Energimyndigheten

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Energimyndighetens titel på projektet – svenska SNODDAS - Snödistribution och data assimilering för bättre vårflodsprognoser och hållbarare reglering av vattenkraftsmagasin	
Energimyndighetens titel på projektet – engelska SNODDAS – Snow Distribution and Data Assimilation for improved spring flood forecasts and sustainable hydropower reservoir regulation	
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Nyckelord: 5-7 st Vattenkraft, snövattenmängder, satellit, hydrologisk modell, snödrevsmodell, observationer,	

Förord

Projektet har främst finansierats genom ett stöd från Energimyndigheten, och samfinansierats från Uppsala universitet, Ångermanälvens vattenregleringsföretag, SMHI (samverkan med andra projekt), samt genom samverkan med Uniper, och Energiforsk AB. Vi är mycket tacksamma till HUVA och vår referensgrupp (Appendix 5) för utbyte av tankar, bollande av idéer, stöd, kloka inspel och data. Ett speciellt tack till Knut Sand, Statkraft, för organisationen av det första arbetsmötet, och med detta hjälpa till att sätta oss på rätt spår.

Innehållsförteckning

Sammanfattning

Sveriges nationella mål är att inom 20 år ha en elproduktion som är fossilfri. I Sverige står vattenkraften för en stor del av den fossilfria produktionen, och med optimering kan vattenkraftsproduktionen ökas. I vårt projekt har vi arbetat med att få ned osäkerheterna som finns inom vattenkraftsbranschen om hur stora snövattenmängder som ligger i fjällterräng, och hur man kan förbättra tillrinningsprognoserna till vattenkraftbranschens regleringsmagasin. Inom kraftbranschen räknar man med att vårflodsprognoserna kan ha en osäkerhet på 20 % i fjällnära terräng. Denna höga osäkerhetsnivå skapar förlust i potentiell vattenkraft om en del av smältvattnet måste spillas förbi kraftverkets turbiner då kraftverksmagasinen är fulla. Vi har med en ny metodik som vi tagit fram i projektet SNODDAS lyckats visa att man kan få ned osäkerheterna till 5 % med befintliga snöobservationer och förbättrade modeller. Detta skapar ett bättre planeringsutrymme för vattenkraften, och gynnar produktionen av hållbar elkraft. I vår metodutveckling har vi integrerat satellitobservationer och distribuerat och nedskalat dem till högre bildupplösning m h a markburna snöobservationer genom en maskininlärningsalgoritm, samt utvecklat en snödrevsmodul till det hydrologiska verktyget HYPE. All data har sedan assimilerats för beräkning av tillrinningsprognoser med lägre osäkerheter som direkt kan tillämpas av vattenkraftindustrin. Ett problem med vår metodik är att den till stor del bygger på manuella snöobservationer längs observationslinjer, vilket ger en relativt hög kostnad. I fortsatta studier vill vi undersöka om man kan ersätta de manuella observationerna med drönarmätningar som kan mäta över större ytor på kortare tid, vilket skulle kunna innebära att vår metod kan utvecklas för användning i industriell produktion i hela älvsystem.

Summary

Sweden's national goal is to have fossil - free electricity production within 20 years. Hydropower accounts for a large part of fossil-free production in Sweden, and with optimization of the prognostic tools, the hydropower production can be increased. In SNODDAS we have worked towards reducing the uncertainties of the snow water volumes that are stored in mountainous terrain, and by this aid towards improved forecasts of the filling rates into hydropower reservoirs. The hydropower industry currently estimate that their spring flood forecasts have an uncertainty of 20% in mountainous terrain. This high level of uncertainty creates a loss of potential hydropower if part of the melt water has to be spilled past the power plant's turbines instead of being used in production. With a new methodology that we developed in the SNODDAS project, we have succeeded in showing that it is possible to reduce the uncertainties to 5% with existing snow observations and improved models. This creates a better planning space for hydropower, and benefits the production of sustainable electricity. In our method development, we have integrated satellite observations and distributed and scaled them down to higher image resolution using ground-based snow observations through a machine learning algorithm, and developed a snow drift module for the hydrological tool HYPE. All data have since been assimilated for the calculation

of inflow forecasts with lower uncertainties that can be applied directly in increased production of hydropower. A problem with our methodology is that it is largely based on manual snow observations along observation lines, which results in a relatively high cost. In further studies, we want to investigate whether it is possible to replace the manual observations with drone measurements that can fly over larger areas in a shorter time, and provide extensive snow depth data. This will increase the possibility to realize our higher ambition, to provide a snow observation methodology designed to be for use in industrial production in entire rivers.

Inledning/Bakgrund

The national goal for energy production in Sweden is to by 2040 be free from fossil fuel, and such be powered by renewable energy resources. By this, the production from hydropower will likely be even more important in the national mix. An increase of hydropower can be achieved without a further exploration of new hydropower dams, as long as the production is increased within the existing hydropower plants. This can be satisfied by: 1), higher flux of water into the hydropower dams, and earlier onset of snow melt which is the prognostic trend in all the climate scenarios for the present century (www.smhi.se/klimat), and 2), higher efficiency in using the potential energy of the incoming water. Here we propose to increase the efficiency of hydropower production as an aid to meet the increasing demands of renewable energy. Due to its large capacity to store potential energy, hydropower is the battery of the national power grid. As the only renewable energy system that presently can store large amounts of potential power for a longer time frame, hydropower will be even more valuable to balance the growing and more volatile parts in the renewable mix, such as solar and wind power. Hydropower will play a key role in the future as a regulator in a future flexible and robust green energy system. One of the challenges for the hydropower industry is to predict the spring flood volume. Knowledge of the melting volumes are important for several reasons, as for dam safety, to be able to follow the regulation rules set up for each reservoir and to regulate the flow in a way that as much as possible will prevent damage on the environment and the public interest of river flow and water levels. Directly related to economic gain by the forecasts is the optimization of the hydropower production. The challenges to optimization rest on two main questions, one part is to achieve better knowledge of the potential production, and another part is the optimization of production during spring flood by minimizing the total spill beside the turbines. Spilling occurs when the inflow of water to reservoirs and rivers from snowmelt and rain is larger than what can be used for power production or can be stored in the reservoirs on a short-term basis. To avoid spill, hydrological forecasts are used to plan the power production on both shorter and longer time horizon, so that the remaining filling capacity in the reservoirs at any time during the snow melt period is large enough for the remaining accumulated snow water storage when it melts. The uncertainties of the total amount of snow water storage in the catchment, and its distribution in the catchment cascade the uncertainty of the water flow into the dam. In our estimates, the spill (loss) of potential energy one anomalous year (2015) due to high inflow amounted 1 % of the net production in Umeälven. This number will vary between rivers and river parts due to difference in buffer capacity, but if we use this number as an average it will build up to significant numbers of lost energy production. It is not likely all of the spill can be avoided, but even a fraction of this will be a gain in the production of renewable energy. A further motivation to better manage the snow storages is the fact that anomalous melt / precipitation patterns seems to get more usual due to the warming trend, and such the melt season is gradually changing from a more finite period into something more like a continuum, or a series of episodes, which makes the characterization of snow storages ever more important for planning purposes.

The estimation of snow water volumes has been a continuous enigma in mountain hydrology (Peck, 1972; Blöschl, 1999; Dozier et al., 2016). Many different methodologies and techniques have been tested and taken forward. With enough instrumentation, a catchment can be monitored; However, due to the inhomogeneous character of the snow cover, it is not economically feasible to cover enough area with instruments. Passive microwave remote sensing has been often used for large-scale snow mass monitoring, but rugged mountain terrain and the failure of current passive microwave sensors to estimate SWE in snow depths > 1 m (Chang et al., 1987; Pulliainen et al., 2020) have posed large obstacles to adopt a methodology solely reliant on satellite observations. One way to remedy the lack of a single standard method to monitor/measure the SWE is to use statistical methods such as assimilation techniques, where different sort of data will be homogenized into a statistically product for a best estimate of the SWE (Magnusson et al., 2014), and/or using machine learning for optimal distribution of patchy high resolution data to nudge well distributed, but low resolution data (Zhang et al., 2021).

In our SNODDAS project we aim to utilize the full power of data assimilation and machine learning to combine manually derived observation data with remote sensing products from both drone and satellite platforms, combined with weather model products to produce transient snow volumes products over our test period 2017-2020 for the Överuman catchment. The project was financed from The Swedish Energy Agency 2018-2021.

Genomförande

OBJECTIVES

The main goal of the project is to improve the spring flood forecasts by developing a methodology for more accurate determination of the snow water equivalent (SWE) reservoir. The project´s aim is to improve the forecasts of the routing of water to an uncertainty better than 10% in mountain catchments, and with this reduce the current uncertainties for inflow into the hydropower reservoirs. Our expected outcomes for the project were to:

1) develop a methodology that systematically integrate information from available remotely sensed snow products and terrestrial snow

measurements as inputs to models for snow and spring flood forecast, with the aim to reduce the part of the spring flow forecast error due to uncertainty in the size of the snow reservoir to below 10% on average, or better.
2) develop a method to determine the volume and distribution of the snow reservoir within a defined catchment and such be well adapted to the needs and the usability for the power industry.
3) broaden the existing forum in the field within Scandinavia to exchange experience and knowledge with regard to snow reservoirs and routing into hydropower dams.

The motivation for this project was the fast development in measurement technology and data assimilation, resulting in a greater precision in the estimate of the spatial distribution of snow and the total water content in a given snow reservoir. The purpose of the project was accordingly to take advantage of the methodological development and apply this where the hydropower industry currently has large uncertainties to determine robust prognosis of the spring flow, decrease these uncertainties, and such enable an increased production of green energy for the society.

This main goal is parted with the following sub-goals, where we aim to:

a. Develop an improved methodology for measuring snow depth and snow water content in montane catchments using ground-bound and remote sensing measurement methods with the aim of reducing uncertainties of snow water volumes .
b. Develop an improved methodology for assimilating satellite and ground-bound measurements in distributed snow models to by upscaling the low-density microwave imagery satellite information using high density data from other sources.
c. Improve our preferred snow model with a snow drift module, to better represent how wind and topography influence the snow distribution. This part will in combination with a) and b) aid to increase the forecast certainty of the inflow.
d. Develop methodologies that can be freely implemented in the various water routing forecast models used.
e. Evaluate the extent to which an improved snow volume forecast can contribute to a more resource-efficient regulation of hydropower dams with regard to established environmental requirements and production optimization.
f. Evaluate the extent to which assimilation of the snow reservoir's water content improves the spring flood forecast as compared to other uncertainties that affects the hydrological routing modeling.
g. Initiate a Scandinavian forum for experience in the field of snow measurements and the use of snow measurement information (instruments, techniques, methods and tools) which would mean increased co-operation in R&D between academy, research institutes and industry.

PROJECT GROUP
The project was carried out as a collaboration between Uppsala University, SMHI, Vattenregleringsföretagen, Uniper and Vattenfall, and disseminated by Energiforsk's program for hydrological development in the hydropower industry (HUVA). People active in the project and their role were:

Uppsala University (UU): Prof. Veijo Pohjola*, snow expert and project leader; Dr. Rickard Pettersson, technical expert on snow measurements from ground measurements and UAV technology; Dr. Jie Zhang, remote sensing and machine learning expert. BSc Viktor Fagerström, UAV/drone engineer. UU was responsible for producing high-resolution data from remote sensing techniques of the snow volume distribution in the test areas.
SMHI: Dr. David Gustafsson*, hydrologist and expert on modeling snow packs and hydrological routing, as well as data assimilation techniques. Dr. Ilaria Clemenzi, hydrologist and snow pack expert, responsible for implementing the snow distribution model and hydrological model calibration. SMHI was responsible for snow distribution modeling, data assimilation, runoff modelling into the dam, and for assessment of the economic value of our improved modeling efforts.
Vattenregleringsföretagen (VRF): Björn Norell*, hydrologist and expert in snow observations and our primus motor providing the links between academia, institutes and industry. Also responsible for snow assessments and the annual field campaigns under the auspices of VRF, and is the project's contact person for Uniper, Vattenfall, and Energiforsk (HUVA) and the other hydropower companies. Dr. Wolf Marchand, SWECO, snow radar expert, hired by Vattenregleringsföretagen to maintain the snow radar observation of snow depths in the annual campaigns at Överuman.
(names with asterix are those who have the main responsibility to SNODDAS in each of the organizations).

