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Distribution of snow depth on Hardangervidda mountain plateau and its correlation with topography and vegetation

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Summary: Analysis of a snow depth (SD) data obtained by airborne laser scanning over Hardangervidda in 2008 and 2009 shows that spatial standard deviation of SD at the chosen scale of aggregation was significantly correlated to the spatial standard deviation of the squared slope of the terrain. In addition, the spatial standard deviation of SD was significantly correlated to landscape class (bare rock and wetland/forest) and to the mean spatial SD. These results have been used to develop a model for the spatial standard deviation of SD.

Keywords: Snow depth, Snow depth distribution, Gamma distribution, LiDAR, Laser scanning, Terrain parameters

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Contents

Preface

In order to describe the variability in snow depth or SWE in catchment scale or large scale hydrological and snow models, snow distribution functions are often used to describe the variability. In rainfall- runoff models, such as the HBV, a predefined log normal distribution is used whereas in the DDD model a dynamical gamma distribution (based on precipitation variability and terrain/vegetation classes) is used to describe the spatial variability in snow depth or SWE. An objective of the research project "Better SNOW models for predictions of natural Hazards and HydroPOwer applications" (SNOWHOW; 244153/E10), was to investigate the spatial distribution of snow at different scales and its dependency terrain and vegetation classes and wind, using an extensive snow data set from Hardangervidda, Southern Norway. This report presents result of this study.

This report is a deliverable to the research project SNOWHOW; funded by the Norwegian Research Council, as well as Glommen and Laagen Brukseierforening, E-CO, Trøndelag Energiverk and HYDRO Energi. In addition, research done within NVE's FoU-project 80208 has also contributed to this report.

Tuomo Saloranta made many corrections and improvements to the text.

Oslo, October 2018

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Summary

In the mountain areas of Norway, snow cover has a major influence on the environment. Due to strong winds and open terrain, the snow is heavily redistributed and the snow depth is highly variable. To investigate snow conditions on Hardangervidda (one of Europe's largest mountain plateaus), the Norwegian Water Resources and Energy Directorate (NVE) has conducted snow measurement campaigns across Hardangervidda in spring 2008 and 2009 using airborne Lidar Scanning at the approximate time of annual snow maximum (mid-April). When aggregating snow and terrain data from 10x10 meters to 0.5 km^2, we find that the standard deviation of the terrain parameter squared slope, land cover and the mean snow depth (SD) to a large degree explains the observed variability of SD. A model for SD variability is proposed that, in addition to addressing the dependencies between the variability of SD and the terrain characteristics also takes into account the observed non-linear relationship between the mean and the standard deviation of SD. When validated against independent observed SD variability, retrieved from the same area, the model explains about 85% of the observed variability. From 48 empirical distributions of SD at Hardangervidda, each comprised of about 4000 SD values, qualitative and quantitative tests have shown that the Gamma distribution is a better fit than the Normal- and Log-Normal distributions. The parameters for the model of the spatial variability of SD can be determined from a GIS analysis of a detailed digital terrain- and land cover model. Implementing such a model in a hydrological rainfall-runoff model will not add any additional calibration parameters and will hence enhance its physical basis and hopefully improve hydrological predictions in ungauged catchments, and for a changed climate.

1 Introduction

Snow is an integral component of many countries', including Norway's, hydrologic, ecological and atmospheric system. In Norway 30% of annual precipitation falls as snow and thus contributes to similar amount of annual runoff (Beldring and others, 1999). In the mountain areas, even a larger part, 50–60% of annual precipitation, falls as snow. The knowledge of snow amounts and its spatial distribution has a critical impact on the prediction of water availability, the timing of snowmelt rates and runoff which are important for the prediction of spring melt floods, hydropower production planning and water resource management. In addition, the spatial features of snow are crucial for avalanche warning/formation, reliable simulations of the energy and mass exchange between land and the atmosphere, ecology (plants and animal life) and the spatial extent and degree of permafrost(Gisnås and others, 2016).

The snow depth (SD) at a given place is a result of the precipitation, snow redistribution and compaction history for each consequtive snow layer (Sturm & Wagner, 2010). At the peak of winter, the snow distribution in mountain areas shows a strong heterogeneity. The complex interaction between spatially variable precipitation, topography, wind, radiation and vegetation, shape the spatial variability of the accumulation and melting of snow. In addition, these processes act on different spatial scales ranging from 10 to 1000s of meters (e.g. Elder and others, 1991, Blöschl, 1999, Liston and others, 2007). These complex interactions make both representative sampling and the modelling of snow challenging.

A multitude of physically- and empirically-based models, of varying degree of complexity, are used for predicting the amount of snow and its spatial distribution. Some models operate on a fine resolution grid scale (ranging from points, a few meters to hundreds of meters) (see e.g. Brun and others, 1992, Liston & Elder, 2006) attempting to include a detailed, multi-layered and physically based process representation. The models requires fine resolution meteorological- and terrain data, and are hence demanding in terms of both information need and computation time and are generally not used for larger areas or at a national scale. Other models are typically more effective in their approach where the aim is to represent the spatial distribution of snow over areas of some extent through the use of probability distribution functions (PDF's). In such models, i.e. catchment hydrological rainfall- runoff models, the frequency of snow amounts over an area is more important than their exact location. Recently, many field-based studies have investigated catchment SD distribution by relating measured SD variability to small-scale terrain parameters and vegetation type (see Clark and others, 2011 for a comprehensive review of recent literature) or just to the mean SD (Pomeroy and others, 2004, Egli & Jonas, 2009, Egli and others, 2011). Both linear or multi-linear regression models and binary regression tree models have been used to relate the mean- and standard deviation of SD or the coefficient of variation of snow to terrain parameters (e.g. slope, aspect and elevation). Typically, these types of models can explain about 18 to 91 % of the SD variability (Grünewald and others, 2013). The models are often site specific and thus not transferable to other sites with other characteristics. Grünewald and others (2013) used multiple linear regression to examine SD data from several mountainous areas around the world. Results from this study shows good model performance at each site but a global model containing all data sets could only explain 23% (or 30% excluding catchments with glaciers), of the variability. Grünewald and others (2013) therefore argued that the SD and terrain is less universally related than hypothesized by Lehning and others (2011) and the application of a global model is limited. The performance of the linear regression model is dependend on the spatial scale of the data for which the model has been developed. Jost and others (2007) showed, for example, that the performance of their model decreased if individual samples were used instead of plot averaged snow values. Similar results were also found in Grünewald and others (2013). At the very small scale, simple local terrain characteristics have been unable to explain the SD distribution (Deems and others, 2006, Trujillo and others, 2009, Grünewald and others, 2010, Grünewald and others, 2013). Much of the fine scale snow variability seems to be a result of small scale terrain effects which are not captured by the local terrain parameters derived from one grid point of a digital terrain model (DTM) (Jost and others, 2007, Grünewald and others, 2013).

Many studies have shown that a realistically modelled spatial distribution of both SD and snow water equivalent (SWE) is important for the temporal evolution of SD, SWE, snowmelt and snow covered area (SCA) (Buttle & McDonnell, 1987, Liston and others, 1999, Luce and others, 1999, Essery & Pomeroy, 2004, Luce & Tarboton, 2004). In large scale meteorological- and catchment scale hydrological models, the subgrid SD variability is often resolved implicitly using subgrid parametrisation. Often, different PDFs' have been used to represent the effect of spatial variability of snow both as result of redistribution (Luce & Tarboton, 2004, Liston, 2004), and as result of spatial varying precipitation (Alfnes and others, 2004, Skaugen, 2007, Skaugen & Weltzien, 2016). Another approach is to assume a relationship between SWE and SCA, i.e. the snow depletion curve. Based on observations, many studies have shown that the snow distribution, especially at the time of maximum accumulation, can be approximated by a two-parameter Log-normal distribution (Donald and others, 1995, Sælthun, 1996), a two-parameter Gamma distribution (Kuchment & Gelfan, 1996, Skaugen, 2007, Kolberg & Gottschalk, 2010, Skaugen & Randen, 2013) or a Normal distribution (Marchand & Killingtveit, 2004, Marchand & Killingtveit, 2005). Helbig and others (2015) investigated the spatial PDF of SD for three large alpine areas close to the time of maximum snow and found that the gamma and the normal distributions were better suited than the Log-normal distribution. Similar results was also found by Winstral and Marks (2014) who investigated 11 year of snow data from a semiarid intermountain watershed. In order to determine the appropriate shape of the PDF, one is obliged to estimate the statistical moments (the mean and standard deviation usually suffice for a two-parameter distribution). Liston (2004) tried to relate fixed statistical moments of the PDF to terrain variability, air temperature and wind. In Alfnes and others (2004), Skaugen (2007) and Skaugen and Randen (2013), however, it was demonstrated through the repeated measurements of the same snow course during the accumulation and melting seasons that the spatial PDF of SWE changed its shape continuously during the periods of accumulation and melting. A consequence of this finding was that Skaugen and Weltzien (2016) chose a dynamical Gamma distribution as the model for the spatial frequency distribution of SWE, due to its attractive mathematical properties and flexibility.

One of the reasons for the quite substantial volume of studies discussing the proper spatial frequency distribution of snow is the difficulty of retrieving datasets of sufficient magnitude to estimate PDF's with a reasonable certainty. This is especially problematic in areas where wind is a dominant influence on snow distribution, as in mountains, tundra and shrub lands (Elder and others, 1991, Sturm and others, 2001b, Sturm and others, 2001a, Hiemstra and others, 2002, Liston & Sturm, 2002, Marchand & Killingtveit, 2004, Schirmer and others, 2011). The large spatial variability in SD and SWE in alpine catchments makes it is difficult to obtain representative snow-depth data by traditional measurement techniques (Elder and others, 1991, Anderton and others, 2004, Erickson and others, 2005). To obtain sufficient information about the actual snow distribution with traditional means, extensive measurement designs with a large number of snow courses are required (e.g. Elder and others, 2009). In recent years the advances in laser ranging technology (LiDAR) both airborne Lidar (AL) and terrestrial (TL) together with digital photogrammetry (DP) have offered powerful tools for SD measurements in both alpine and forest areas and several studies have used these techniques (e.g. Hopkinson and others, 2004, Deems and others, 2006). These relative new techniques give reliable high quality, high resolution (spatially) and accurate SD information, and thus allow for analysing the distribution of SD over multiple scales (e.g. Melvold & Skaugen, 2013). Recently AL, TL and DP data have also been used to investigate possible relations between SD and terrain characteristic (e.g. elevation, slope, aspect, Winstral's wind index, terrain roughness, etc) (e.g. Grünewald and others, 2010, Lehning and others, 2011, Veitinger and others, 2014, Helbig and others, 2015). Lidar snow-depth data have also been used to verify different snow modelling approaches, from the relatively simple statistical model to high-resolution dynamical models (Trujillo and others, 2007, Trujillo and others, 2009, Mott and others, 2010).

