1986; Wood 2006: 121). GAM has been used for mountain snow depth modelling by López-Moreno & Nogúes-Bravo (2005) and López-Moreno *et al.* (2010). GCV (Generalized Cross-Validation) was used as model selection criteria (Craven and Wahba 1979; Wood 2006: 177–185). Models were built with different link functions and Gamma and Gaussian distributions (Zuur *et al.* 2009). Leave-one-out cross-validation and mean absolute error were used for model evaluation and comparison (Willmott 1981; Guisan *et al.* 2002; Wood 2006; James *et al.* 2013). Local spatial autocorrelation was examined visually from residual plot (Anselin 2005; Zuur *et al.* 2009; Le Rest *et al.* 2014).

Results

Upwind exposure to westerly winds and plan curvature contributed to the selected model. Model's explained deviance was 21,4%. It followed Gamma distribution with logarithmic link function. The mean absolute error was 23 and 24 cm in training and validation phases, respectively.

The model was used to predict the snow depth distribution. Figure 1 shows

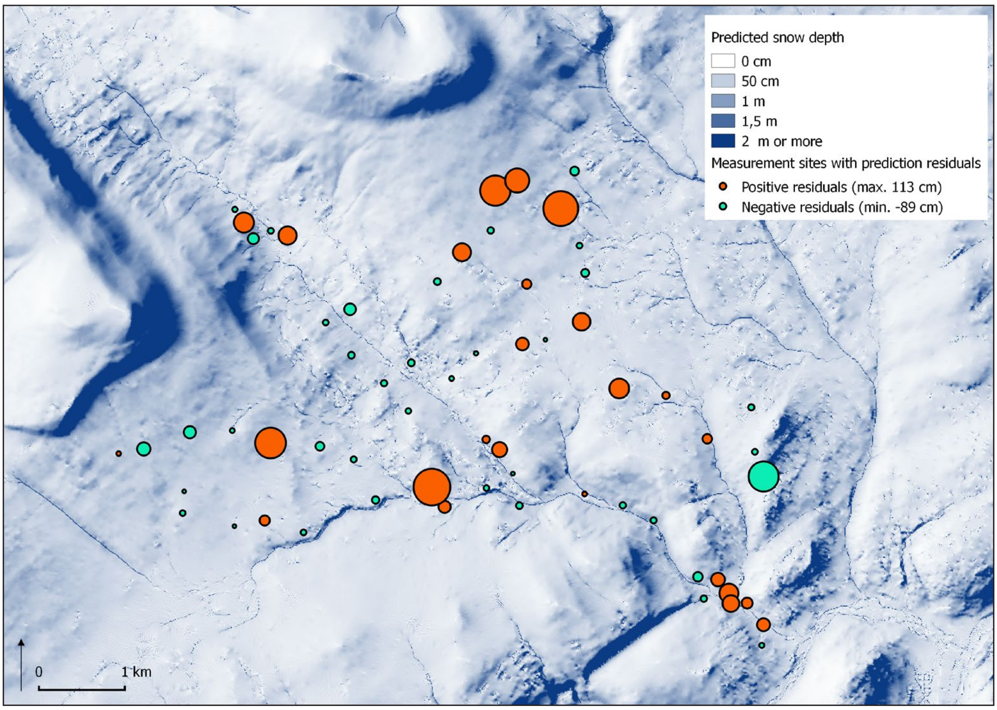

Figure 1. The snow depth prediction for the study area is presented with colour gradient from bare ground to 200 cm which covers the range of the observations. The prediction contains also higher values but these are located in the unvisited steep-slopes. The circles show the residuals at measurement sites. Orange residuals are positive and light green are negative, sizes are relative to the residuals absolute values.

the prediction and measurement sites with residuals. Large clusters of high negative or positive residuals are not visible, indicating that spatial autocorrelation is not significant. Five distinctly deeper observations are visible with large positive residuals. The model is not able to predict small-scale drifts. Deeper snowpack with few unrealistically high values (up to 2.5 x 10^{17} m) is predicted to unvisited, steep eastern slopes.