WORK PACKAGES
Work package 1: Ground-based snow observations.
Observations of snow depth (SD) and snow water equivalent (SWE) volumes in the Överuman catchment. This WP engaged all three partners, where VRF carried the main responsibility for the field operations, and in particular for the ground-based snow line surveys, UU managed the UAV/drone-based observations/validations, and SMHI the snow drift observations/validations. Our industry contacts provided us snow observation data from two other catchments we used further in our assessment of our methodology.

Work package 2: Snow cover modeling and data assimilation.
Modeling of the distribution of SD and SWE in the terrain with assimilation of satellite and ground-based observations: a). *Satellite data module* - development of a methodology to estimate downscaled distributions of SD and SWE from satellite microwave imagery (UU); b). *Distributed snow modelling module* - development of a distributed snow model for integration in hydrological models, and for assimilation of distributed snow observations (SMHI); and c). *Data*

assimilation module - development of a data assimilation scheme to enable assimilation of the distributed snow data developed in WP1 and in WP2 a) in the snow model developed in task b (SMHI).

Work package 3: Hydrological model forecasting and snow data assimilation.
Assimilation of snow data in hydrological models and hydropower reservoir inflow forecasting: The data assimilation methods developed in WP2 were adapted to hydrological modelling, to enable assimilation of the ground and satellite-based snow data from WP1 and 2 in spring flood runoff forecasting models. The objectives of the work package were twofold: a) to develop and demonstrate a set of data assimilation methods that could be applied in the hydrological models available to the hydropower industry, and b) to assess the degree of improvement in spring flood forecasting skill gained by assimilating the snow data developed in WP1 and WP2 compared to traditional and climatological forecasting methods. First, we compared the direct updating methodology used by VRF to assimilate the ground-based snow survey data in the HBV model to the more advanced Ensemble Kalman data assimilation scheme available in the HYPE model used by SMHI. Secondly, we assessed the added value of assimilating the snow products from WP2 compared to the original snow data from WP1. In all cases, the improvement in spring flood forecasts were compared with the degree of improvement in the assimilation of other available satellite-based snow products. In addition, the choice of snow model complexity, and the snow model calibration strategy was further assessed as part of the spring flood forecasting experiments.

Work package 4: Evaluation.
Evaluation of how the improved spring flood forecasts can contribute to a more resource-efficient water management with regard to both production optimization and established environmental requirements. Within H2020 IMPREX, SMHI has developed a simplified economic model for comparing the production value of different spring flood forecasts, considering current production capacity, degree of filling of the reservoirs, and established rules for degree of filling and bottling. This model will be further developed to include different types of environmental requirements that may limit regulation in the magazines. The work package will develop a method for estimating at a given location the degree to which the uncertainty in the spring flood forecast depends on the start condition (snow information) compared with the weather development during the spring flood period. This knowledge can be used to assess the value of adding information from snow measurements at this site, and is partly a co-financing through the IMPREX project.

Work Package 5: Delivery.
This work package is the dissemination of our results, including scientific publications, dissemination and discussion of our results with the scientific society and the hydropower industry as well as our reporting to the Swedish Energy Agency.

Resultat

Specific results per work package:

WP1 Ground-based snow observations

Methods: snow profiles, control points using snow density samplers and snow probing, continuous snow density using snow mobile pulled ground penetrating radar (GPR), SMHI snow depth observations at Mjölkbäcken, airborne drones produced snow depth (SD) using photogrammetry 2020.

Frequency: Snow profiles one week per year à 2 years within SNODDAS framework (2019, 2020), but Vattenregleringsföretagen started these surveys 2017, and maintained the observations also over 2021. Drone observations was only performed 2020 as a test of the concept.

Method development: testing the accuracy of different snow tubes, developing new hard and software för the GPR system by SWECO, contracted by Vattenregleringsföretagen to manage the snow profile radar observations, testing how efficient drone platforms combined with photogrammetry are to observe SD, and testing if Lantmäteriets laser data is a useful data base to make a snow free DTM, and such cut costs of the observations.

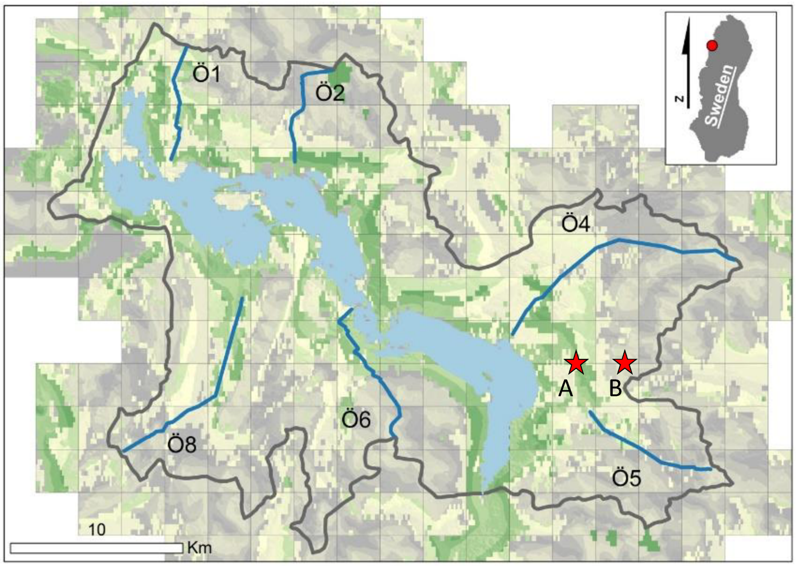


Figure 1. The Lake Överuman catchment (650km2) in northern part of Sweden, its upper part of Umeälven river. Watershed boundary is shown with thick black line, and snow courses by blue lines. The rectangular grid (2.5x2.5 km2) represent the hydrological model sub-catchments as used in the gridded model setup, extending to a buffer area of about 12.5 km outside the watershed (to enable assimilation of SWE data of coarser resolution). The red starts mark the two sites we mapped using drones 2020.

Energimyndigheten

Snow courses

The HBV model has been used by the hydropower industry in the Nordic countries since the 1970th for short- and long-term inflow forecasts to regulated dams to enable management and optimization of water regulation and power production. As input the model has data on precipitation and temperature from meteorological stations. By calibrating the output (inflow) against measured inflow the model is used for calculation of inflow to the dams along the river and by use of meteorological forecasts the model gives predictions of inflow up to one week in advance and long-term forecasts are made by use of weather statistics.

In mountainous areas the meteorological network is often very sparse, which affects the accuracy of the model. The upper part of river Umeälven is a good example where the lack of weather stations is noticeable. Due to the uncertainty of the spring flood forecasts of lake Överuman the water management during the last years has caused both uncomfortably high and low water levels after the end of the melting period. Therefore, in 2017 Umeälvens Vattenregleringsföretag started a snow survey program to enhance the model spring flood calculations. During 2019 – 2020 the measurements were made in cooperation with SNODDAS and 2021 it was included in the Vinnova SnowSat project.The Överuman catchment cover 652 km^2 of mountain terrain spanning from 524 to 1575 m a.sl.. The lower part of the catchment is covered by birch forest, which compose ca 31 % of the total area (Figure 1).

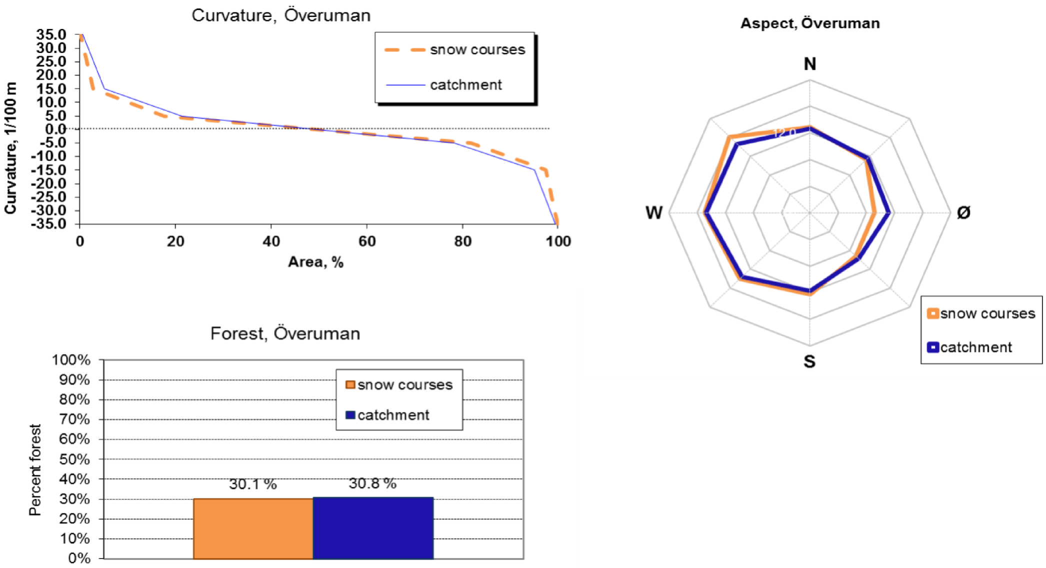


Figure 2. Assessing the representativity of the snow courses with the general topography of Överuman (also refer to Appendix 9).

The measurement program was set up by Wolf Marchand at Sweco Norway, with snow courses selected to represent the terrain of the catchment area in terms of slope, aspect, curvature and areal representation as well as the representation of the forested area. In Figure 2 the representation of some of the parameters are shown. The annual campaigns mapping the snow properties along the snow lines used a snowmobile pulled ground penetrating radar (GPR) system developed by Wolf Marchand at SWECO, managing a continuous record of snow depths along the lines. The observations were completed by a team following the GPR unit, that stopped at a series of snow observation points, were the snow depths were probed, and the snow density was measured by bulk samples. There are totally 70 observation points spread along with an even distance along the eight observations lines (Appendix 6). The snow measurements were performed during field campaigns, once per year, close to the start of snowmelt by accurate snow depth radar measurements and manual sampling of density. The eight snow courses together have a total length of 75 km. Table 7:1 in Appendix 7, show the properties of the snow lines.

Snow depth
The measurements of snow depth were made by ground penetrating radar (GPR) with the measuring equipment mounted on a sledge. During the measurement the GPR transmitter sends a diverging beam of energy pulses into the subsurface and the receiver collects the energy reflected from interfaces between media of differing electrical properties. The large contrast between the snow and the underlying base (*e.g.* soil, rock and ice) makes it possible to effectively measure the snow structure (Ragulina et al., 1995).

The snow depth is calculated from the two-way time (TWT) by:

$$SD = \mathrm{v}\frac{\mathrm{TWT}}{2}$$

where v is the velocity of the radar pulse.

For dry snow v can be estimated by an empirical formula of the relative real dielectric constant for snow, which is dependent on the specific density of snow (Kovacs et al., 1995). Therefore, the snow depth calculations are dependent on good estimates on the snow density.

To be able to verify and calibrate the radar signal the snow depth is checked manually at specific control points. The control points, a total of 72, are located at each kilometer with the coordinates located from the map which means that they are randomly distributed regarding the snow conditions. A plot of all snow depths is shown in Appendix 1.

The reason why the snow depth measurements is prioritized with such a number of samples is the natural variation of the accumulated snow. According to the measurements the range of snow depth along the snow courses normally is between zero and 5-9 m (Appendix 7, Table 7:2). Snow course #6 usually have the deepest snow with the highest value 2018 when 10,2 m was found. Courses #2 and #7 have the highest mean value, but also the highest variation of the mean value. All together the variation of snow depth is 64 % of the mean value.

Snow density
By use of a McCall snow sampler the snow density was sampled at each control point along the snow courses. The sampler is pushed preferably through the whole

snowpack, the snow depth noted on the sampler and a snow core taken up and weighed. Care must be taken not to lose any snow before weighing.

With density measurements at different snow depths at the control points the relationship between the snow depth and the density can be determined. The relationship is then been used to interpolate the density to every radar point along the snow course. By taking an additional sample to a-bout the half snow depth at sites where the snow is deeper than 2 m this relationship can be further accurately established. Normally the density is between 350 and 550, where the highest values mostly are found in very deep snow. The maximum allowed density in the interpolation is 600 kg·m^{-3}. The density variation (standard deviation) is 8 % of the mean density, which defends the sparse number of density measurements in the survey, compared to the depth sampling.