In this study we intend to further investigate the relationship between the spatial variability of SD and terrain parameters. We will use spatially very detailed measurements of both SD and the terrain obtained through AL data from Hardangervidda, Southern-Norway. In addition, we will implement and test the model for the PDF of snow presented in Skaugen and Weltzien (2016) with parameters estimated from terrain parameters instead of the observed variability of precipitation. This represents a development of the model, since terrain parameters, in principle, are obtainable everywhere, provided there is a sufficiently detailed DTM. Information on the spatial variability of precipitation, however, can be difficult to obtain, especially in mountainous areas where snow information is of particular interest and precipitation observations are scarce. This study uses SD as its snow variable instead of SWE simply because SD is the variable measured by AL. We, nevertheless, believe that the results from this study will give relevant insights on the spatial variability of SWE, which is the commonly used snow variable in hydrological models. In the conversion between SD and SWE we need the snow density, which is believed to vary less in space than SD (Sturm and others, 2010). A similarity in the relationships between SD and terrain and SWE and terrain is therefore reasonable.

2 Study area and data

2.1 Study area

Hardangervidda is a mountain plateau situated in the eastern part of the western coastal mountain range of Norway (Figure 1). It is one of the largest mountain plateaus in northern Europe and covers an area of about 6500 km^2. Most of the plateau is above 1000 m above sea level (m a.s.l.) and hence above the treeline. There are many lakes, streams and rivers and most of the plateau is treeless and covered by boulders, gravel, bogs, coarse grasses, mosses and lichens. The low alpine regions in the northeast and southwest are dominated by grass heaths and dwarf shrub. In the highest part in the west and southwest there is mostly bare rock or lichen/marsh tundra. In the east, the landscape is open and flat at about 1100 m a.s.l while in the west and south there are mountain ranges up to 1700 m a.s.l. In the far northwest, the terrain plunges abruptly down to the fjord Sørfjorden. The western coastal mountain range is a significant orographic feature oriented normally to the prevailing westerly wind flow that dominates the weather in Norway. Moist air masses are lifted by the large-scale bulk of the mountain and produce an increase in precipitation with elevation on the windward slopes, as well as a decrease on the leeward side of the range and thus on the eastern part of Hardangervidda. Based on the information from *SeNorge.no* (http://www.SeNorge.no) the snow accumulation period begins in mid-September in the highest areas and snowfalls persist throughout the winter months. Maximum snow accumulation is usually in mid- to late April which give 7 months of snow accumulation on Hardangervidda mountain plateau. Hardangervidda is characterized by large variations in precipitation, mostly due to the complex topography of the area and a strong west-east gradient in precipitation. Mean annual precipitation can vary between 750 mm and < 3000 mm over a distance of a few tens of kilometres and 50–60% of annual precipitation, falls as snow. The weather station at Sandhaug is the most relevant to our study since the station is situated in the middle of one of our 80 km long snow measurement transects at the elevation of 1250 m a.s.l. (Figure 1). The station is operated by the Norwegian meteorological institute and is situated in a relative flat, insheltered area. The wind recorded there is expected to be representative for the overall wind condition of this part of Hardangervidda (all data from the station were downloaded from (www.met.no)). It automatically measures wind direction and speed (10 m above ground), maximum gust for the last 10 and 60 minutes, air temperature including maximum and minimum temperatures and dew point temperature as well as relative air humidity. Unfortunately, the station does not measure precipitation nor SD.

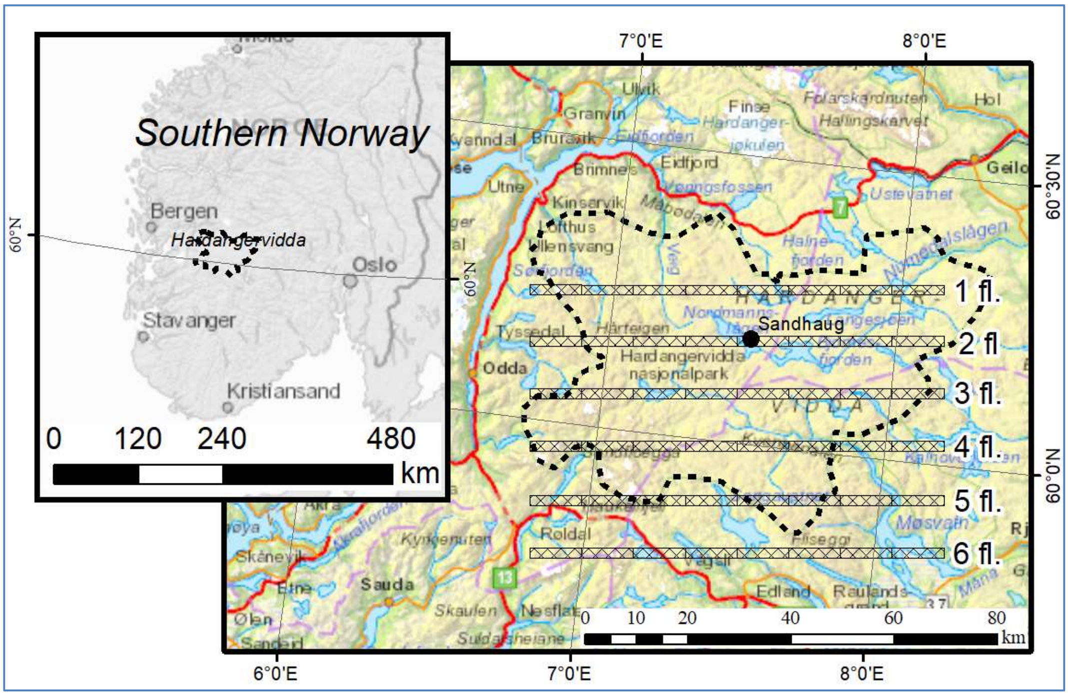

Figure 1. Map of southern Norway and of Hardangervidda showing location of flight-lines (fl.), and the Sandhaug meteorological station.

Snow conditions at Hardangervidda are important for hydropower production and recreation. Snow cover and depth also influence the reindeer semi-nomadic use of their winter habitat (Strand and others, 2006). Snow cover and SD is one of the main factors determining the distribution of plants in alpine areas by affecting the soil temperature, growing season and soil water content (Odland & Munkejord, 2008b, Odland & Munkejord, 2008a). On lakes at Hardangervidda the spring SD effects the growth of brown trout since it controls the break-up time of ice (Borgstrøm & Museth, 2005). The annual temperatures at Hardangervidda vary from -5 to +2°C depending on the location *seNorge.no*.

2.2 Snow depth from laser ranging technology (LiDAR)

In order to study the SD distribution close to snow maximum in spring 2008 and 2009 at Hardangervidda, we adopted AL altimetry due to its high resolution and cost-efficient features. AL data were collected at a nominal 1.5x1.5 m ground-point spacing for a 240 km^2 area. The AL data were collected using a Leica ALS50-II instrument with a 1064 nm wavelength scanning lidar mounted in a fixed-wing aircraft with a flying height above the ground of ~1800 m. The intensity per pulse of the first and last returns were recorded. Data were collected between 3-21 April 2008, 21-24 April 2009 and 21 September 2008. The spring survey dates represent the approximate time of maximum snow accumulation. The autumn dataset represents the minimum snow cover where only perennial snow patches still exist and with leaf-off conditions. For the three surveys, six flight lines of AL data were collected to determine the overall snow condition on Hardangervidda (see Figure 1). Each flight line is 80 km long, follows a west-east orientation and has a scanning width of 1000 m. In order to reduce slope-induced errors, only a 500 m wide central part of the swath width was used. Each flight line is separated by 10 km in the north/south direction in order to investigate any change from north to south. In addition, the lidar contractor (Terratec AS) used one flight line that was perpendicular to the main direction in order to adjust the lines against each other. The lidar contractor collected and post-processed all data. Automated post-processing of the lidar returns were performed, using waveform analysis and spatial filters. All the AL datasets were delivered in Universal Tranverse Mercator (UTM) coordinates with orthometric heights. The delivered products included lidar returns classified as ground (in order to remove vegetation and buildings from the terrain), not classified and intensity. The dataset of lidar returns for Hardangervidda contained over $400*10^6$ points for each survey time.

2.3 Surface DEM generation and snow depth

Based on point clouds of 1.5 m resolution, winter and summer DTMs were produced using a gridding scheme in which each original data point classified as ground was assigned to the nearest 2 m grid cell and assumed to represent the height of the entire cell. If a subsequent data point was located in the same cell, we used the mean height to represent the height of the entire cell. The number of original data points per grid cell varied from 0 (in steep slopes and on water bodies) to 9, with a modal value of 2-3. Areas with zero original data points create large or small voids in the DTM and only the smallest were interpolated using an interpolation method for hydrologically corrected raster surface based on Hutchinson (1989). A horizontal and vertical co-registration between DTMs was performed to avoid having erroneous SD changes from systematic shifts between DTMs.

Following the rasterization of the lidar data, the "snow free" September 2008 DTM was subtracted from the snow surface elevation, the April DTMs to produce grids of SD. In the SD data set both negative and very high (36 m) SDs exists and some of these values are obviously erroneous. Following Melvold and Skaugen (2013) the large negative values (defined as <-10m) and large positive values (defined as > +10m) were excluded from the dataset. The rest of the negative SD were set to zero (see Melvold & Skaugen, 2013 for more information). In practice, the data points removed represent <0.01% of the total area sampled and had a negligible influence on the snow-depth statistics. We also neglected all measurements from water bodies (lakes and rivers). In total we obtained ~8 x 10^6 SD measurements for each flight line which gives about ~ 48 x 10^6 points for each season. Melvold and Skaugen (2013) have compared AL derived DTM data with global navigation satellite systems (GNSS) obtained in spring 2008 along flight-line 2 in order to investigate the accuracy of the AL data. They found elevation error ranged from -0.95 m to +0.51 m with a mean error of 0.012 m. The standard error was 0.12 m, very close to the error of 0.11 m as stated by the manufacturer. A more detailed description of errors is found in Melvold and Skaugen (2013) and in general for AL data by Baltsavias (1999) and Hodgson and Bresnahan (2004) and for snow in particular in McCreight and others (2014).

3 Methods

3.1 Terrain parameters

In addition to the snow information, AL data gives also high-resolution terrain information since AL gives area-wide surface topography information. Based on the September AL data it is possible to create a 2x2 m DTM from a, more or less, snow free surface. In this study the 2 m resolution DTM was resampled to 10 m resolution (LasDTM) in order to compare to the national DTM of 10 m resolution (DTM10), provided by the Norwegian mapping authorities (Statens kartverk). The resampling takes the average of all input elevations that are encompassed by the extent of the coarser cell. This procedure result in a smoothing of the terrain and reduce the amount of data voids. The reduction of data voids are important when terrain parameters are to be estimated since their calculation is based on a 3x3 neighbourhood operation on a grid.

Based on the new LasDTM we computed several standard terrain parameters. Most terrain variables used in the classification of terrain are local, i.e calculated using the first and second derivatives of the immediate terrain surface. Terrain parameters chosen for our analysis were: elevation, relative elevation, aspect, aspect classes (e.g. northing), mean squared slope, wind shelter index (S) and vector roughness measure (VRM).

The standard topographical variables elevation, slope, and aspect were obtained using standard GIS software (ArcGIS software, ESRI). In addition to elevation, we also evaluated the relative elevation estimated as the difference between the absolute and the minimum elevation in a given area.