Discussion

According to the study, the interaction of wind and topography defines the winter near-maximum snow depth in the study area. Terrain sheltering from westerly winds and concave topography show increases in snow depth. While upwind exposure represents both wind direction and speed, curvature has impact on local surface wind velocity (Mott *et al.* 2010; Sturm & Wagner 2010). Upwind exposure has often shown its capability in mountain snow distribution models (e.g. Winstral *et al.* 2002; Molotch *et al.* 2005; Mott et al 2010; Tabari *et al.* 2010; Schirmer *et al.* 2011; Marofi *et al.* 2011; Schön *et al.* 2015). Various different curvature measures have been used in snow models (López-Moreno *et al.* 2010; Revuelto *et al.* 2014; Sexstone & Fassnacht 2014; Dvornikov *et al.* 2015). Plan curvature was also important for Gharaei-Manesh *et al.* (2016).

Other topography variables did not contribute to the model statistically significantly. The impact of NDVI was two-fold. Mountain birch forest had relatively even, greater than average snow depth while open area above had highly varying snow cover. Marchand and Killingtveit (2005) divided their South-Norwegian research area into birch-forest and open mountain environment, this kind of division would have been also possible in this study area. Dvornikov *et al.* (2015) found vegetation height impacting the snow depth in tundra environment with finer DEM resolution. Solar radiation has been an important variable in lower latitudes (Anderton 2004; Erickson *et al.* 2005; López-Moreno & Nogúes-Bravo 2005; López-Moreno *et al.* 2010; Revuelto *et al* 2014) but did not show reducing impact on the snow cover in this study.

The sample size of 63 was small compared to a recommendation of 200 (López-Moreno & Nogúes-Bravo 2005). The distribution of the observations in windblown environment resembles Gamma distribution. Observations were positively skewed with only occasional deep drifts in the long tail, which is typical in wind-dominated environments (Winstral & Marks 2014). There were no observations between 70 cm and 114 cm, the gap impacts the model performance in this range. This kind of piecewice continuous distribution of observations may be one reason for common usage of decision trees with mountain snow models (e.g. Winstral *et al.* 2002; Anderton *et al.* 2004; Molotch *et al.* 2005; Litaor *et al.* 2008; Ĺópez-Moreno *et al.* 2010; Revuelto *et al.* 2014; Gharaei-Manesh *et al.* 2016).

The residual plot indicates that the model cannot predict the deepest measured sites correctly. The five deep observations show certain trends with explanatory variables, but they are too few to make any conclusions. On the contrary, the shallow snowpack observations were not trending with the explanatory variables although their number was more adequate. High subgrid variation provides one explanation. The variation of shallow and deep snow cover was often smaller in distance than the DEM grid size.

The prediction shows unrealistically high values at unvisited, steep east-facing slopes and in steep ravines. Manual measuring would not have been safe at these slopes. Furthermore, Grünewald & Lehning (2015) do not recommend extrapolating flat-field snow-measurement information to nearby steeper areas. User should be cautious to the prediction in these areas.

Before using the model, one should also pay attention to the interannual consistency of the model, which was build based on one-year observations only. Multiyear mountain snow research has found both consistent patterns (Deems *et al.* 2008; Mott *et al.* 2010; Schirmer *et al.* 2011; Grünewald *et al.* 2013; Winstral & Marks 2014) and change between years (Marchand & Killingtveit 2005). Average snow depth varies between years (senorge.no 2016) but do the drifts and shallows form at the same sites? Based on global simulation of wind components (Rienecker *et al.* 2011), the wind force has varied in 30-year period but the same directions, west and south, dominated the whole period. It can be assumed that the built model is reasonably consistent between the years.

Being far from perfect, this model provides the best available local-scale estimate of the near-maximum snow depth in this area. It can be applied in studies considering growing season length or ground temperatures.

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