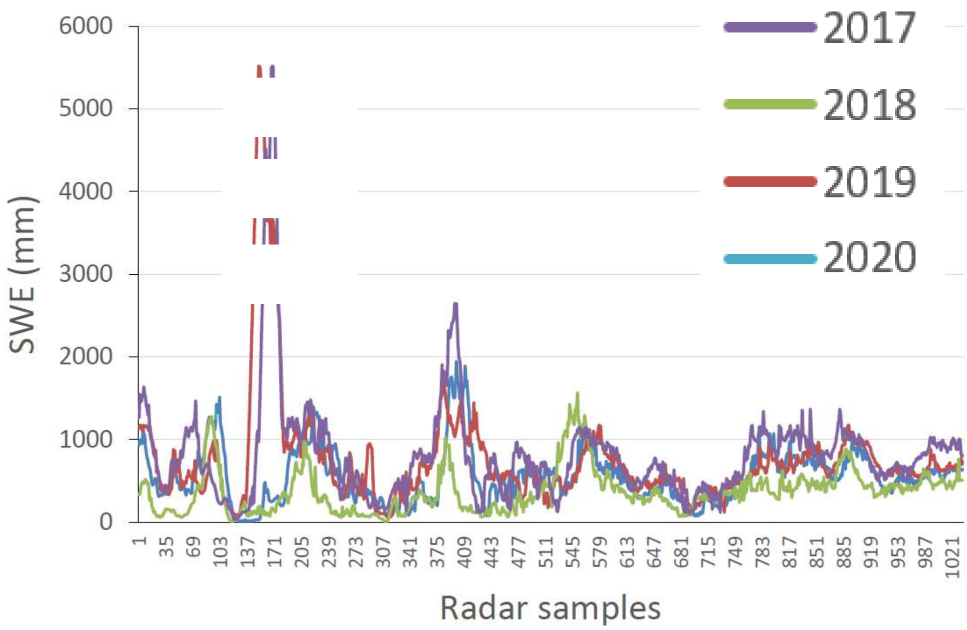


Figure 3 show the SWE along snow line 1, which is situated in the northeastern corner of the catchment (Figure 1). Data from all of the lines and all of the years are shown in Appendices 1 and 2. The dashed distribution between radar samples 120-180 are values we do not trust.

Snow water equivalent

The direct purpose of establishing the measurement program was to give additional data of snow water equivalent (SWE) for updating of the operational HBV inflow forecasting model. An additional goal was also to gain data for the continuation of the development of hydrological tools for hydrological forecasting models. The SWE is the amount of water received in a defined area of the snowpack calculated by multiplying the relation between the snow density and the density of water with the snow density:

$$SWE = \frac{\text{density snow}}{\text{density water}} \cdot \text{SD}$$

where the density of water = 1000 kg·m^{-3}.

Snow course #8 was not measured in 2018 and #3 and #7 not measured in 2019. The calculations of the total SWE in the catchment is dependent on all eight snow courses and the missing measurements has been completed by estimations, where the factor of the mean snow depth divided by the total SWE the earlier years was used. The measurement system has been set up and evaluated with all snow course samples together, which means that the length of the snow courses should be included in the calculations if the mean values of the snow courses are used. The result of the snow measurements during the five years show an accuracy between ±5 % of the value of an updated model.

Statistics on the SWE data is shown in Appendix 7 (Table 7:4). As in the snow depth data it is apparent that the variation in the yearly maximum is much bigger in snow course #1 than in the other snow courses. The variation (standard deviation) among the SWE data is bigger than among the snow depths, 0,77 % of the mean value.

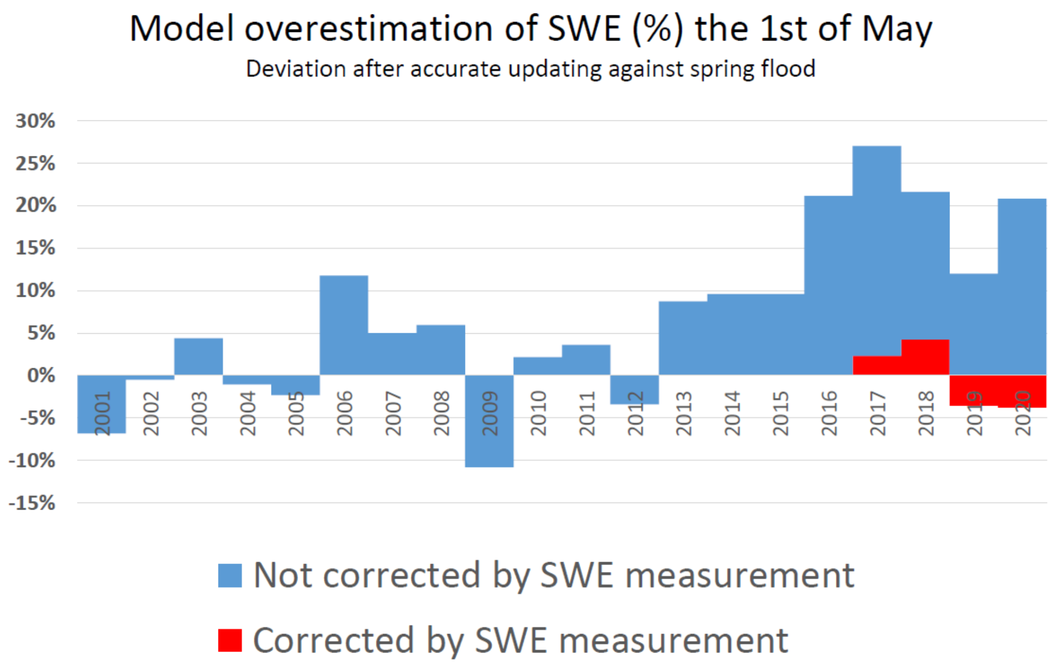


Figure 4. Overestimation of the model simulated SWE in percent of the value in the model after updating the snow to give the same inflow volume as the measured spring flood.

<u>Calibration of filling rates using snow course SWE</u>

The simulated snow storage in the operational inflow model was each year corrected directly after obtaining the measurement result. Figure 4 show an evaluation of the error in the HBV simulated SWE the 1st of May, which is the date of the last spring flood forecast. The blue bars describe the error without snow correction and the red bars with correction. The comparison was made against the same model after correcting the snow storage to give the same simulated spring flood inflow volume as the measured volume.

Snow observations from UAV

One problem with the snow line observations is the cost of manpower to maintain them. It takes about 3 days to cover all lines assuming good weather, using three or more in personnel. To save time in manpower we tested if we could use airborne drones/UAVs to get air photography from a part of the snowline, and by photogrammetry derive snow depths over the flown area. We used the drone technology during the campaign 2020 over two test areas between snow line 4 and 5 (Figure 1) at ca 800 (site A, steep terrain, some vegetation) and 950 (site B, tundra) m a.sl. Both tests covered an area of ca 0.16 km^2.

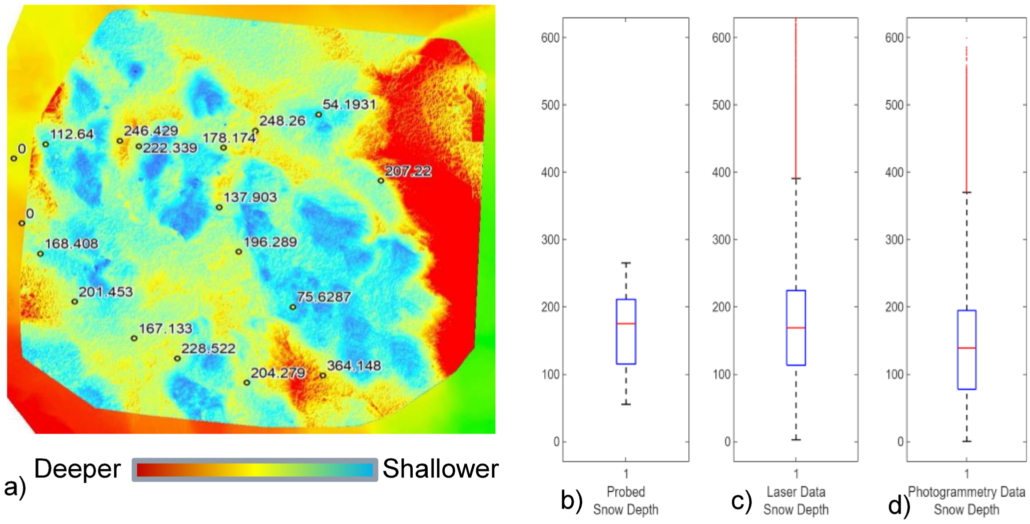


Figure 5. a) snow depths (SD) from UAV flown photogrammetry on site B, The numbers modeled snow depth of this site in cm SD. b) show the distribution of SD from the manual probing c). show the distribution of SD using laser data from Lantmäteriet as the snow free DEM. d) show the distribution of SD from the using UAV summer data as the snow free DEM.

<u>Methodology</u>

Digital elevation models (DEM) from photographs captured with Unmanned Aerial Vehicles (UAVs/Drones) were tested to extend the snow depth data from the snow lines. We used a DJI Matrice 210 V2 drone with a high-resolution camera as payload, providing high resolution imagery (2cm/pixel) data over small to medium sized areas at relatively fast speed. The flight speed was ca 15 km/h, giving a flight time of about 15 minutes over each area. Total time spent at each test area was 1.5 hours, where unpacking/packing up the equipment, probing for snow depths, and measuring the position of a set of control points of the grid using geodetic GPS were the more time-consuming parts of the operation. Overlapping photographs were used to calculate a photogrammetric 3d point cloud model of a surface using the Pix4Dmapper software. The Matrice 210 V2 drone was a stable platform even up to 12 m/s wind speeds as well during both cold winter condition and rainy September weather. Major problem with the flights was the somewhat short flight times due to the size of the batteries and the cold weather which decreased the capacity of the batteries to some degree, and hence restricting the flight times to 20-30 minutes and approximately 0.5km^2 of coverage.

We flew over the two test surfaces A and B during the spring campaign March 2020 to get the winter (snow) surface DEM (H_w) and repeated the same mission in September to get the bare ground surface DEM (H_s). The snow depth (SD) was then calculated by subtracting the winter surface from the summer surface for each coordinate, such as SD = H_w–H_s. During the spring campaign we also managed manual probing for validation of the drone derived snow depths. In addition to these measures, we also tested if it was possible to use the airborne laser data DEM from Lantmäteriet (H_L), to assess the cost of lower uncertainties by having two sets of campaigns. Similarly, the subscript U denote UAV borne measurements.

<u>Results</u>

Figure 5a show the calculated snow depths from test area B using H_s as reference.,with the point measurement of H_{Uw} at the exact spot of the manual probing. The number of probings on this site were 18, and the distribution of the probing, with an average snow depth of 1.61 m is shown in the boxplot 5b. The distribution of the calculated SD from the UAV survey generated a point cloud of 2 10^5 data points using H_{Ls} as reference and 5 10^7 data points using H_{Us} as reference. The distribution of these data clouds is shown in Figure 5c and 5d respectively. Table 1 present the data from the study of the two test areas.

Table 1. Statistics from the different methods to derive snow depth (SD) in the two test areas A and B. The subscripts P, L, and U, mark manual probing, H_L, and H_U respectively. We used the nearest point of L and U to P here.

	Site A	n	$\dot{X}$	σ	**Site B**	n	$\dot{X}$ (m)	σ (m)
SD_P		8	0.74	0.52		18	1.57	0.64
SD_L		8	0.85	0.79		18	1.76	0.71
SD_U		8	0.73	0.75		18	1.69	0.66

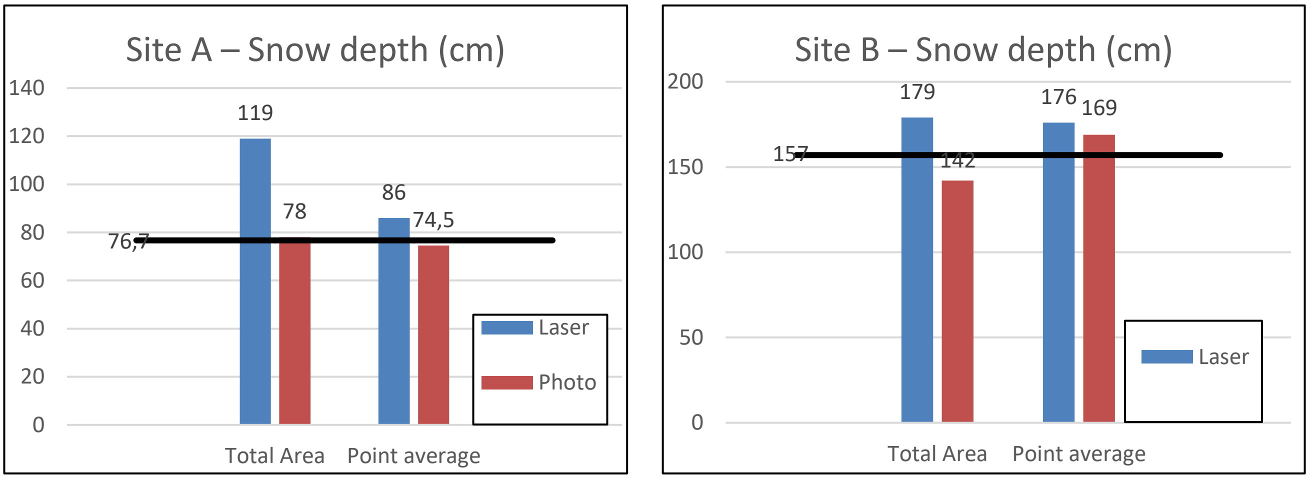


Figure 6. Assessment of UAV derived snow depths (SD). Both panels show the average SD using the two different models for the snow free surface H_{Ls} (blue)and H_{Us} (red)), compared to the probed average SD. The averaged SD data is shown both as total average and an average of model data only at the probed positions.