Aspect identifies the slope direction, i.e. the downslope direction of the maximum rate of change in value from each cell to its neighbours (measured in radians). As aspect is a circular terrain parameters, it is often classified into compass orientation. In our case, we used eight aspect classes north, northeast, east, southeast, south, southwest, west, northwest.

Mean squared slope represents the rate of maximum change in elevation value from each cell (in radians).

Wind shelter index (Si) is a terrain-based upwind/downwind slope predictor developed by Winstral and others (2002) describing the exposure or shelter to prevailing winds of a location. The index ranges from -1 to 1 where negative values correspond to wind-exposed terrain and positive values corresponds to wind-sheltered terrain. The wind shelter index we used is a version of the Winstral algorithm modified by Plattner and others (2004) for modelling snow accumulation patterns on a glacier in the Austrian Alps. The wind shelter index of Plattner and others (2004) is defined as:

$$Si = \arctan(\max\left\{\frac{z(x_0)-z(x)}{|x_0-x|} : x \in S\right\}), \qquad (1)$$

where $Si = Si(x_0, a, \Delta a, d)$, is the set of grid nodes within a distance $\leq d$ from x_0, only considering grid nodes in directions between $(a - \Delta a)$ and $(a + \Delta a)$ from x_0. Si the degree of shelter or exposure range from -1 to 1, where negative values corresponds to exposure. The S values was transformed according to $S = e^{si}$ in order be in line with previous study by Gisnås and others (2016). To determine necessary parameters

$(a, \Delta a, d)$ temporal development of wind during the accumulation seasons was studied using data from Sandhaug meteorological station (Fig.1). The station has been operating since autumn 2008 and does not cover the time of the first lidar scanning survey in spring 2008. Analysis of prevailing winds at Sandhaug for 2009-2011, showed that most often wind comes from west to northwest (300°) and from east to southeast (120°). The daily mean wind velocities from those directions are also rather high: 6-8 and 5-7 m/s respectively in 2009-2010, and 7-9 and 4-6 m/s in 2010-2011. Based on the wind data from Sandhaug the prevailing wind direction (a) were set to 300°. As in Gisnås and others (2016) we used a maximum search distance (d = 100 m) and a chosen width of 30° with the two azimuths extending (Δa) 15° to each side of a.

Surface roughness of a terrain has been defined as variability of a topographical surface at a given scale. A range of methods and definitions of roughness exist for different scientific disciplines (e.g. biology, geomorphology), see Grohmann and others (2011) for an overview often used in geomorphology. VRM has been developed for GIS from a vector approach of Hobson (1972) by Sappington and others (2010). In order to calculate the VRM, one must decompose the unit vectors normal (orthogonal) to each grid cell into their, x, y and z components using slope and aspect. Based on this unit vector a resultant vector is then obtained by summing up the single components over a 3 x 3 neighbourhood centred one each cell, using a moving window operation (see figure 2 in Sappington and others (2010)). The magnitude of the resultant vector is normalised over the same neighbourhood and subtracted from 1 which results in a dimensionless VRM. VRM is a measure of surface roughness that range from 0 (flat) to 1 (most rugged). See Sappington and others (2010) for a more detailed description of the derivation of VRM.

In addition to the terrain and the wind-based parameter, also the effect of vegetation have been investigated. The AL data covers areas with low-growing vegetation composed of most of heather (*Calluna*), segdes and grasses in the central part of Hardangervidda. In the lower areas in e.g. in the south part of Hardangervidda the AL data covers areas of open boreal deciduous forest (e.g. Kastdalen & Hjeltnes, 2012). A vegetation/canopy fraction is calculated for each grid cell using the National Land Cover Data (AR50 https://register.geonorge.no/register/versjoner/produktark/norsk-institutt-for-biookonomi/ar50) vegetation class. Only grid cells with more than 20 percent of deciduous forest and/or heather were classified as vegetated.

3.2 Spatial aggregation of snow depth- and terrain parameters

In Norway, daily maps of interpolated temperature and precipitation on a 1x1 km grid have for more than a decade been used by the Norwegian water Resources and Energy Directorate as the meteorological basis for various operational forecasting services, such as flood forecasting, landslide- and avalanche forecasting. In addition, daily maps of various snow parameters are produced based on the gridded meteorological maps (the seNorge.no snow model Engeset and others, 2004, Saloranta, 2012, Saloranta, 2016). In order to explain the subgrid spatial variability of SD at a scale similar to the operational hydrological services, including the *seNorge.no* snow model, we calculated the statistical moments of SD (mean, standard deviation, skewness, and kurtosis) from the individual SDs for a rectangular grid of 500x1000 m. Such a procedure is in line with the observation of Jost and others (2007), enhancing the correlation between snow statistics and terrain. Since our AL data only covers a 500 m wide transect we calculated the statistical moments for 500x1000 m grid cells instead of 1x1 km grids (Fig. 2). The statistical moments were only calculated for grid cells with more than 80 % (i.e. ~4000) of valid SD values. In addition to calculating the statistical moments the 500 x 1000 m SD data were also used to determine which analytical statistical model that best suit the empirical distributions of SD. This strategy allowed us to use as many observations as possible over as large an extent as possible while trying to maintain sufficient sampling density to ensure unbiased estimates of the statistical moments and to decide on a model for the probably density function of SD. The analysis can, of course, be extended to other grid sizes and to a more random shift of the origin of the grid in order to perform an analysis of scale dependence, but this is considered to be out of the scope of the present study.

To relate the SD to terrain parameters the corresponding statistical moments are also calculated for each of the seven terrain parameters. When aggregating the terrain parameters over 500x1000 m grid cells we ensured a match in areal support between the independent variable (SD) and the dependent variables (terrain characteristics) (Erxleben and others, 2002).

3.3 A model for the spatial variability of snow depth

The dynamic input to a model for the PDF of snow (SD or SWE) will typically be (solid) precipitation, i.e. a mean areal value of snow being representative for a grid cell, a catchment or parts of a catchment. We hence need a functional relationship between the mean and higher statistical moments (we settle for the variance in this study) in order to estimate a spatial PDF of snow. In (Skaugen and Weltzien, 2016), the observed relationship between the spatial mean and standard deviation of precipitation was used to formulate such a relationship. It was further noticed that the relationship between the spatial mean and the standard deviation of precipitation was nonlinear in that the rate of increase of the spatial standard deviation deviated from that of the spatial mean as the spatial mean increased. For small values of the spatial mean the relationship between the mean and the standard deviation was approximately linear, whereas for higher values of the spatial mean, the standard deviation increased with a smaller rate or not at all. Such a behaviour has been observed for measurements of SWE during the accumulation season. The coefficient of variation, CV (spatial standard deviation over the spatial mean) decreases as the accumulation seasons proceeds (see Alfnes and others, 2004). Skaugen and Weltzien (2016) presented a model for the spatial variance of SWE in which decreasing temporal correlation is the cause of an attenuating contribution of variance as the accumulation proceeds. The parameters for the model for the spatial variances were estimated from the observed spatial mean *E(Z')* and spatial variability *Var(Z')* of precipitation. Given an input of the spatial mean of (solid) precipitation, the spatial variability and the spatial mean of the accumulated sum of SWE (Z') is estimated as:

$$Var(Z') = E(Z')\frac{1}{\alpha_0}[1 + (n-1)exp(-n/D)] = \frac{\nu}{\alpha^2}, \tag{2}$$

$$E(Z') = n\frac{\nu_0}{\alpha_0} = \frac{\nu}{\alpha}, \tag{3}$$

where ν_0 and α_0 are the shape and scale parameters of a gamma distributed unit snowfall (0.1 mm), n is the number of accumulated unit snowfalls, D is the decorrelation range where the correlation between snowfall units equals $1/e$ (Zawadski, 1973) and ν, and α, are the shape and scale parameters of the gamma distributed accumulated SWE. The relation between the spatial mean and the spatial variability to the parameters of the gamma distribution are:

$$\nu = \frac{E(Z')^2}{Var(Z')} \text{ and } \alpha = \frac{E(Z')}{Var(Z')}. \quad (4)$$

In this study we intend to test this model for the spatial variability of SD, and estimate its parameters ($\propto_0,\ \nu_0$ and D) using terrain information. If the two first moments of the distribution for the PDF of snow are estimated (the spatial mean and the spatial variance), a suitable statistical model (Log-normal, Gamma, Normal) can be used to represent the spatial PDF of snow in hydrological models.

3.4 Exploratory analysis

In order to investigate possible relationships between the terrain parameters and SD variability, an analysis using scatterplots and correlation matrices was carried out. The analysis was performed at a local scale where all 10x10 m grid cells located within each larger grid cell (500x1000 m) were used. Based on this approach the maximum number of observation N was 5000 for each larger grid. The analysis was also performed for grid cells of 500x1000 m between snow- and terrain statistics and between snow statistics. The symbols used for the statistics are shown in Table 1. The analysis was performed for each of the six flight lines, for the pooled data of all six flight lines and for the different landscape classes. The Spearman rank correlation method was used since it has no assumption of normally distributed variables.

Table 1. List of prefix us on for snow S and terrain T statistics.

Variable	Explanation
Med	Median for max 5000 10x10 m grid-cell values within 500x1000 m.
M	Mean for max 5000 10x10 m grid-cell values within 500x1000 m
Std	Standard deviation for max 5000 10x10 m grid-cell values within 500 x1000 m
Skw	Skewness for max 5000 10x10 m grid-cell values within 500x1000 m
Kurt	Kurtosis for max 5000 10x10 m grid-cell values within 500x1000 m
Sh	Shape parameter of the gamma distribution estimated from max 5000 10x10 m grid-cell values within 500x1000 m
Sc	Scale parameter of the gamma distribution estimated from max 5000 10x10 m grid-cell values within 500x1000 m
CV	Coefficient of variation for max 5000 10x10 m grid-cell values within 500x1000 m
LSC	Landscape class: 1= bare rock, 2= more than 20% wetlands/forest

4 Results

A main objective of this study is to investigate if terrain- or other variables can be used to estimate the parameters of the spatial frequency distribution of snow. In this section, we will hence investigate the linear and non-linear relations between the snow- and terrain characteristics in addition to take advantage of the wealth of the AL data to investigate the shape of the empirical distributions of SD and their possible analytical expressions.