Figure 6 and Table 1 summarizes the results from our test campaign using UAV/drone as a tool to collect snow depths over an extended area. Figure 5 show the average SD using the two different models for the snow free surface (H_{Ls} (blue)and H_{Us} (red)), compared to the probed average SD. The averaged SD data is shown both as total average and H_{Us} at the probed position. This shows a relatively good comparison of the modelled SD with comparison the probed SD. Using H_{Us} brings a significant better fit with probed SD than H_{Ls} does. Not surprising, there is a generally better fit using the point average modelled SD at the probed points, rather than using a total average of modelled SD using all data. The better fit using H_l in Site B than in Site A can probably be explained by the fact that the airborne laser data from Lantmäteriet may have larger uncertainties in the steep terrain with more vegetation than in the tree free tundra land unit at site B. It seems from this study that the cost for taking forward a snow free DEM using UAV for reference has a better argument in more complex terrain/land cover, than in terrain with simpler cover. The conclusion of this study is that UAV borne photogrammetry provide a good and reliable tool to estimate snow depths, even in complex terrain, and prove a good tool to measure/monitor the snow cover and the snow depth distribution over larger areas.

WP2 Snow cover modeling and data assimilation

Summary: The snow cover of the Överuman catchment was modelled in several steps, and using a set of methodologies over the period 2017-2020: 1. The GPR observations from WP 1 was re-gridded and used as input in all the steps below; 2. In the satellite data module we used passive microwave (AMSR2) data as a proxy for snow amount (SD/SWE) in combination with the ground observations to calculate the distribution of the snow pack using a machine learning application to 500 m resolution for the field observation week as a control point 2019 and 2020; 3. We further downscaled the Copernicus SWE product to 500 m resolution over the catchment to create a continuous satellite product with daily resolution between 2018 - 2020; 4. In the snow model module, a distributed snow model was developed and implemented in the hydrological model HYPE. The snow model simulates SWE distribution as a result of the spatial distribution of temperature, precipitation, including an explicit snowfall distribution as a function of wind direction and topographical sheltering effects. The model was calibrated using the snow GPR data from WP1 and reservoir inflow data, using a novel methodology for calibration considering the snow distribution characteristics; 5. the data assimilation module of the HYPE modelling system was further developed to enable assimilation of the different datasets of distributed snow information developed in the project and developed in other parallel projects, including the GPR survey data from WP1, the machine learning SWE and downscaled satellite-SWE data from WP2, fractional snow cover data from the European Space Agency projects Snow CCI and AI4Arctic, and from the EU FP7 CryoLand project.

Satellite data module

Introduction

Due to inaccessibility and a lack of ground measurement networks, accurate quantification of snow water storage in mountainous terrains still remains a major challenge. Remote sensing can provide dynamic observations with extensive spatial coverage, and has proved a useful means to characterize snow water equivalent (SWE) at a large scale. However, current SWE products show very low quality in the mountainous areas due to very coarse spatial resolution, complex terrain, large spatial heterogeneity and deep snow. More information on factors that impact the snow distribution, such as topography and vegetation (Dong et al, 2005; Stähli and Gustafsson, 2006; Veitinger et al., 2014), should be incorporated to improve the mountain SWE retrieval from satellites.

Different from traditional statistical methods, machine learning techniques are able to reproduce nonlinear effects and interactions among variables and are also robust to overfitting (Hastie et al., 2009, Alpaydin, 2020), and provide great potentials for better explaining the complex snow processes in the mountain environments. Random forest regression is an ensemble machine learning technique based on multiple decision trees to get more accurate and stable predictions (Breiman, 2001; Segal 2004; Hastie et al., 2009). Compared with other machine learning methods, random forest regression shows its advantages due to its high interpretability and ability in reducing overfitting, measuring feature importance, and dealing with smaller sample sizes.

We explored the potential of random forest regression for improving the estimation of mountain snow water storage in the Överuman Catchment, using satellite observations, topographic factors, land cover information and ground SWE measurements from the spatially-distributed snow survey in WP1. A random forest regression model for SWE estimation was developed and then applied to the entire catchment for per-pixel SWE estimation. For comparison, a multiple linear regression model using the same input parameters was also developed in parallel for spatial SWE estimation.

In addition to machine learning approach, to ensure the continuous monitoring of snow amount during the entire snow season, we have also used another approach based on snow distribution probability derived to downscale the current existing Copernicus SWE product, thus leveraging the temporal coverage and daily temporal resolution of Copernicus SWE product and at the same time increasing the spatial resolution. The work implements the downscaling based on the snow distribution probability derived from the climatological snow cover duration. The overview of those two approaches are described below.

Machine learning approach

Methods: A machine learning (random forest regression) model is developed to improve the estimation of mountain snow water storage in the Överuman Catchment (Figure 7).

Frequency**:** The method is developed based on the ground truth data collected during the field campaign, and thus follows the frequency of field campaigns.

Method development: first time:The method uses a machine learning approach, by integrating satellite observations, topographic factors, land cover information and ground SWE measurements from the spatially-distributed snow survey in WP1. To our knowledge, this has been the first efforts that the machine learning approach has been introduced for improving the quantification of snow water storage in Swedish mountain catchments from satellite and ground observations. To further test the method, we have also applied our model in another hydropower catchment (Ankarvattnet/Blåsjön).

Outcome: Spatial distribution of SWE in the Överuman Catchment close to the peak of snow accumulation at 500m resolution., and spatial distribution of SWE in the Ankarvattnet/Blåsjön Catchment close to the peak of snow accumulation at 500 resolution

Evaluation/comments**:** Advantages: the method shows improved SWE estimation in terms of both spatial resolution and accuracy, demonstrating great potential for regional applications (especially in areas with large spatial heterogeneity like mountains). Limitations: limited frequency constrained by the frequency of ground truth from field campaigns

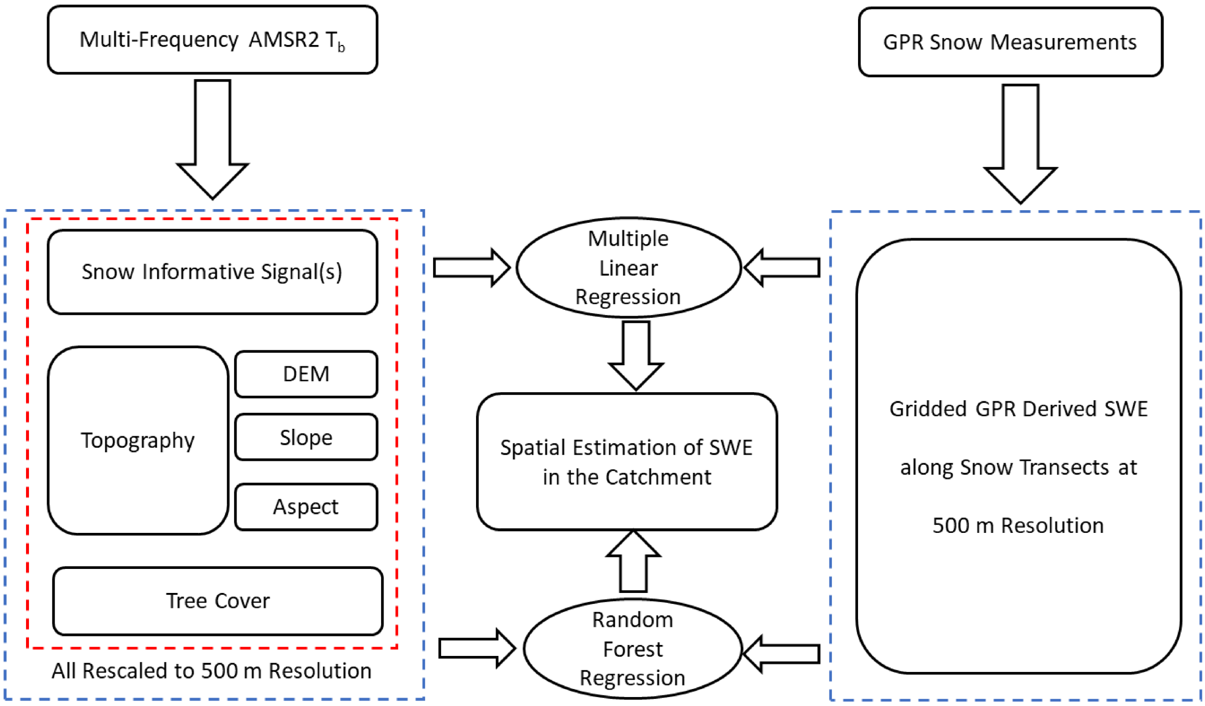


Figure 7. Flowchart of machine learning based SWE estimation.

SWE downscaling from snow distribution probability

Methods: The coarse resolution SWE product is downscaled based on the snow distribution probability derived from the climatological snow cover (Figure 8).

Frequency: The downscaling is based on Copernicus SWE product, and thus follows the frequency of original Copernicus SWE product (daily).

Method development: The work implements the downscaling based on the snow distribution probability derived from the climatological snow cover duration (SCD), similarly with Mhawej et al. (2014). The climatological SCD is calculated from multi-year MODIS (Terra and Aqua) snow cover fraction (SCF) product (2002-2019) using cloud computing platform Google Earth Engine, which is closely connected with the work presented in Appendix 3.

Outcome: Spatial distribution of SWE in the Överuman Catchment at 500m resolution (0.005 degree) and daily intervals during the snow season 2018-2020.

Evaluation/comments: Advantages: improved spatial resolution (500m), good temporal resolution (daily) and long temporal coverage (during the snow season); Limitations: uncertainty of SCD from frequent and continuous cloud coverage, underestimation is intrinsic in the original low resolution SWE product and data gap due to water, mountain and glacier masks or missing values from the original low resolution SWE product

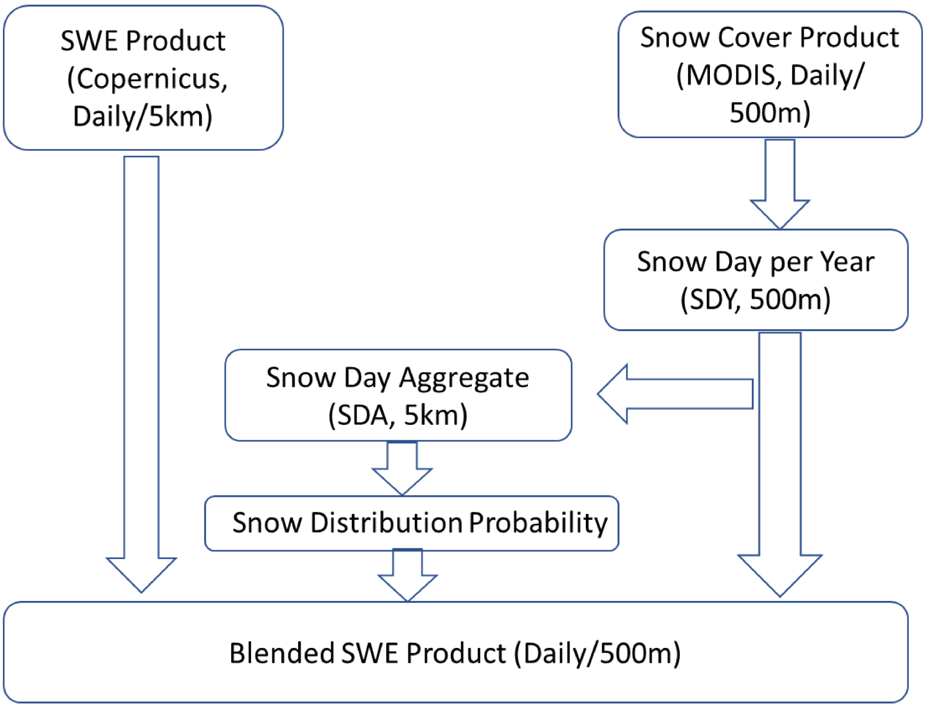


Figure 8. Flowchart of snow distribution probability based SWE downscaling

<u>Results satellite module-SWE estimation from machine learning</u>

Figure 9 shows the spatial distribution of SWE in the catchment during the 2019 field campaign period as derived from the random forest regression and multiple linear regression. As seen from Figure 9, the random forest regression can describe SWE at a much larger range, which is more consistent with the ground truth based on the field campaign and demonstrates its better ability for deep snow characterization. The relationship between predicted and measured SWE for the validation dataset also demonstrates that the random forest regression can yield much improved SWE estimation as compared to the traditional multiple linear regression, in terms of both r^2 and RMSE (much higher r^2 and lower RMSE). The results show that significantly improved SWE estimation close to the peak of snow accumulation can be achieved in the catchment using the random forest regression, demonstrating the potentials of machine learning for better understanding the snow water storage in mountainous areas. For more details of this machine learning based work, please refer to Zhang et al. (2021).