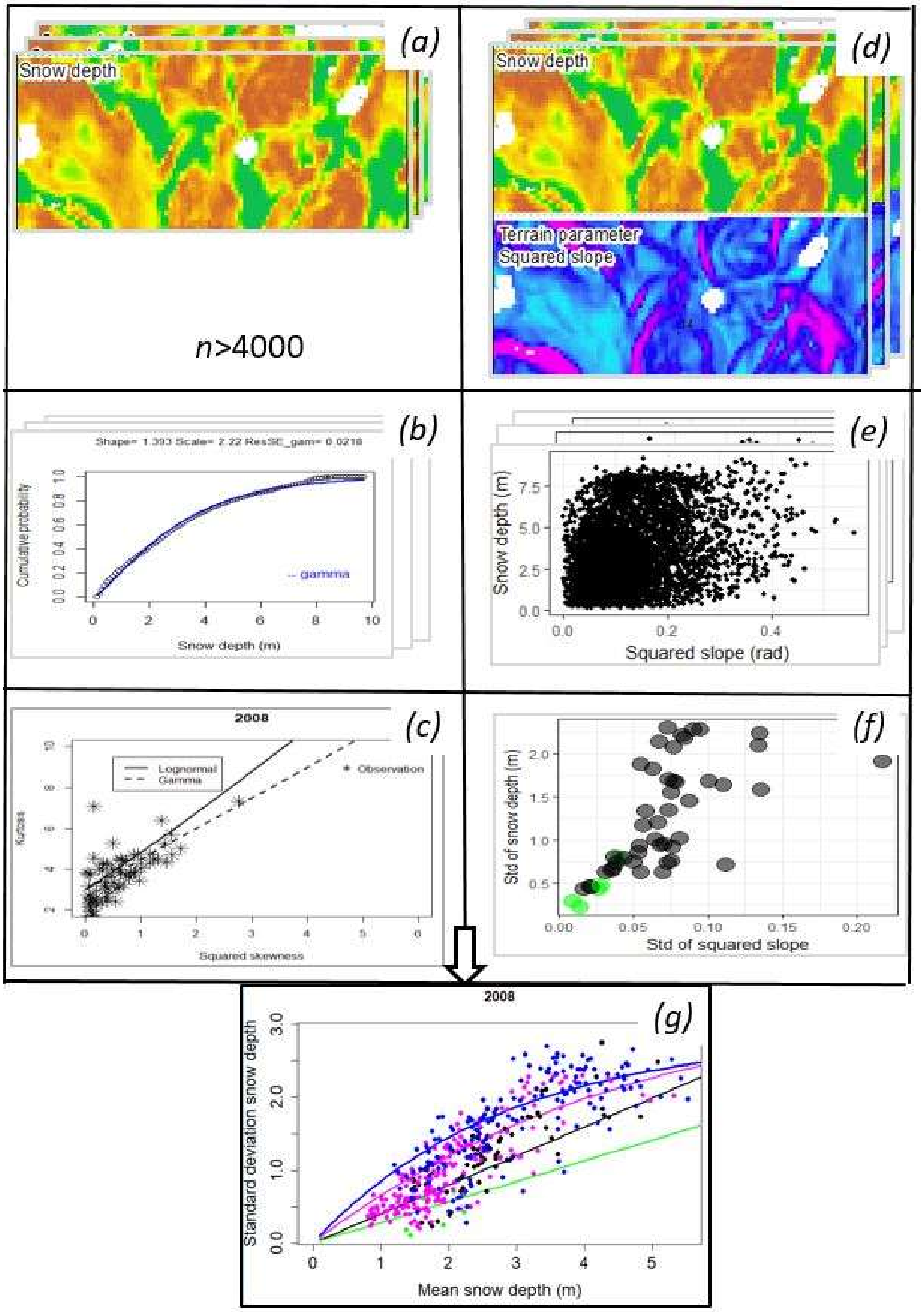

Figure 2. The figure gives an overview of the processing steps used in order to develop a model for subgrid variability of snow. On the left hand side of the figure, *a-c,* we show the process of finding a suitable statistical model for the spatial PDF of SD. On the right hand side (*d-f*) we show the process of relation standard deviation of snow to a terrain parameter. *a)*, the initial SD pattern found in a rectangle of 500 x 1000 m from the western part of Hardangervidda. SD ranges from 0.0 (orange) to 8 (green) meters. *b*), the cumulative distribution function of SD shown in (*a*). *c*), the skewness and kurtosis of SD data from Hardangervidda for all flight lines for the year 2008 (for explanation see text). *d*), the snow depth as shown in (*a*) in addition the spatial pattern of squared slope for the same area. *e*), shows high resolution, 10x10 m, SD shown in (*d*) plotted against the high resolution squared slope shown in (*d*). *f*), shows standard deviation of SD and squared slope after spatial aggregation. Only data for flight line 2 for the year 2008 is shown. *g*), model of the spatial variability of SD fitted to the 2008 AL data for different terrain- and landscape classes, see figure 5 and text for explanation.

4.1 What is a suitable statistical model for the spatial PDF of snow depth?

There has been an ongoing debate in the literature on which statistical model is best suited for describing the spatial frequency distribution of SWE (or SD) (see references above). A consensus seems to have been reached that the distribution appears to be (positively) skewed for alpine areas and more normal (symmetric) for forested areas. Figure 2a shows the spatial pattern of SD for a rectangular grid of 500 x 1000 m from the western part of Hardangervidda. The snow depth range from 0 to 8 meters. Figure 2b shows a typical cumulative distribution function of SD. The distribution is clearly skewed and the empirical distribution is well approximated using a Gamma distribution. Given the high number of data points (each statistic is estimated from approximately 4000 values) in this study, we have the opportunity to estimate statistical moments of high order with reasonable certainties. A Cullen and Frey graph (Cullen & Frey, 1999) compares the skew and kurtosis of observed data to theoretical values for different statistical models, such as the Gamma and the Lognormal. These two models are typical candidates when an analytical expression for the spatial frequency distribution of snow is needed. In a Cullen and Frey graph, normally distributed values will be located at the point skewness = 0 and kurtosis = 3 (Yevjevich, 1972 p.128). Figure 2 c and Figure 3 a, b shows how the skewness and kurtosis of SD data from Hardangervidda for all flight lines for the years 2008 (a) and 2009 (b) compare to the theoretical values of the Normal, Log-normal and Gamma distribution. There is a substantial scatter for both years, but if one have to choose, the Gamma distribution seems to be the best suited. A random sample of four 500 x 1000 cells were drawn from each of the six flight lines each year. When subjected to goodness of fit tests for choice of distribution, such as the Anderson-Darling test and the Kolmogorov-Smirnov test (see Delignette-Muller & Dutang, 2015), 38 out of 48 (80%) empirical distributions were best approximated using the Gamma distribution (not shown).

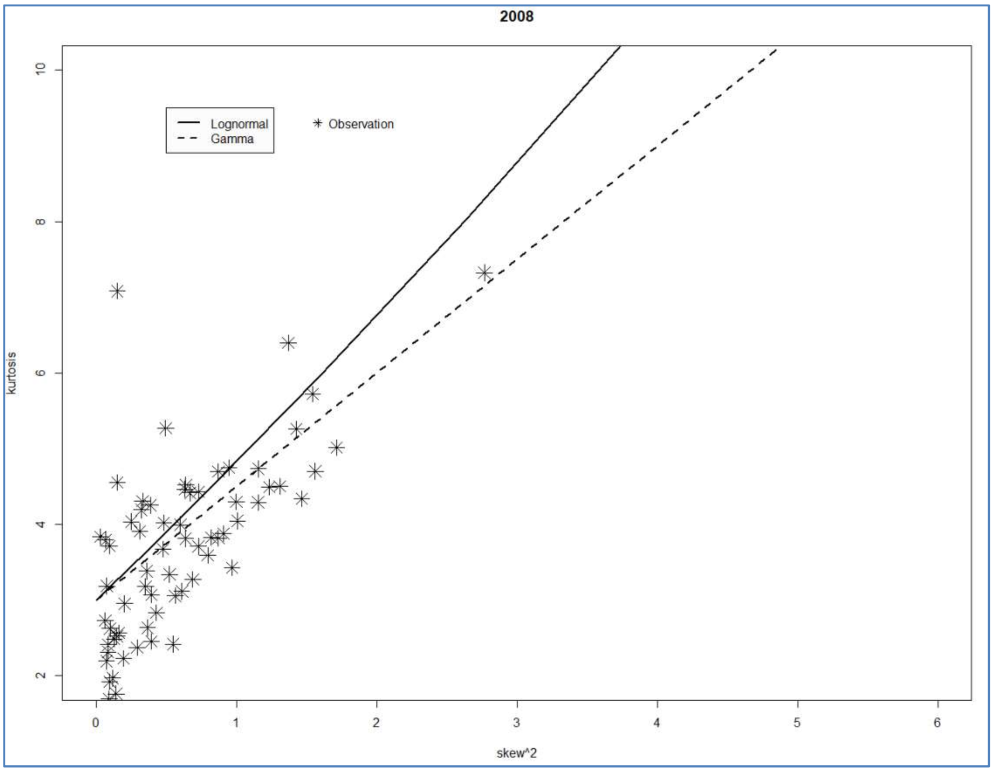

Figure 3 a. Cullen and Frey graph of the skew and kurtosis of observations for 500 X 1000 meter grid cells at Hardangervidda 2008 compared to the theoretical values of the Gamma and Lognormal distribution.

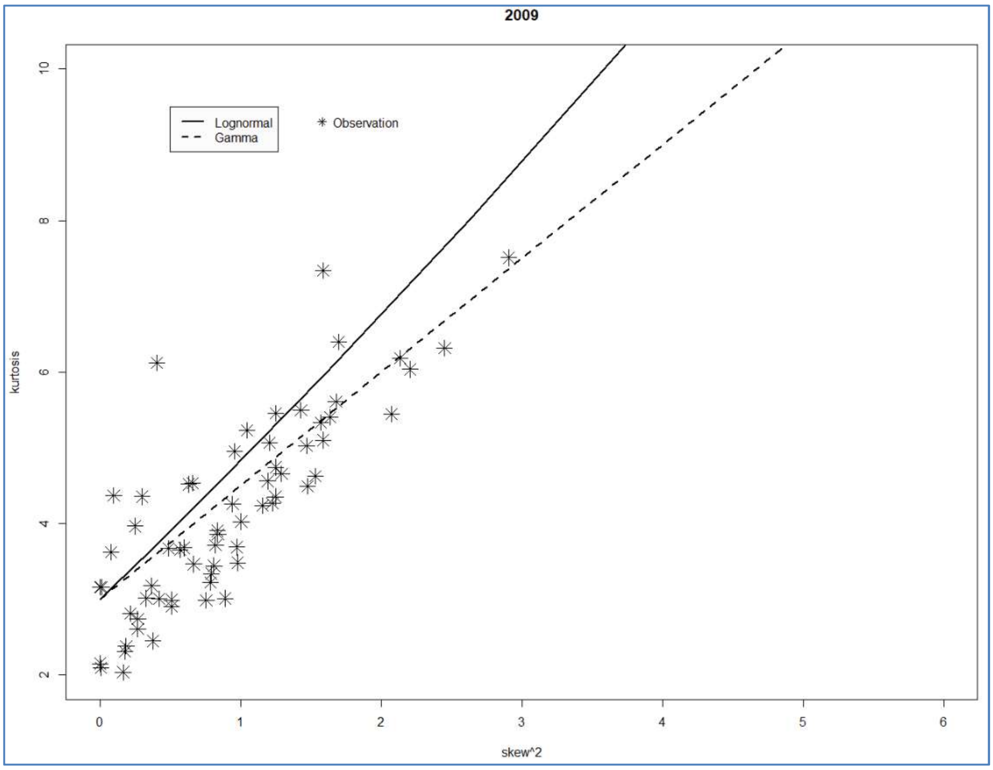

Figure 3 b. Cullen and Frey graph of the skew and kurtosis of observations for 500 X 1000 meter grid cells at Hardangervidda 2009 compared to the theoretical values of the Gamma and Lognormal distribution.