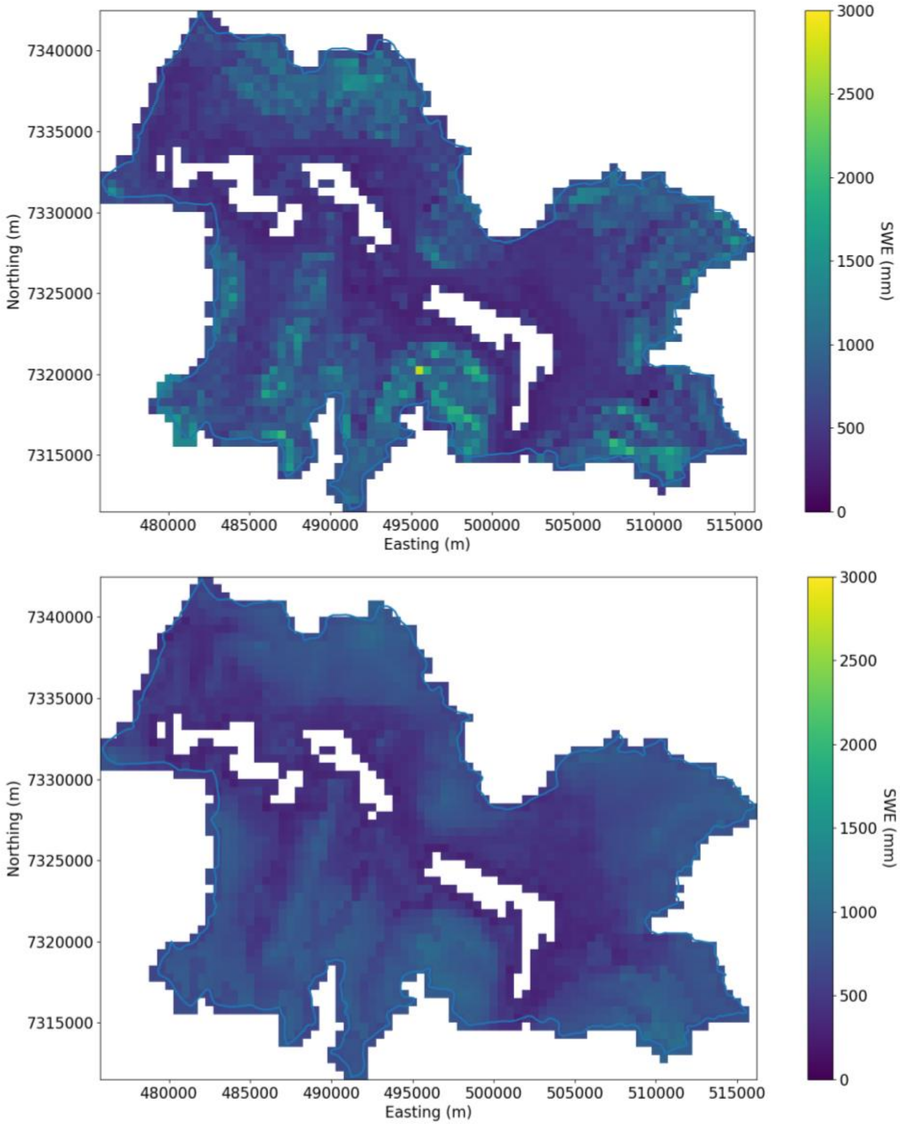
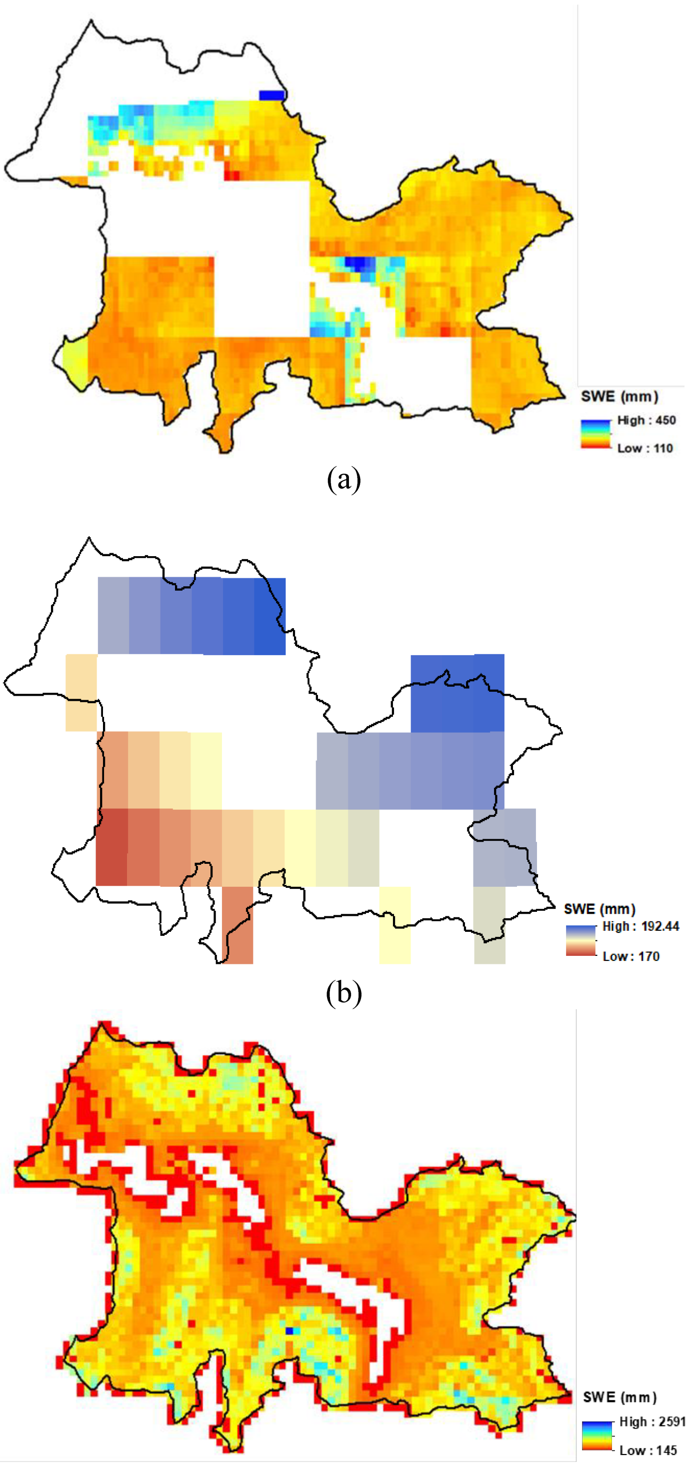


Figure 9. SWE distribution in the Överuman Catchment from random forest regression (upper) and multiple linear regression (lower) 2019-03-27.

<u>Results satellite module-SWE downscaling from snow distribution probability</u>

Figure 10a shows the spatial distribution of SWE in the catchment during the 2019 field campaign period as downscaled from the Copernicus SWE product, and a comparison with the original Copernicus SWE product (Figure 10b) and the SWE product based on machine learning approach (Figure 10c). As seen from



(c)

Figure 10. Spatial distribution of SWE on 20190327 in the Överuman Catchment from (a) downscaled Copernicus product (b) original SWE product and (c) machine learning approach.

Figure 10, in addition to the coarse resolution and a lot of missing data, the original Copernicus SWE product also shows severe underestimation in the mountain areas. The downscaled Copernicus SWE product shows much improved quality in term of spatial details and higher SWE values, but still have significant missing data and underestimation.

HYPE module

Methods: dynamic snow pack mass balance modelling integrating meteorological information such as time-series of air temperature and precipitation to produce timeseries of snow water equivalent, snow depth, and snow density, and snow melt runoff averaged and distributed over the hydropower reservoir catchment.

Frequency: Daily

Method development: 1. a snow fall distribution model implemented in the HYPE hydrological model, 2. Observational operators for assimilation of the distributed SWE, SD, and fractional snow cover data in HYPE, 3. Objective criteria functions for calibration of snow distribution using high resolution snow survey SWE data,

Outcome: 1. a lumped and distributed setup of the HYPE model for the Lake Överuman catchment, calibrated with the local runoff data and the GPR snow survey data (Clemenzi et al, in prep.), 2. New knowledge about the relative importance for simulation of snow melt runoff of a. how snow distribution is represented in hydrological models, b. how snow distribution is taken into account in the model calibration, and c. by preserving spatial distribution in the meteorological data versus aggregating to the catchment scale (Clemenzi et al, in prep.)

Evaluation/comments: Anticipated improvements in snow distribution modelling and utilization of distributed snow data for model calibration and for data assimilation were achieved according to plan. Direct assimilation of raw microwave emission observations in the snow hydrological models are still limited by the simplified representation of the land surface physical processes in our models, and need further developments to be completed as initially planned.

<u>Introduction</u>

Accurate predictions of water volumes stored in snow and released during the spring flood are fundamental in regulated catchment for hydropower production. In order to improve the predictions of snow water equivalent and spring flood volumes in the Överuman catchment, we developed a novel approach to represent the spatial distribution of snow produced by precipitation, topography and wind at catchment scale. This modelling approach was included in the semi-distributed hydrological HYPE model (Lindström et al., 2010).

The HYPE model consists of several routines where the different hydrological processes, e.g., snow accumulation and melt, soil processes, evaporation, and runoff, are described. The landscape can be divided in different units (sub-basins) and each unit into sub-units which represent different soil and land use classes (e.g., forest, open land), linking the landscape characteristics to the physical processes by means of the model parameters.

In the standard HYPE snow distribution is implicitly represented in the function used to calculate fractional snow cover, the snow depletion curve by Samuelsson et al (2006). The snow depletion curve predicts how the fraction of snow-covered area within a sub-unit changes as a function of the snow water equivalent (Figure 11 c). In the new approach the snow spatial variability was explicitly modelled with a function, which distributed snowfall rates between the different model land use classes based on wind direction and topography (Figure 11 a,b,d).

To calibrate the HYPE model, i.e. to select a set of model parameters properly describing the hydrological behaviour of the catchment, we used different type of observations. In addition to the traditional method with runoff data, we included information provided by the GPR snow observations.

The added value of including a new snow modelling and calibration approach was assessed comparing modelled snow distribution and runoff for four different cases when using the: 1) snowfall distribution function, 2) the snow depletion function, 3) the combination of snowfall distribution and depletion functions and 4) without snow distribution functions at all.

The value of the different snow distribution representations for modelling snow distribution and runoff was, in addition, assessed in relation to the spatial discretization used in the HYPE model and the spatial variability of the meteorological data. For this we consider two configurations consisting of both one (lumped) and multiple sub-basins (gridded) for the Överuman.

Data

Meteorological forcing consisting of precipitation, air temperature and wind direction was used to force the HYPE model in the period 2015-2020. Precipitation was provided by the gridded products PTHBV at the spatial resolution of 4x4 km^2 (Johansson and Chen, 2003). Hourly wind direction and air temperature data was available with spatial resolutions 2,5x2,5 km^2 from SMHI's MESAN analysis (Häggmark et al., 2000), both available at SMHI. Data were used at daily time scale and at the resolution of 2.5x2.5 km^2.

Snow surveys were provided by WP1 and resampled at the spatial resolution of 25 m. They were used for model calibration and validation of the simulated snow water equivalent distributions. Daily average values of observed outflow from the Överuman lake were provided by Vattenregleringsföretagen.

Model setup

The lumped configuration consisted of one model basin covering the Överuman catchment (Figure 1), and the gridded configuration consisted in 2.5x2.5 km^2 sub-basins. The HYPE model units (basin or sub-basin) were further divided into 38 sub-units representing combinations of 3 elevation zones, 4 aspect zones (north, east, south, and west facing slopes), 5 land use classes (water, bare soil, shrubs, forest, and glacier) and 1 soil class. The hydrological processes were simulated in the sub-units within each model unit.

Snow distribution modelling

The snow distribution was modelled by a snowfall function based on the wind shelter factor concept (Winstral et al., 2002). Snowfall is distributed within the model sub-units by a wind shelter factor (WSF), which accounts for if a sub-unit is sheltered or exposed to wind, and controlling the amount of snow falling on them. The wind shelter factor WSF is a physical characteristic input variable, derived separately for each sub-unit and each sub-basin from high resolution topography data. It represents the slope to the horizon in the wind direction and was derived for 8 wind directions using a 25x25 m^2 digital elevation model based on the Arctic-DEM dataset (Figure 11 a).

The snowfall is distributed following the relation:

$$\frac{S_{sub-unit}}{S_{mean}} = w_N \cdot 10^{(wsfscale \cdot WSF_{sub-unit})}$$

where S_{mean} is the mean snowfall in the model unit (sub-basin), $S_{sub-unit}$ and $WSF_{sub-unit}$ are the corrected snowfall and wind shelter factor for the sub-unit, respectively. The *wsfscale* is a parameter related to the snowfall distribution induced by wind, topography and vegetation interaction.

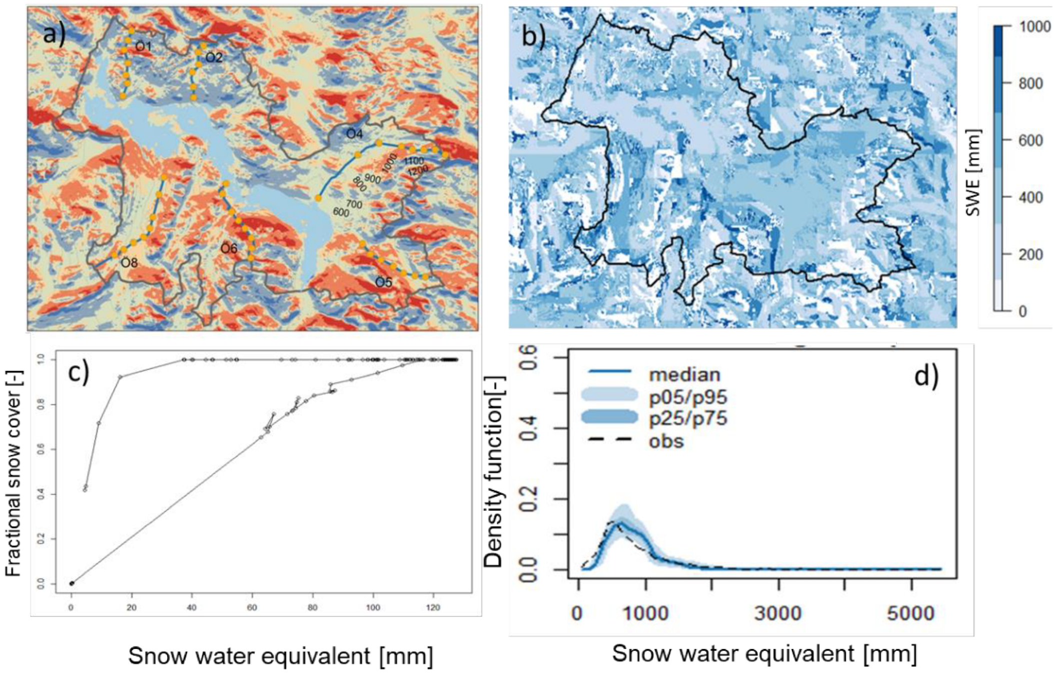


Figure 11. a) map over Överuman with wind shelter factors (WSF) for one wind direction; red and blue colours indicate wind sheltered and exposed areas, b) map with simulated snow water equivalent down sampled to 25x25 m^2, c) Snow depletion curve (DC) example, d) Density function of snow water equivalent simulated with the snowfall distribution function compared to observations.

The *sfdmax* is a maximum value with which the snowfall distribution function will be truncated before the normalization and w_N is a set of wind shelter weights calculated for each sub-unit and sub-basin so that the negative and positive snowfall corrections add up to zero within each sub-basin.

HYPE calibration and validation

The HYPE model with the two spatial configurations was calibrated using inflow and snow water equivalent observations. A number of 10,000 simulations were performed with a Monte Carlo sampling from a feasible parameter space with uniform distribution for both the lumped and the gridded HYPE models. Model parameters and their ranges were defined on previous applications of HYPE in cold environments (e.g., Gelfan et al., 2017; Strömqvist et al., 2012). Different criteria were considered: Nash-Sutcliffe efficiency (nse_q), volume error of local inflow (re_q) and catchment SWE mean (re_{swe})and Pearson-correlation coefficient between the computed and observed SWE spatial distribution ($cc_{\mathrm{swe\ pdf}}$). The four-years study period was divided in sub-periods of two years, the hydrological years 2016-2018 and 2018-2020, over which these criteria were calculated. Based on the GLUE approach (Beven and Binley, 1992, Beven et al., 2000) a likelihood function was defined for each criterion. Solutions were selected by choosing a threshold on the likelihood function. The different likelihood functions were then combined in multi-likelihood functions with regard to inflow and snow water equivalent. The posterior parameter distribution and model realizations were then resampled based on the relative weights of each parameter set or simulated value. The Nash-Sutcliffe efficiency (NSE Q) and the Pearson-correlation coefficient (CC SWE PDF) were used to evaluate model performances in relation to inflow and snow water equivalent distribution for the different criteria with a cross-validation. In this way parameters realizations selected in the first calibration period by the different criteria were used to select model realizations in the second period and the other way around.

Results

The results of the HYPE model performance in simulating inflow and snow water equivalent simulations with and without snow distribution representations and for the two model configurations (lumped and gridded) are showed in Figure 12. Improved model simulations of the catchment inflow were achieved when the new snowfall distribution function was included in the HYPE model (Figure 12; upper panel). This result was found both for lumped and gridded configuration, showing that improved inflow simulations could be obtained with the simplest hydrological process representation by calibrating with snow distributed observations in addition to inflow data. Improvements in the simulations of the snow water equivalent distribution in the catchment were also achieved when the snowfall distribution function was used (Figure 12; lower panel). In this case, higher model performances were found with the gridded configuration. This result suggests that the use of distributed meteorological forcing with the snowfall distribution function had an added value to model the snow distribution in the catchment.

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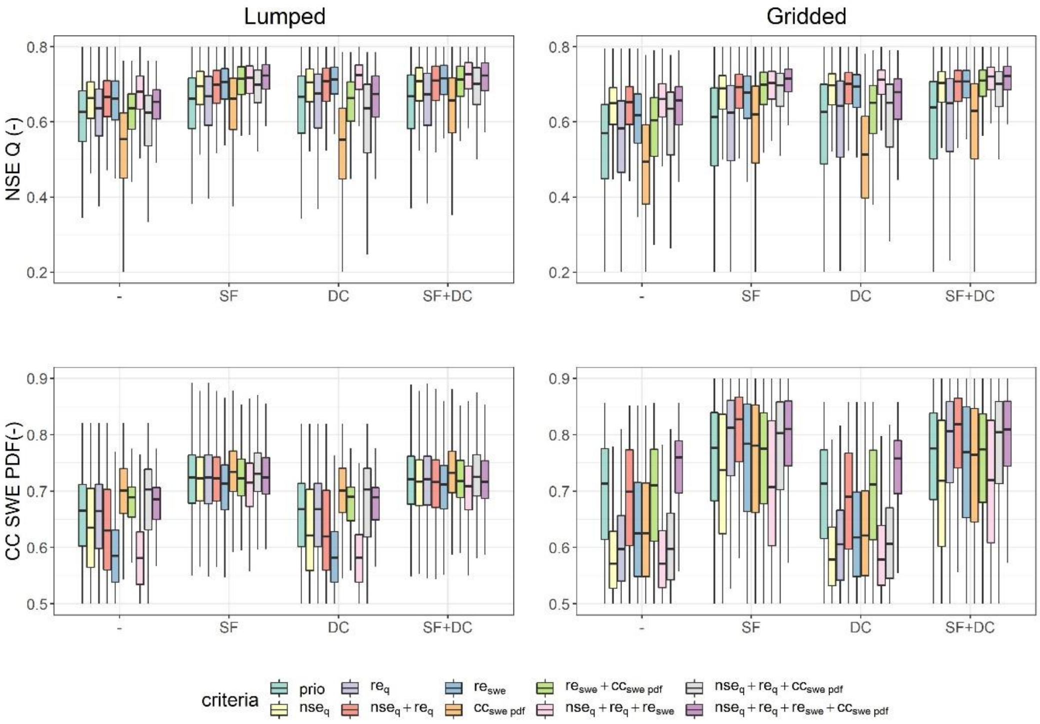

Figure 12. Boxplot of the model performance indicators for inflow (NSE Q) and snow water equivalent distributions (CC SWE PDF) before (prio) and after the weighting likelihood selection for the different criteria. Model performance indicators are reported for model realizations with (SF: snowfall distribution; DC: depletion curve) and without (-) snow distribution representation and for the lumped and gridded HYPE configurations.

WP3 Data assimilation and assessment of forecast skill improvement

Methods: Semi-distributed dynamic hydrological simulation models (HBV and HYPE), seasonal reservoir inflow forecasting, data assimilation, Ensemble Kalman Filter

Frequency: Daily, Monthly, Seasonal

Method developments: Seasonal forecast skill evaluation methods using the Continuously Ranked Probability Skill Score; Perturbation of meteorological data for Ensemble Kalman Filter data assimilation including spatial and temporal correlation; observational functions for local runoff data and in-situ snow depth data, in addition to the functions developed for distributed snow data in WP2.

Outcomes: 1. Calibration of hydrological models using distributed snow data improved the reservoir forecasting skill compared to calibration with runoff data alone. 2. Assimilation of snow data improves hydrological model forecasts, also with poorly calibrated models. 3. Comparison of snow data assimilation with the HBV model using direct replacement and the HYPE model using Ensemble Kalman Filter provided similar improvements of the reservoir inflow forecasting skill. 4. Additional improvement of reservoir inflow forecasting skill was achieved by assimilation of snow data extrapolated by the machine learning approach compared to assimilation of the original snow survey data.

Methods

Hydrological models HBV and HYPE

The HBV model (Bergström, 1976) is a conceptual hydrological model developed at SMHI to support hydropower reservoir management in the early 1970s'. It is used operationally by VRF and many other hydropower reservoir managers in their daily operation, to provide analysis of the current hydrological conditions, and short and long-term forecasts of reservoir inflow. As already mentioned under WP2, the HYPE model (Lindström et al, 2010) is another hydrological model developed at SMHI for simulation of water fluxes, temperature, nutrients, sediments, and other aspects of water quality. The HYPE model is an open-source project, with a special data assimilation module based on the Ensemble Kalman Filter (EnKF) method (Evensen, 1994; Musuuza et al, 2020), which provides more options for data assimilation experiments than the version of the HBV model currently used in the hydropower industry.

SNODDAS contributions: The conceptual similarities and discrepancies of the HBV and HYPE models with regard to snow modelling were assessed by Reynolds et al (2021).

Data assimilation with the Ensemble Kalman filter

The EnKF method can be used to assimilate any observation that can be predicted by the model, even observations that are not part of the model state variables. Thus, both SWE, SD, FSC and inflow data can be assimilated individually or in combination, which enables consistent assessment of the added value of different types of data products. Assumptions of model and observational error variances and spatial/temporal correlations for the meteorological forcing data are critical input parameters to the method.

SNODDAS contribution: EnKF parameters were established for assimilation of the various snow and inflow observations, and for generation of random perturbations to the necessary meteorological forcing data (air temperature, precipitation, and wind speed). Developments to include temporal correlation in addition to the spatial for perturbing the meteorological conditions (Gustafsson et al, in prep.).