4.2 Correlation between snow and terrain parameters

We have investigated the relationship between the different snow and terrain parameters both at local (10x10 m) and at aggregated scale (500x1000 m, the approximate *seNorge.no* scale). In order to identify relations between snow and terrain parameters.

At the local scale we found no significant correlation between high-resolution 10x10 m SD data and terrain data. Figure 2 e and 4 illustrate how SD averaged over the 10x10 m grid cells comprised in a 500x1000 m grid cell relates to squared slope averaged over the same resolution. Clearly, no pattern can be seen and the correlation is low and not significant. Similar results are found for the other terrain parameters and for other areas (not shown).

Correlation analysis was also performed for snow- and terrain statistics derived at the 500x1000 m scale (the approximate *seNorge.no* scale). For both years, the highest correlations were found between standard deviation of SD and the terrain parameters expressing slope variability (standard deviation of slope squared slope and VRM) and S (see Table 2). The relationships between mean SD and the mean of terrain parameters are weaker (see Table 3) than for the standard deviation. The parameters expressing mean slope and mean VRM show the highest correlations to mean SD. For the other statistics, the relationships are weaker as shown for CV in Table 4 (higher moments are not shown).

For the individual flight lines the correlation between standard deviation of SD and squared slope ranged from 0.42 to 0.82 (in 2008) and 0.43 to 0.81 (in 2009). For the pooled data the correlation coefficients were 0.67 and 0.61 for 2008 and 2009 respectively. The standard deviation of wind shelter index (S) as well as the VRM also correlate well with the standard deviation of SD but correlations are slightly weaker (see Table 1). From Tables 1 and 2 one can also see the high correlation among the terrain parameters. This suggests that only one of the parameters should be used since little new information is obtained by including additional terrain parameters. Since the slope is simpler to calculate than VRM, and is independent of wind data (unlike S) it was decided to use the (squared) slope as the chosen terrain parameters for this study. Figure 2 *f,* illustrates how the Std of SD relates to the Std of squared slope on average for each 500 x 1000 m rectangle along flight lines 2 for year 2008 (correlation 0.75 and n = 51).

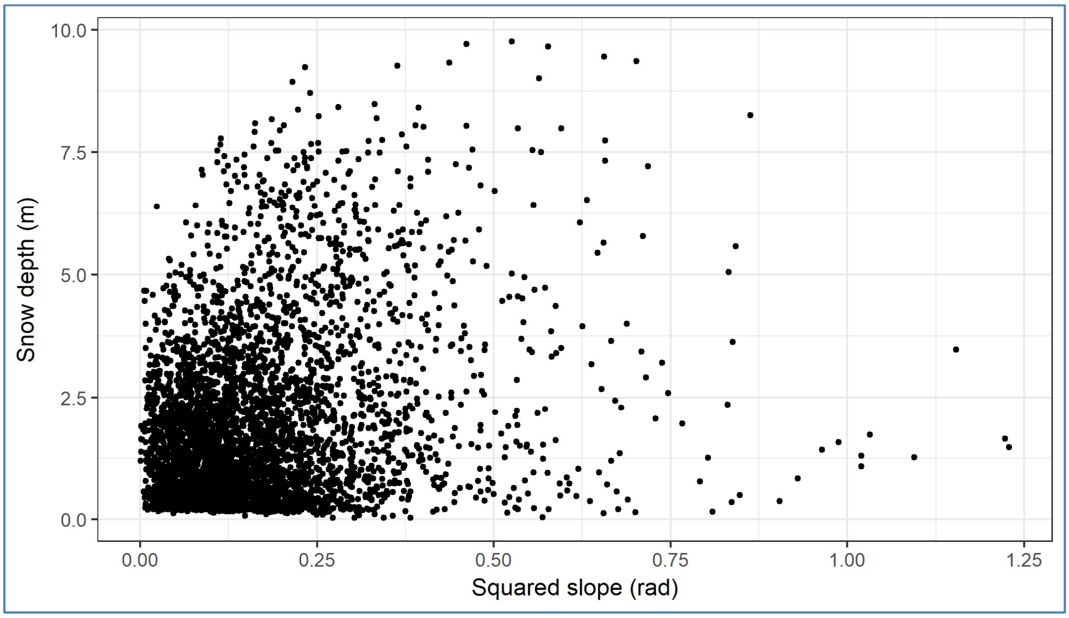

Figure 4. SD against squared slope at averaged over 10x10 m grid cell sampled from one grid cell of 500x1000 m. This example is for flight line 1 from 2018.

Table 2. Rank correlation between standard deviation of SD and the standard deviation of different terrain parameters for pooled data sets in 2008 and 2009. Only significant (p-value < 0.001) correlation are shown.

2008	Std Slope	Std Sq slope	Std Aspect	Std VRM	Std exp(S)	Std Elevation	Std SD
Std Slope	1.00	1.00		0.92	0.89	0.78	0.66
Std Sq slope		1.00		0.92	0.88	0.78	0.67
Std Aspect			1.00			-0.25	
Std VRM				1.00	0.87	0.67	0.70
Std exp(S)					1.00	0.64	0.63
Std Elevation						1.00	0.55
Std SD							1.00
2009	Std Slope	Std Sq slope	Std Aspect	Std VRM	Std exp(S)	Std Elevation	Std SD
Std Slope	1.00	1.00		0.92	0.89	0.78	0.60
Std Sq slope		1.00		0.92	0.89	0.79	0.61
Std Aspect			1.00			-0.25	0.18
Std VRM				1.00	0.87	0.68	0.64
Std exp(S)					1.00	0.65	0.56
Std Elevation						1.00	0.49
Std SD							1.00

Table 3. Rank correlation between mean of SD and the mean of different terrain parameters for pooled data sets in 2008 and 2009. Only significant (p-value < 0.001) correlation are shown.

2008	M Slope	M Sq slope	M Aspect	M VRM	M exp(S)	M Elevation	M SD
M Slope	1.00	1.00	NA	0.88	0.34	0.24	0.59
M Sq slope		1.00	NA	0.88	0.34	0.24	0.60
M Aspect			1.00	NA	-0.51		
M VRM				1.00	0.33	0.27	0.61
M exp(S)					1.00		
M Elevation						1.00	0.41
M SD							1.00
2009	M Slope	M Sq slope	M Aspect	M VRM	M exp(S)	M Elevation	M SD
M Slope	1.00	1.00		0.88	0.34	0.25	0.44
M Sq slope		1.00		0.89	0.35	0.25	0.44
M Aspect			1.00		-0.50		
M VRM				1.00	0.34	0.28	0.48
M exp(S)					1.00		
M Elevation						1.00	0.62
M SD							1.00

Table 4. Rank correlation between CV of SD and the CV of different terrain parameters for pooled data sets in 2008 and 2009. Only significant (p-value < 0.001) correlation are shown.

2008	CV Slope	CV Sq slope	CV Aspect	CV VRM	CV exp(S)	CV Elevation	CV SD
CV Slope	1.00	0.93				-0.43	
CV Sq slope		1.00				-0.19	
CV Aspect			1.00				
CV VRM				1.00	0.88	0.64	0.49
CV exp(S)					1.00	0.62	0.49
CV Elevation						1.00	0.18
CV SD							1.00
2009	CV Slope	CV Sq slope	CV Aspect	CV VRM	CV exp(S)	CV Elevation	CV SD
CV Slope	1.00	0.93				-0.44	
CV Sq slope		1.00				-0.20	
CV Aspect			1.00				
CV VRM				1.00	0.88	0.65	0.52
CV exp(S)					1.00	0.62	0.54
CV Elevation						1.00	0.25
CV SD							1.00

4.3 Correlation analysis for the statistical moments of snow depth and squared slope

Based on the finding in the previous section we will further investigated the relations between snow and the terrain parameter squared slope (hereafter denoted T). In addition, we will also look at the relations between various statistics of snow. Since the number of values used to estimate the statistics was so high (~4000), statistics normally associated with a high degree of uncertainty such as skewness and kurtosis where also included in the analysis. The 500x1000 m grid cells were classified into bare-rock and wetland/forest types and when pooling all 500x1000 m grid cells for the 6 courses together for the 2009 data, we could see that the snow statistics were significantly correlated to land scape classes (LSC) (see Table 5).

Table 5. Rank correlation between snow statistics and terrain statistics for all courses, 2009. Prefixscript used are defined in Table 1. Subscript _S denotes snow and subscript _T denotes the terrain, variable squared slope. Only significant (p-value < 0.001) correlations are shown.

	Med_T	M_T	Std_T	Skw_T	Kurt_T	Sh_T	Sc_T	CV_T	LSC
Med_S	0.30	0.32	0.36	0.23	0.23		-0.23		-0.35
M_S	0.36	0.39	0.43	0.23	0.24		-0.23		-0.42
Std_S	0.53	0.56	0.60	0.21	0.24		-0.21		-0.55
Skw_S									
Kurt_S	-0.18	-0,18	-0.17						0.27
Sh_S									
Sc_S									
CV_S	0.45	0.47	0.51						-0.49
LSC	-0.22	-0.23	-0.25						1

Based on this finding, we continue the correlation analysis for separate landscape classes. The number of 500x1000 m classified, as bare rock is 382 and 66 cells are classified as wetland/forest. Tables 6 and 7 show correlation matrices for snow statistics against terrain statistics. Similarly, we conducted a correlation analysis between snow statistics in order to investigate relationship between SD parameters (e.g. M_S versus Std_S). The correlation matrices are shown in tables 8 and 9.

Table 6. Correlation between snow statistics and terrain statistics for all courses, 2008 and 2009 for LSC = 1, bare rock. Prefixscript used are defined in Table 1. S denotes snow and T denotes terrain. Only significant (p-value < 0.001) correlations are shown.

2008	Med_T	M_T	Std_T	Skw_T	Kurt_T	Sh_T	Sc_T	CV_T
Med_S	0.49	0.50	0.49	0.20	0.22		-0.20	
M_S	0.53	0.55	0.54	0.22	0.24		-0.22	
Std_S	0.64	0.66	0.67	0.25	0.27		-0.25	
Skw_S								
Kurt_S	-0.33	-0.33	-0.30					
Sh_S	-0.28	-0.28	-0.26					
Sc_S								
CV_S	0.37	0.39	0.43			-0.18		
2009	Med_T	M_T	Std_T	Skw_T	Kurt_T	Sh_T	Sc_T	CV_T
Med_S	0.36	0.38	0.40	0.25	0.26		-0.25	
M_S	0.42	0.45	0.47	0.27	0.27		-0.27	
Std_S	0.57	0.60	0.63	0.28	0.29		-0.28	
Skw_S								
Kurt_S	-0.22	-0.21	-0.20					
Sh_S	-0.21	-0.21	-0.20		-0.17			
Sc_S								
CV_S	0.39	0.41	0.45			-0.2		

Table 7. Correlation between snow and terrain statistics for all courses, 2008 and 2009 for LSC = 2, wetlands/forest. Only significant (p-value < 0.01) correlations are shown.

2008	Med_T	M_T	Std_T	Skw_T	Kurt_T	Sh_T	Sc_T	CV_T
Med_S	0.34	0.34	0.37					
M_S	0.32	0.33	0.36					
Std_S			0.38					
Skw_S								
Kurt_S								
Sh_S								
Sc_S								
CV_S								
2009	Med_T	M_T	Std_T	Skw_T	Kurt_T	Sh_T	Sc_T	CV_T
Med_S	-0.55	-0.56	-0.49			0.45		
M_S	-0.53	-0.53	-0.45			0.44		0.4
Std_S								
Skw_S								
Kurt_S								
Sh_S								
Sc_S								
CV_S			0.43					

Table 8. Correlation between snow statistics for all courses, LSC=1, bare rock 2008 and 2009. Only significant (p-value < 0.001) correlations are shown.

2008	Med_S	M_S	Std_S	Skw_S	Kurt_S	Sh_S	Sc_S	CV_S
Med_S	1	0.99	0.18	-0.68	-0.71	-0.82	0.66	
M_S		1	0.87	-0.62	-0.70	-0.77	0.6	
Std_S			1	-0.37	-0.64	-0.54	0.36	0.47
Skw_S				1	0.86	0.96	-0.99	0.43
Kurt_S					1	0.87	-0.85	
Sh_S						1	-0.97	0.32
Sc_S							1	-0.42
CV_S								1
2009	Med_S	M_S	Std_S	Skw_S	Kurt_S	Sh_S	Sc_S	CV_S
Med_S	1		0.81	-0.69	-0.72	-0.85	0.69	
M_S	0.98	1	0.89	-0.61	-0.69	-0.80	0.61	
Std_S			1	-0.38	-0.58	-0.58	0.38	0.42
Skw_S				1	0.92	0.96	-1.0	0.47
Kurt_S					1	0.93	-0.92	0.18
Sh_S						1	-0.96	0.35
Sc_S							1	-0.47
CV_S								1

From Table 6 which show the results from bare-rock classes we note that especially the mean and standard deviation of snow are well correlated with the mean and standard deviation of squared slope. The higher statistical moments for snow, such as the skewness and kurtosis are not significantly, or very weakly correlated with squared slope. Table 8, on the other hand, shows how the first moment, the mean of snow is highly correlated to the higher moments of snow (variance, skewness and kurtosis). In addition, we see that the shape and scale of the gamma distribution is highly correlated to the mean SD.

Table 9. Correlation between snow statistics for all courses, 2008 and 2009 for LSC = 2, wetlands/forest. Only significant (p-value < 0.001) correlations are shown.

2008	Med_S	M_S	Std_S	Skw_S	Kurt_S	Sh_S	Sc_S	CV_S
Med_S	1	0.99	0.44					
M_S		1	0.48					
Std_S			1					0.78
Skw_S				1	0.59	0.96	-0.98	
Kurt_S					1	0.61	-0.63	
Sh_S						1	-0.98	
Sc_S							1	
CV_S								1
2009	Med_S	M_S	Std_S	Skw_S	Kurt_S	Sh_S	Sc_S	CV_S
Med_S	1	0.99	0.51			-0.43		
M_S		1	0.60					
Std_S			1					0.74
Skw_S				1		0.98	-1.0	0.61
Kurt_S					1	0.87	-0.87	0.40
Sh_S						1	-0.98	0.58
Sc_S							1	-0.61
CV_S								1

As very few data points describe the snow/terrain statistics for forest/wetlands, very few correlations were found significantly different from zero. Indeed, in Table 7, we see that M_S is correlated to the M_T and Std_T, but with opposite signs for the two years. The Std_S is only significantly correlated to Std_T for 2009. In Table 9, we find that the M_S is correlated to Std_S, but not to the higher statistical moments of snow.

4.4 Application of model for the spatial variability for the Hardangervidda data

The correlation analysis above has shown that parameters describing the variability of the terrain are highly correlated to the variability of snow at least for the bare rock class (LSC=1). We can also see that the variability of snow, and higher moments such as skew and kurtosis are highly correlated with the mean of snow. Hence we conclude that the spatial variability of snow is a function of the mean of snow, a dynamic variable and the spatial variability of the terrain, a static variable. In addition, figures 4 and 5 show that the relation between M_S vs Std_S, often is non-linear, which in Skaugen and Weltzien (2016) was explained by the presence of correlation between the snowfall (precipitation) units.

Figures 5 and 6 show scatter plots of M_S vs Std_S and the fitted model developed in Skaugen and Weltzien (2016) for the Hardangervidda data for 2008 and 2009. The models are fitted to different classes of Std_T for LSC=1, 0.0< Std_T <0.05, 0.05< Std_T < 0.1, Std_T >0.1 and to the landscape class LSC=2, Wetland/Forest. It was not possible do differentiate with respect to Std_T for LSC=2. The thresholds for Std_T were decided from a qualitative assessment that appeared consistent for both 2008 and 2009.

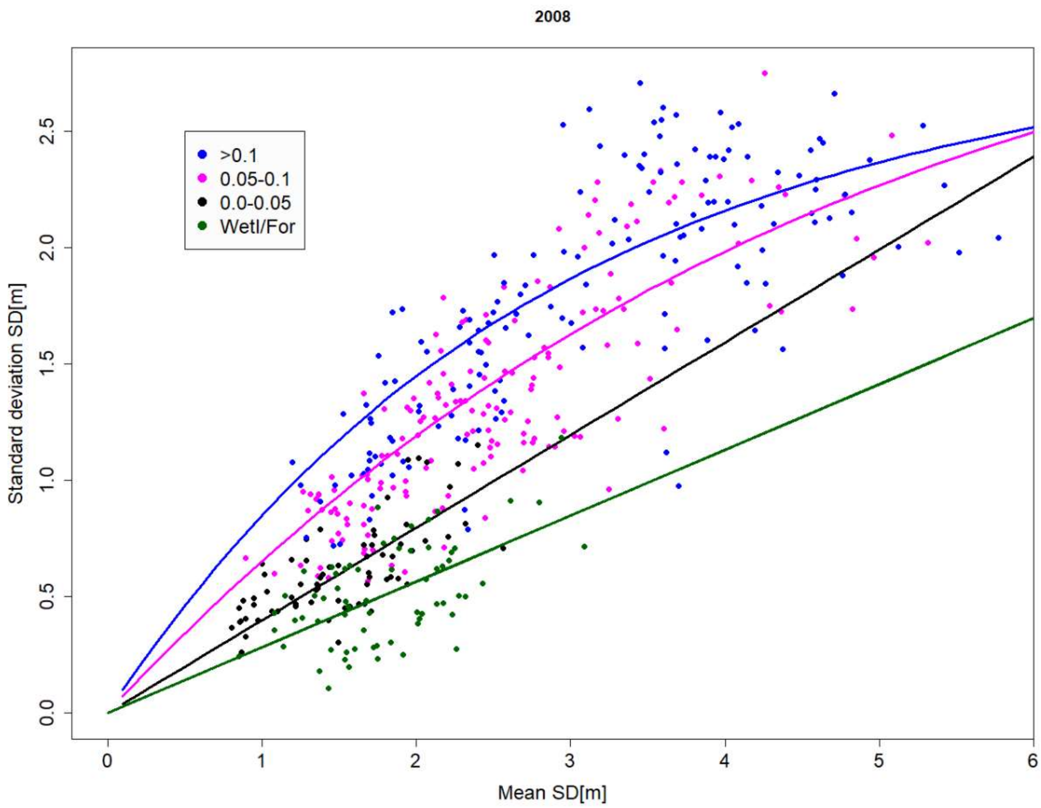

Figure 5. Model of the spatial variability of SD fitted to the 2008 AL data. The colours indicate model and observations for different classes of squared slope and landscapes. Blue: Std_T >0.1, magenta: 0.05 < Std_T < 0.1, black: 0.0< Std_T < 0.05 and green: wetlands and forest. All units are in meters.

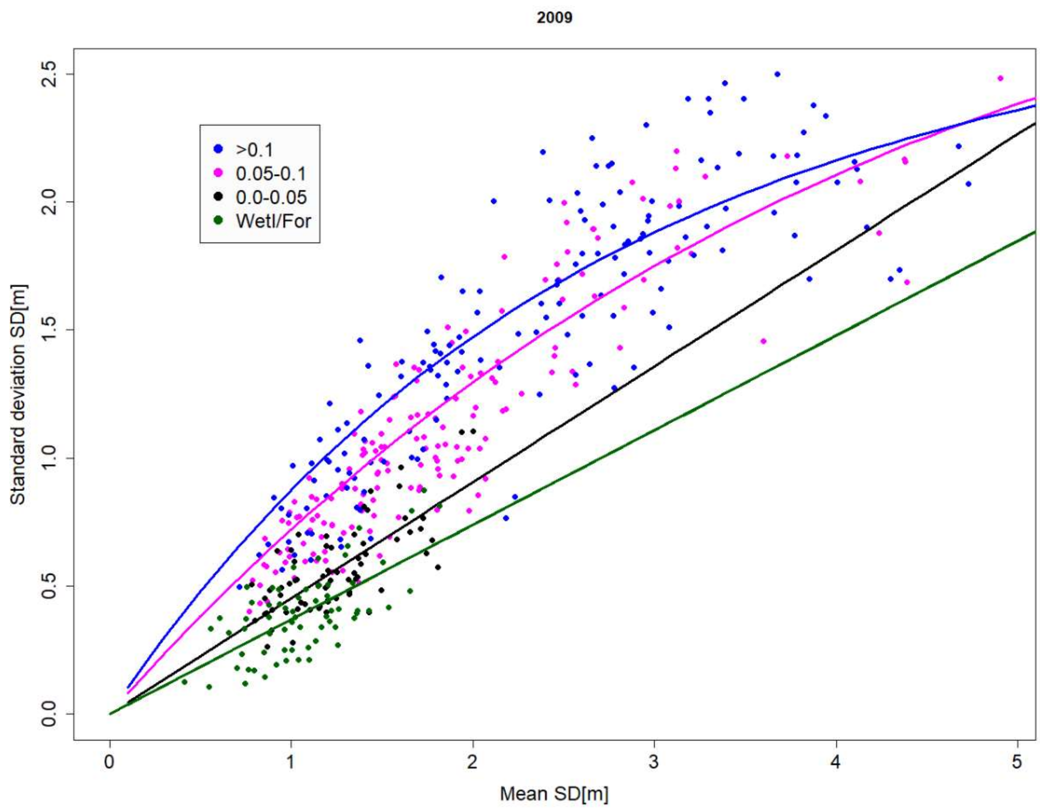

Figure 6. Model of the spatial variability of SD fitted to the 2009 AL data. The colours indicate model and observations for different classes of squared slope and landscapes. Blue: Std_T >0.1, magenta: 0.05 < Std_T < 0.1, black: 0.0< Std_T < 0.05 and green: wetlands and forest. All units are in meters

Table 10 shows the estimated parameters, the scale of the unit snowfall α_0, and the decorrelations length (measured in meters of snow) D of the developed models. Non-linear functions were fitted to the LSC=1 and Std_T greater than 0.05. For Sdt_T <0.05 and for LSC=2 it was only possible to fit linear curves.