Data assimilation and spring flood forecasting experiments

Spring flood reservoir inflow forecast were generated using the so-called Extended Streamflow Prediction method - which is the standard method used by VRF and SMHI for hydropower reservoir management. The essence of that method is to 1) initialize the forecast models by a spin-up simulation covering the time period before and up to the forecast issue dates (in our case the 1st of each month from January to July were used as forecast issue dates) using the current

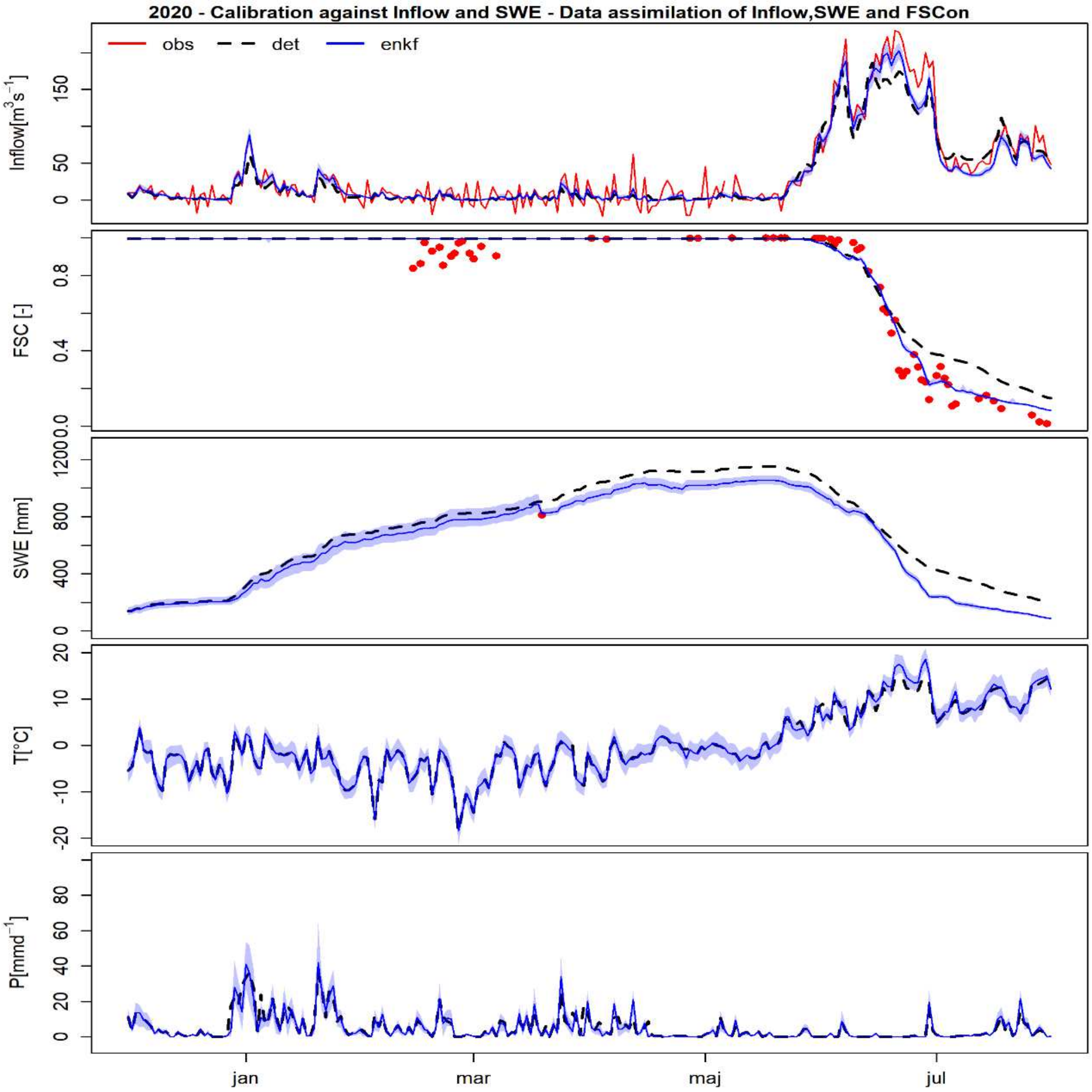

Figure 13. Impact of data assimilation on simulated inflow, snow water equivalent, fractional snow cover, and the meteorological conditions for lake Överuman in the winter and spring 2020 in the HYPE model. Obs are observed reservoir inflow, and catchment mean fractional snow cover and SWE, resepectively, Det is deterministic model without EnKF data assimilation, and enkf is model with EnKF.

year´s meteorological data as input, and 2) to generate a forecast ensemble by simulating the forecast period from the initial state (in our case until 31st of July) with the meteorological input data taken from each of the historical years available in the database (in our case all years between 1998 and 2020). In this context, data assimilation is used to improve the initialization of the forecast models, by assimilating the different available observations during the spin-up simulation. An example of assimilating a combination of observed reservoir inflow, SWE from the snow surveys, and satellite-based fractional snow cover in the HYPE model is shown in Figure 13 – the impact of assimilating the single snow survey data point is clearly seen as a drop in the simulated SWE. Corresponding impacts can also be seen by the assimilation of the fractional snow cover data, and the reservoir inflow data.

SNODDAS contribution: A series of spring flood forecasting and data assimilation experiments were performed with the HBV and HYPE models to investigate the impact on forecast skill of a) the spatial model configuration, b) the representation of snow distribution processes, c) the model calibration strategies, and d) data assimilation of one or several types of observations. The study by Reynolds et al (2021) also assessed the conceptual similarities and discrepancies in the EnKF data assimilation method compared to the corresponding methods available in the HBV model.

Climatological reference forecasts and assessment of forecast skill

Spring flood forecast experiments were conducted for the first 4 years with snow survey data in Överuman 2017–2020. In all experiments, the spring flood period was defined as the period from the forecast issue date (1st of each month from January to July) until the 31st of July. The 4 years in the study period represented a large variation in snow conditions and spring flood inflow volumes - the observed reservoir inflows from 1st April–31st July in 2018 and 2020 were the 3rd lowest and 3rd highest, respectively during the available data period 1965–2020.

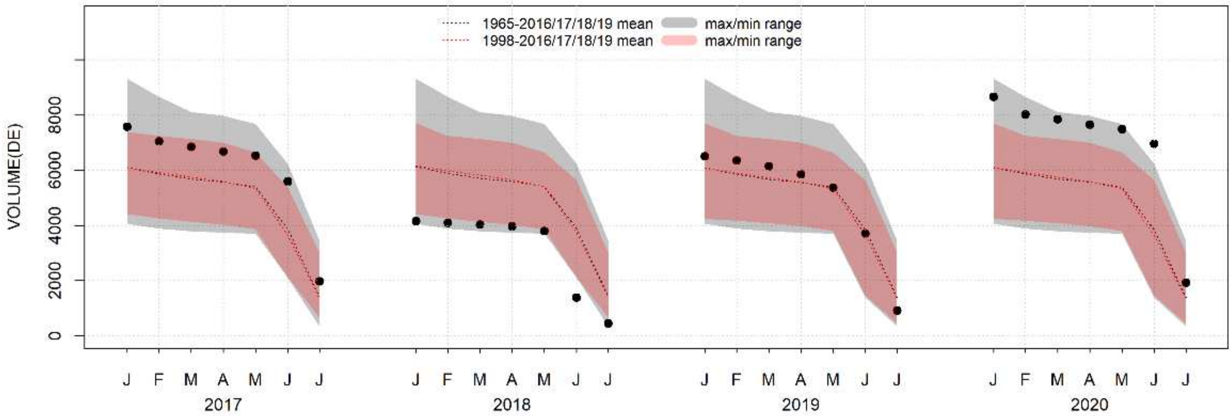

Figure 14. Observed local inflow in Överuman from 1st of each month until 31st July for the months January–July 2017–2020 (black dots) compared to the climatological reference forecast based on all previous recorded inflow observations since 1965 (black dotted line/shaded area) and since 1998 (red dotted line/shaded area). Spring flood volumes are in day equivalent units (DE= 86,400 m^3).

The observed inflows of all previous years since 1965 were used to generate a climatological reference forecast (Figure 14). As already noted, 3 years out of the 4 in the study period had either close to record low or record high recorded inflows, and consequently the reference forecast largely failed for these years. 2019 on the other hand, the reservoir inflows were close to the climatological mean. As a consequence of these conditions, it will be more difficult to improve upon the reference forecast during 2019, and relatively easy to improve during the other years. The bias and the variance of the reference forecast is later used to assess the relative improvement in the hydrological model forecasting skill using the so-called Continuously Ranked Probability Skill Score (CRPSS; Hersbach, 2000): CRPSS>0 indicate an improvement in forecasting skill compared to the reference forecast, and CRPSS=1 indicate a perfect forecast with zero bias and zero variance.

Results

Spring flood forecasting and snow data assimilation in the HBV and HYPE models

As a joint effort of tSNODDAS and a project funded by Energiforsk, a comparison of the HBV and HYPE models were made with regard to the ability to assimilate snow data in calibration and to improve spring flood forecasts (Reynolds et al, 2021). The main outcome of this study was that 1) the HBV and HYPE models responded similarly when including the manual snow survey SWE data from WP1 in calibration and in assimilation, and 2) assimilation of the SWE data consistently improved the spring flood forecast skill compared to forecasts based on deterministic model initialization (Table 2). This was a major outcome for the SNODDAS project, since it showed first of all, that snow observations do have the potential to improve hydropower reservoir inflow forecasting, and secondly that the snow data developed by the project can be used in combination with the data assimilation methods currently available in the HBV modelling tool, which is commonly used by the hydropower industry. In addition, it was demonstrated that the explicit snowfall distribution model developed within the SNODDAS project (see WP2) has a corresponding representation in the HBV model through the so-called snow accumulation classes. As an outcome, it would thus be possible to tune the empirical snow distribution parameters in HBV by a topographic analysis using the same physically based wind-shelter parameterization as developed for the HYPE model.

Spring flood forecasting assimilating the SNODDAS snow products

The final set of spring flood experiments focused on investigating the potential forecast skill improvements by assimilation of the SWE products developed in WP2 compared to SWE data from other satellite projects, as well as the snow data from WP1 and other ground-based data sources. These experiments were made with the HYPE model and the EnKF data assimilation method only.

An initial comparison of simulated catchment average snow water equivalent to the full range of available SWE data illustrates challenge of state-of-the-art satellite-based microwave retrieval products to estimate SWE in the mountainous Överuman catchment (Figure 15). The ESA CCI SWE products (v1.0 and v1.2) as well as the WP2 downscaling product provide SWE estimates that largely underestimate the SWE estimates of the WP1 ground-based GPR snow survey data. On the other hand, both the WP2 Machine learning product and the WP2 distributed snow model – which both have been calibrated towards the GPR data – provided much higher and more realistic estimates of SWE.

Table 2. (Results from Reynolds et al, 2021) Average Continuously Ranked Probability Skill Score (CRPSS) for spring flood forecasts issued 1st of April, May, and June for different calibrations and data assimilation configurations of the HBV and HYPE models for the Överuman reservoir. Green color indicates improved forecast skill by data assimilation compared to the deterministic initialization run with the same model/calibration method. Underscore marks the forecast initialization with highest CRPSS for the particular model/calibration configuration, and bold underscore marks the forecasts with overall highest CRPSS scores. Curr stands for the current or established operational HBV model at Överuman. Calibration strategy F1, F2, F3, and F4 corresponds to calibration using inflow only, inflow and SWE, inflow and FSC, and inflow, SWE and FSC, respectively. HYPE label on/off corresponds to models with and without the snow cover depletion curve (See WP2 for details).

Model	**Variables used in calibretion**	**Label**	**Data-assimilation approach for forecast initialization**								
			Det	Open	Q	SWE	Q SWE	FSC	Q FSC	Q SWE FSC	SWE FSC
HBV	Q (Curr)	*Curr*	-0,50		*-0,67*	0,52	0,50				
	Q	*F1*	0,39		0,65	0,65	**0,72**				
	Q, SWE	*F2,F4*	0,14		0,43	0,53	0,67				
	Q, SWE, FSC										
	Q, FSC	*F3*	0,28		0,59	0,61	**0,72**				
HYPE	Q	*F1,off*	0,54	0,52	0,58	0,66	**0,72**	0,57	0,55	0,70	0,68
	Q, SWE	*F2,off*	0,50	0,49	0,61	0,68	**0,73**	0,52	0,60	**0,73**	0,68
	Q, SWE, FSC	*F2,on*	0,55	0,45	0,54	0,45	0,55	0,64	0,60	0,56	0,57
	Q, FSC	*F1,on*	0,54	0,46	0,58	0,51	0,60	0,63	0,63	0,60	0,61

The improvement in the hydrological model forecast skill when assimilating the different data products depends a lot on the performance of the climatological reference model and the deterministic calibrated hydrological model for each particular year as well as on the forecast issue month, as illustrated in Figure 16:

showing the spring flood forecasts and forecast skill scores for the lumped HYPE model with explicit snow fall distribution, calibrated with inflow and relative error of SWE, and assimilation of inflow and the SWE estimates from GPR data and the Machine learning method. There is a general increase in forecast skill by data assimilation for forecasts issued after the onset of snowmelt in April/May, which is logical since the information from the inflow signal as well as the estimate snow storage cannot influence the forecasts until the snow starts to melt.