The snow variability for the two years shows a very similar behaviour and the models for both years and the mean for the two years are shown in Figure 7.

Table 10. Parameters of Std_S model 2008 and 2009 and mean model for different Std_T values for LSC=1, and for LSC=2.

Std_T	α_0	D	Type
2008			
>0.1	1.3886	2.5275	Non-Linear
0.05-0.1	2.3428	4.7912	Non-Linear
0.0-0.05	0.3982		Linear
Wtl/Forest	0.2825		Linear
2009			
>0.1	1.3066	2.3010	Non-Linear
0.05-0.1	1.9227	4.11	Non-Linear
0.0-0.05	0.4530		Linear
Wtl/Forest	0.3696		Linear
Mean model			
>0.1	1.3476	2.4143	Non-Linear
0.05-0.1	2.1328	4.4506	Non-Linear
0.0-0.05	0.4256		Linear
Wtl/Forest	0.3261		Linear

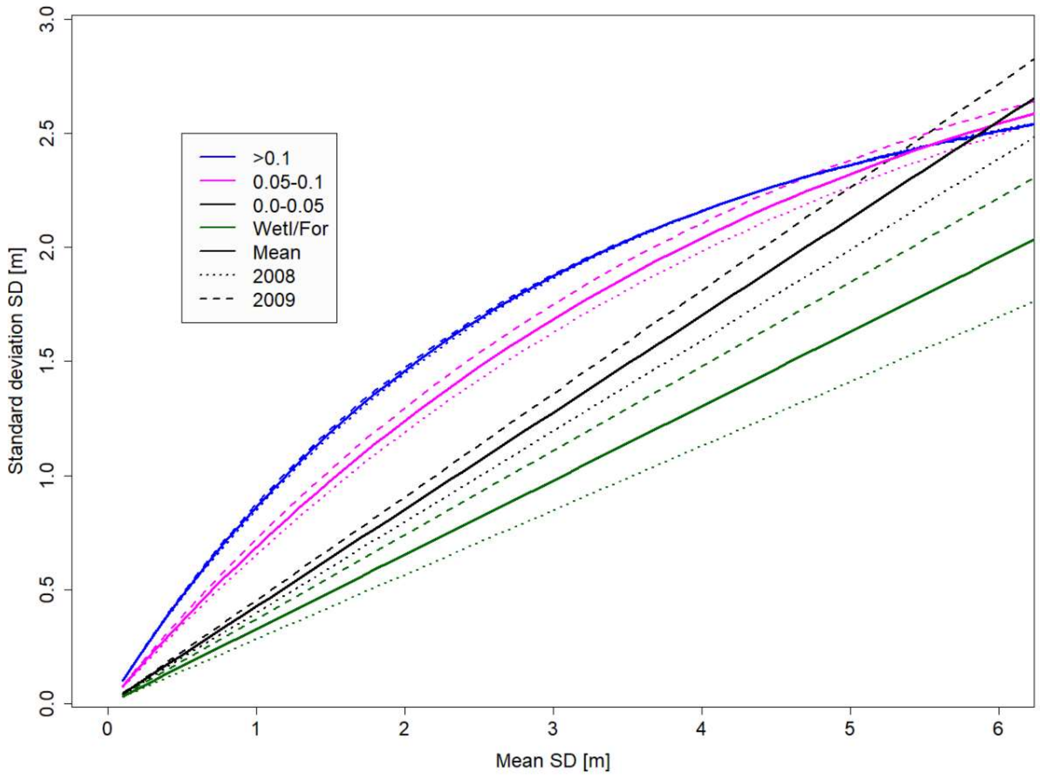

Figure 7. Snow variability models estimated for 2008, 2009 and mean model. All units are in meters.

4.5 Model validation

In a previous section, we have demonstrated that the gamma distribution is an appropriate model for describing the spatial frequency distribution of SD. The model we have presented in the above section is for estimating the spatial variability of SD and through the correlation analysis we have found that the spatial variability of SD is dependent on the mean SD and the spatial variability of the terrain estimated as the standard deviation of the variable T (Eq. 2). From Figure 7 we conclude that the data from 2008 and 2009 from Hardangervidda give grounds for different models dependent on threshold values of Std_T and for classes of landscape types (LSC= 1, bare rock and LSC = 2, wetlands/forests). In figures 8-19 we show how the spatial variability of SD from observations from 4 randomly selected cells for each of the six flight lines for each of the years 2008 and 2009 compare with the models based on 2008 and 2009 data and for the mean model. For the model based on 2008 data we validate using 2009 data and vice versa. The mean model is validated on 2008 and 2009 data. In Table 8, very high correlations are shown between the mean snow depth and the standard deviation of snow depth with 0.87 and 0.89 respectively for the years 2008 and 2009. It is therefore instructive to investigate if such a linear relationship between the standard deviation and the spatial mean as input can be an alternative, or even a better model. Such a linear model is equivalent to assume a constant coefficient of variation of snow depth. Figure 11 shows the result of a model where the spatial standard deviation of snow depth is a linear function of the spatial mean. The value of the constant CV, based on the selected cells from 2008 and 2009 is $CV = 0.58$.

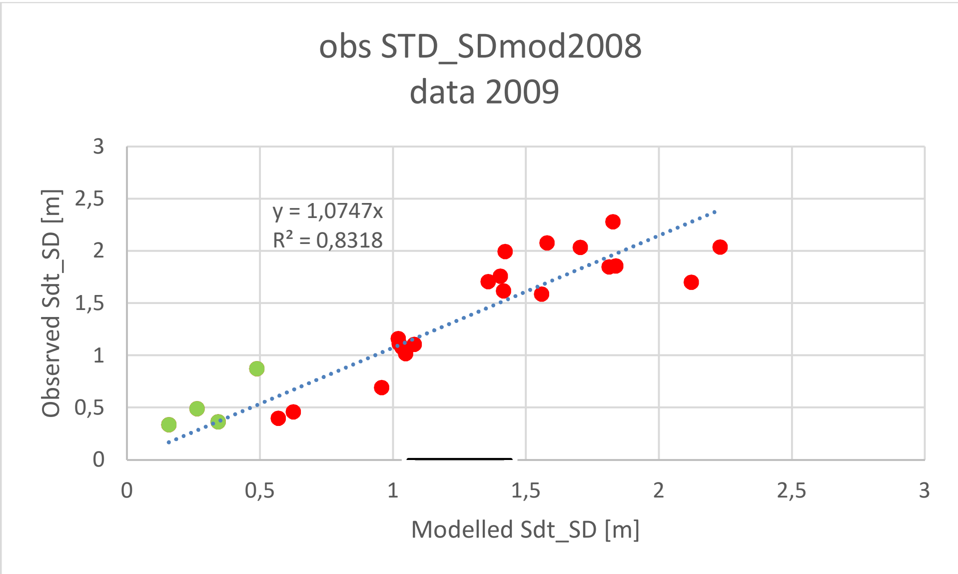

Figure 8. Model for the spatial variability of SD (Eq.2) based on 2008 data validated on 2009 data. Green circles indicate estimates for wetlands/forest.

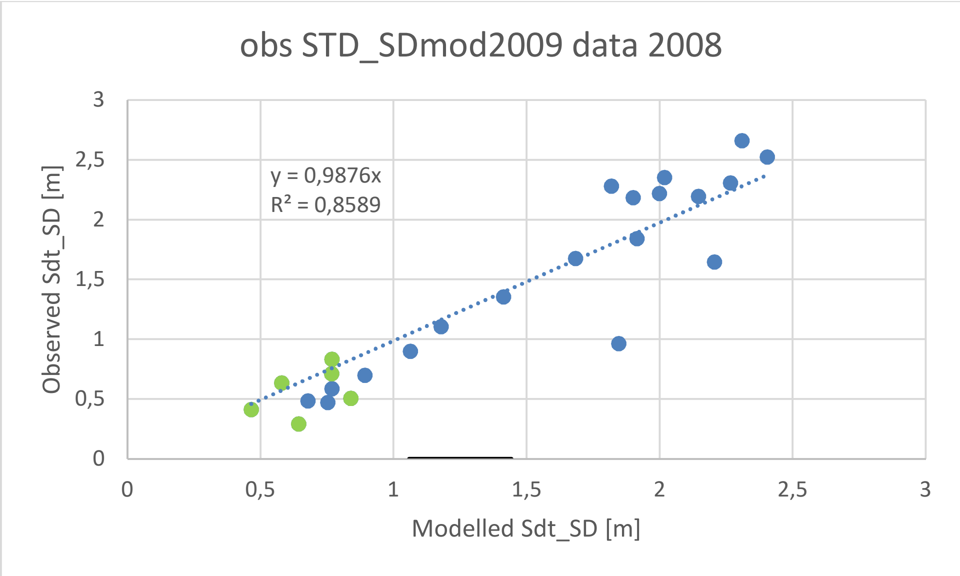

Figure 9. Model for the spatial variability of SD (Eq.2) based on 2009 data validated on 2008 data. Green circles indicate estimates for wetlands/forest.

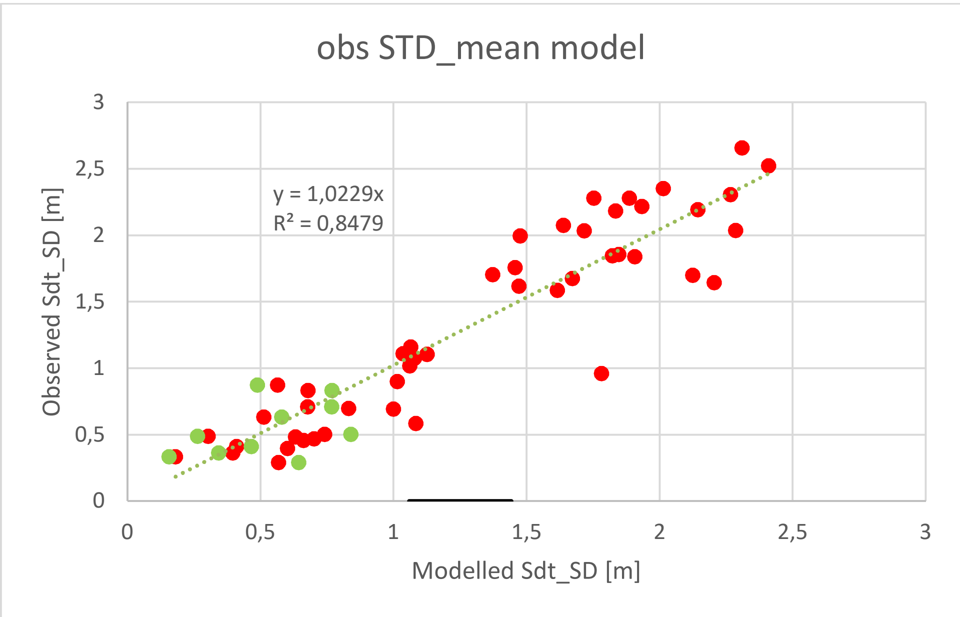

Figure 10. Mean model for the spatial variability of SD (Eq.2) validated on 2008 and 2009 data. Green circles indicate estimates for wetlands/forest.

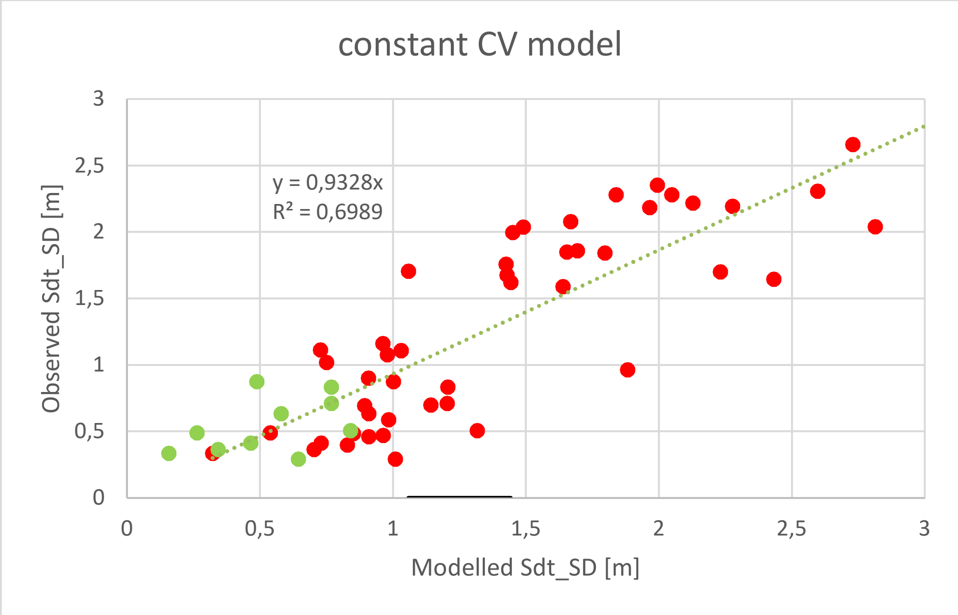

Figure 11. Model for the spatial variability of SD assuming a linear relationship between M_S and Std_S (constant CV) validated on 2008 and 2009 data. Green circles indicate estimates for wetlands/forest.

Table 11. Explained variance and bias for estimating the observed spatial variability of SD for 24 empirical distributions of SD (48 empirical distributions are used for the mean model and constant CV model).

Model	Explained variance, R2	Bias (modelled/observed)
Mod_2009 for 2008 data	0.86	1.01
Mod_2008 for 2009 data	0.83	0.93
Mean model for 2008 and 2009 data	0.85	0.98
Constant CV model (CV=0.58) for 2008 and 2009 data	0.70	1.07

From Table 11 we see that the explained variance for the proposed model is quite high, and clearly higher than the model which assumes a constant CV. The bias is generally small, and very small for the mean model. Note that the mean model and the constant CV model are not validated against independent data, but rather from a random sample from the values with which they were calibrated.

5 Discussion

5.1 Terrain parameters and spatial aggregation

As expected, we found no significant correlation between high-resolution 10x10 m SD data and terrain data. Figure 4 illustrates the lack of correlation between terrain parameter squared slope and snow depth averaged over a 10x10 m grid. Similar results were also found for the other terrain parameters (not shown). These results are in line with the studies of Deems and others (2006), Jost and others (2007), Trujillo and others (2009), Grünewald and others (2010) and Grünewald and others (2013). These studies show that at very small scale, local terrain characteristics cannot explain the SD variability. Much of the local snow variability seems to be a result of small scale snow and terrain effects which are not captured by the terrain parameters derived for one grid point of a DTM. The local terrain parameter is typically calculated by a moving window operation (often 3x3 cells) and is hence representative of a larger scale than the SD data. In addition, the snow depth variation may be the result of processes that may have been initiated at some distance from the point in question. Such features include cornices and avalanches; snow slugging etc. A good correlation with terrain parameters thus requires averaging (Grünewald and others, 2013, Jost and others, 2007). These results highlight that the scale of observation of SD needs to match the observational scale of the terrain variables supposed to explain its variability.

5.2 Linear relationships between terrain and snow

It has been a longstanding ambition to model snow variables from topographical and vegetation characteristics of the landscape. Many studies report quite modest correlations between snow and these characteristics (Jost and others, 2007, Lehning and others, 2011, Gisnås and others, 2016) and furthermore, these correlations are dependent on the spatial support of the dependent variable and the independent variables (Erxleben and others, 2002, Jost and others, 2007). Jost and others (2007) highlights that correlations decrease together with scale and that good correlations between snow parameters and terrain require averaging. For the applied scale in this study, 0.5 km^2 we find significant correlations between snow statistics, such as the mean and the standard deviation of SD and the statistics (mean and standard deviation) of the squared slope calculated from the 10x10m grid cell values comprised by the 0.5 km^2 grid. In addition, we find significant correlations to landscape classes (Table 5) when we stratify the data into bare rock (LSC=1) and wetland/forest (LSC=2). For stratified data according to LSC, we find, on average for 2008 and 2009,that the correlation between the standard deviation of squared slope and the standard deviation of SD is 0.65 for LSC=1 (Table 6). For LSC=2 these correlations are lower (Table 7), or not significant. Gisnås and others (2016) and Lehning and others (2011) also found high correlations in Norway and Switzerland respectively, when relating SD variability to various roughness indexes for alpine areas.

The tables 8 and 9 show correlations between snow statistics. Especially for LSC=1, the correlations between the mean and the standard deviation of SD is high. Pomeroy and others (2004) found similar correlations for various landscape types in Canada.

The results from these correlation analysis show that the spatial variability of SD is highly correlated with the mean SD (see also constant CV model in section 4.5). In addition, the spatial variability of snow is also correlated to the terrain roughness, here quantified by squared slope and also to landscape classes. These features form the basis of the model for spatial variability of snow which is proposed in this paper.

5.3 Statistical model for the PDF of snow

The Cullen and Frey graphs (figures 2 and 3 Cullen & Frey, 1999) show that the Normal, the Log-Normal and the Gamma distribution may, for individual snow courses, all be reasonable choices for the spatial frequency distribution of snow. If, however, we have to choose one type of distribution, the Gamma distribution tends to be in best agreement with the empirical distributions, which was also the conclusion of Gisnås and others (2016). In addition to being the best fit to the empirical distributions, the Gamma distribution has attractive mathematical features, which have been used to model spatial distribution of SWE in hydrological models (Skaugen, 2007, Skaugen & Randen, 2013, Skaugen & Weltzien, 2016). In such a model, the spatial distribution of SWE is dynamical, i.e. its shape evolves according to accumulation and melting events in a way similar to what is observed for measured spatial distributions of SWE (see Alfnes and others, 2004, Skaugen, 2007).

5.4 Modelling the spatial variability of snow

The abundance of data presented in this study confirms and illustrates quite clearly the non-linear relationship between the spatial mean and standard deviation of SD (see figures 4 and 5). Although a linear approach seem appropriate for small and medium mean SDs, we can see, in figures 4 and 5, that the rate of increase for the standard deviation decreases as the mean increases. The validation of the models in section 4.5 illustrates that the additional information carried in terrain and landscape type information allows for a higher precision in estimating the spatial standard deviation of snow depth.(see also Helbig and others, 2015 for a discussion on this topic). The presented model captures the nonlinear relationship by introducing correlation (Eq. 2), and by stratifying the model according to squared slope and landscape classes, the results for estimating the spatial variability of SD shown in figures 7-9 are quite convincing with explained variance for validation dataset of about 86% (see table 11). The models are validated for a random collection grid cells within the same region but for a different year. These results compare well to results presented in Jost and others (2007) for catchment-scale snow variability and to Grünewald and others (2013), where the spatial variability was modelled locally with explained variance of 30 to 91 % but the global model only achieved 23% explained variance. Although the results are presented for data acquired at a time of (the assumed) "peak accumulation", the model (figures 7-9) performs well over a range of mean SD values, which suggests that the model can be used to estimate the spatial variability at any time during the snow season. In addition, the model appears to work well for both landscape classes. The model needs, however to be further validated for larger areas (> 0.5 km^2) and for different regions.

In Skaugen and Weltzien (2016) the spatial variability of precipitation, measured at 2 meters above the ground was used to determine a_0 and D. It is not surprising that the spatial variability of precipitation and the spatial variability of the terrain both carry relevant information for describing the spatial distribution of snow. Johansson and Chen (2003) demonstrate the relation between between wind and topography on the spatial distribution of precipitation, and Lehning and others (2008) find that the topography-induced modification of the wind field close to the surface plays an important role for the spatial distribution of snow. In addition, Skaugen and Weltzien (2016),showed that the parameter a_0, estimated from the spatial variability of precipitation measured at 2 meters above the ground was found to be significantly correlated to the landscape type (forest and alpine).

The obvious next step is to implement the snow distribution model in a hydrological model. From a pre-analysis of the catchment in question, landscape classes and squared slope can be estimated. From the internal accounting of the mean SWE of the hydrological model, an estimate of the spatial variability, and hence the parameters of the gamma distribution can be calculated. This can be achieved without including any additional calibration parameters to the hydrological model.

6 Conclusions and outlook

At the local scale (10x10 m) we found no significant correlation between terrain parameters and SD. In order to investigate any possible correlation we aggregated our snow and terrain parameters to a larger scale. In this study we have aggregated the data to 500x1000 m (the approximate *seNorge.no* scale) since one of our goals have been to developed subgrid snow distribution for the *seNorge.no* snow model and other operational nation-wide models using the same resolution. A natural next step is to repeat this study for other spatial resolutions and for other regions. We demonstrated that the standard deviation of several terrain parameters are highly correlated with the standard deviation of SD. The terrain parameters, and the squared slope in particular, could thus be used to explain large parts of the spatial variability of snow. The collection of terrain parameters investigated in this study were highly correlated, which suggests that little additional information is gained by including more than one terrain parameter.

In order to establish which analytical statistical distribution best represents the SD distribution at Harangervidda, we analysed 48 empirical distributions, of which each consisted of approximately 4000 SDs. Visually, by inspecting Cullen and Frey graphs, and quantitatively, by Anderson-Darlington test and Kolmogorov-Smirov test, the Gamma distribution emerged as the most suitable distribution.

A correlation analysis showed that the observed, spatial standard deviation of SD at the chosen scale of aggregation was significantly correlated to the spatial standard deviation of the squared slope. In addition, the spatial standard deviation of SD was significantly correlated to landscape class (bare rock and wetland/forest) and to the mean spatial SD.

A model for the spatial standard deviation of SD has been proposed that takes into account the dependence of snowdepth variability to terrain roughness, landscape class, mean spatial SD and the non-linear relationship between SD variability and mean spatial SD. When validated against data from different years, the model explained about 85% of the observed variability of SD. With this model, the parameters of the Gamma distribution can be estimated. The Gamma distribution can hence serve as a model for snow distribution in hydrological models.

This exercise needs to be repeated for increasingly larger spatial scales so that model application for elevation zones of catchments or entire catchments is ensured. In addition, AL data from a different region (or a country) should be investigated to verify the generality of the method.

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