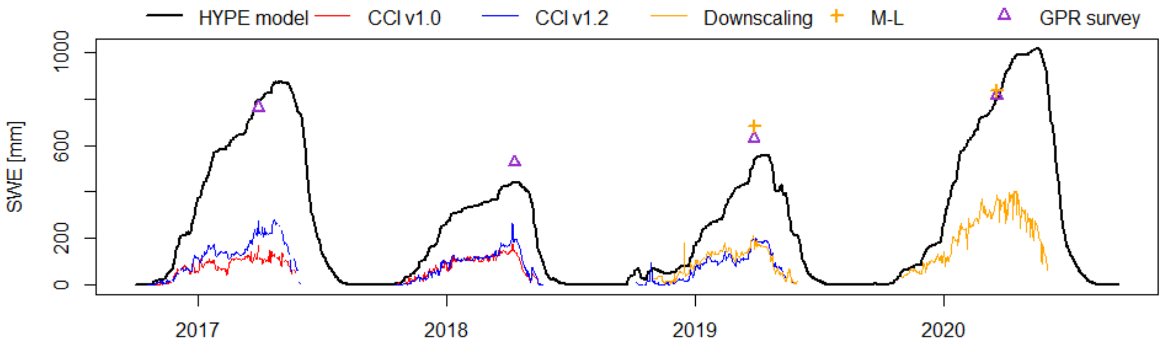

Figure 15. Comparison of mean SWE [mm] in the Lake Överuman catchment, as simulated by the calibrated HYPE model with the snowfall distribution and snow depletion curve (lumped SF+DC), by the satellite products from ESA SNOW CCI, the satellite product developed in the SNODDAS project (downscaling and machine learning), as well as the ground based GPR surveys.

The largest forecast skill scores were found in the years 2017, 2018, and 2020; which were years with extremely large or low snow accumulation and accumulated spring flood volumes. For these years, the calibrated hydrological model without data assimilation provided a large improvement in forecast skill in relation to the climatological reference. There is also a general increase in forecast skill over the course of the winter as a result of more and more information from the current meteorological conditions integrated into the forecasts. The added value of assimilating SWE observations was relatively low even though small improvement can be seen in forecasts issued in May, June and July. However, the improvement of assimilating the SWE estimates was largest in 2019, where deterministic model was worse than the climatological reference for all forecast issue dates except 1st July. It should be noted that the Swe-ML data were only available for 2019 and 2020, so improvements seen in the results for 2017 and 2018 are just an effect of the ensemble perturbations compared to the deterministic model. The overall improvements generated by the Swe-ML data were thus mainly related to 2019.

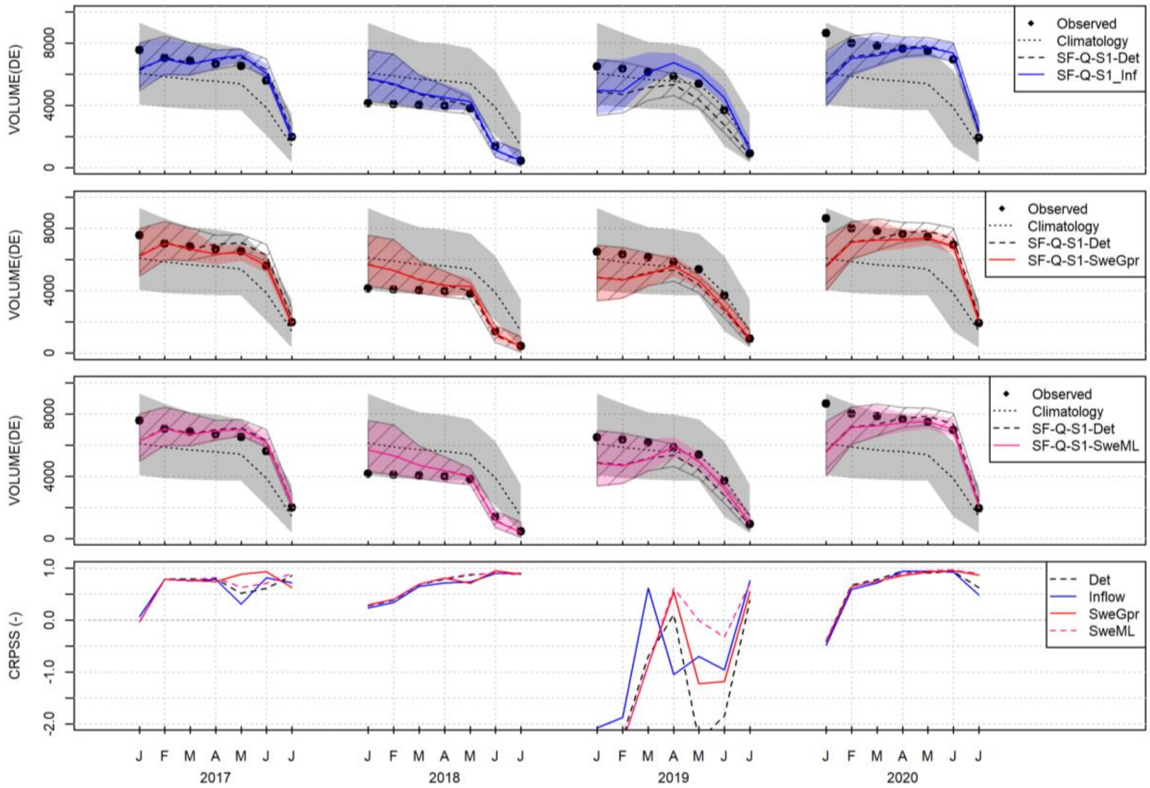

Figure 16. Spring-flood inflow forecasts for Lake Överuman 2017–2020 with the lumped HYPE model configured with explicit snowfall distribution and calibrated with inflow and relative error in SWE (SF-Q-S1), without (black hashed area) and with assimilation of reservoir inflow (blue shade/line, top panel), mean of the original SWE survey data (red shade/line, second panel) and mean of the machine learning SWE estimates (deep pink shade/line, third panel) compared to climatological reference forecast (based on all observations since 1965) and the observed inflow volumes for each respective year (black dots). Bottom panel: Continuous Ranked Probability Skill Score (CRPSS) for the different HYPE model forecasts, using the climatological forecasts as reference. Spring flood volumes for each month are defined as the total reservoir inflow volumes between the 1st of each month until the 31 July (in day equivalent units, DE= 86,400 m3). Mean, min and max values are shown for each ensemble.

The same analysis was repeated for all snow distribution and calibration configurations, as well as combination of assimilation variables but not shown here. A summary of the improved forecast skill for the years 2019-2020 is presented in Table 2 and 3, where the mean absolute relative error for the forecast issued in April-July are given for all models and a selection of data assimilation experiments. Several interesting results can be seen in Table 3:

- The overall improvement in forecast skill compared to the climatological reference SF-Q1-S1 model (explicit snowfall calibrated with inflow and mean catchment SWE)

- Assimilation of the reservoir inflow data and/or the SWE-ML data reduced the mean absolute volume error to 5% or better, and assimilation of either inflow, SWE-GPR, SWE-ML and in some cases also FSC reduced the mean absolute volume error to 5% or better.
- Similar analyses were made for all years and will be presented further in Gustafsson et al (in prep.).

Table 3. Mean absolute relative error in spring flood forecasts 1 April-1 July 2019-2020 for different configuration of snow distribution models: none (-), depletion curve (DC), snowfall distribution (SF); hydrological model calibration: inflow only (Q), inflow and mean SWE (Q+S1), inflow+mean SWE+SWE distribution (Q-S1-S2), for the climatological reference (Ref), the deterministic (lumped) HYPE models, and with different data assimilation configurations: inflow (Inf), SWE GPR or Machine learning, fractional snow cover from Cryoland and AI4Arctic projects, and combinations of inflow and SWE, and inflow+SWE+FSC.

					SWE		FSC		Inflow+	Inflow+
Dist	**Cal**	**Ref**	**Det**	**Inf**	**GPR**	**ML**	**Cryo**	**AI4A**	**SWE_{ML}**	**SWE_{ML}+ FSC_{Cryo}**
-	Q	23	18	10	13	11	24	22	9	13
-	Q-S1	23	17	10	14	11	22	19	8	14
-	Q-S1-S2	23	25	12	15	12	27	23	9	12
DC	Q	23	14	5	9	5	15	11	4	6
DC	Q-S1	23	12	5	9	5	13	11	4	7
DC	Q-S1-S2	23	23	6	12	8	19	16	5	7
SF	Q	23	13	8	8	5	14	15	4	5
SF	Q-S1	23	12	10	8	4	15	15	3	5
SF	Q-S1-S2	23	11	13	8	6	9	15	4	9
DC+SF	Q	23	13	9	9	7	10	17	6	6
DC+SF	Q-S1	23	10	10	9	7	9	15	6	6
DC+SF	Q-S1-S2	23	11	12	10	9	10	17	7	6

Our results can be generalized as above to serve as goals for future work, but it is also important to study the details of our results such the fact that every year has its character and the generalized improvement cannot be expected every year. At first, it might even look as a contradiction, that the added value of the snow measurements for the spring flood forecast skill were lowest in the years with extremely high or extremely low snow amounts (Figure 16), such as the year 2017, 2018, and 2020, and highest during years with snow conditions close to normal, such as in 2019. However, in these cases we must also remember that the snow model itself – calibrated by runoff and snow data – provided the added value in relation to the climatological reference forecasts during the extreme snow-rich and snow-poor years.

The result of the distributed snow model development and calibration show the importance of representing the spatial distribution of snow in hydrological modelling. While this is not new knowledge *per se*, we investigated thoroughly the difference of using an explicit snowfall distribution model driven by wind-direction and wind-shelter factors derived from topographical data and a more traditional snow depletion curve formulation, where the snow distribution is only implicitly represented in the model. The results both of the calibration exercise, and the forecast data assimilation experiments show that it is essential to represent snow distribution – either by the snow depletion curve or by the snowfall distribution. So far, our results indicate that the combination of the two methods rather contributed to a lower model performance and forecast skill – but this might be a result of not including fractional snow cover data in the calibration.

WP4 Economic assessment

The simplified economic model developed in the previous EU FP7 IMPREX project was planned to be used to assess the potential economic gain from the improved reservoir inflow forecasting. The SNODDAS contribution was mainly to update the necessary input data to the current period, and contribute to the scientific evaluation and publication of the method. This work is still in progress, and a publication is planned to be completed later this year (Gustafsson et al, in prep.). This assessment method is built around the formulation of a 'forecast cost' equal to the production value of water that would have to be released as 'unproductive spill' at the end of the spring flood period as a consequence of the difference in forecasted reservoir inflow and the real observed inflow in the same period. The maximum forecast gain is set to the forecast cost of a reference forecast, and the forecast gain is then given by the reduction in cost from the reference forecast. The main limitation of the current method is that it is dependent on data about the reservoir filling level at the time of the forecast issue date, which is a function of the reservoir management decisions made based on the forecasts and electricity market data available at that time. The assessment methods could thus be improved if it would include a simulation of adjustments in reservoir management based on improved inflow forecasts.

An alternative assessment is to use the data from Umeälven of water discharge and of hydropower production since that exists from 1993 and forwards to assess the production / loss of potential production ratio in the Umeälven river system over those 27 years. With the improved prognostic capacity from this work lowering the uncertainty in the filling rates to 5 % we can speculate in a somewhat contrafactual way how the SNODDAS prognostic tools could have increased the freedom to plan hydropower production in the past.

We know a total of 4 TWh of production in Umeälven was not used for production due to spill from the hydropower dams between 1993-2020 (spill is the term used to overflow the water in the dam in a spillway outside the turbine chute to drain the stage of safety or environmental cause). This spill was caused by a number of different reasons, and the larger part of that spill would never have been able to use for production. A normal number used in the hydropower industry of the uncertainties of the filling rates due to water from snow storage in mountain terrain is 20%. If we assume we could have lowered that uncertainty to 5 % using SNODDAS methodology in the past, then 75 % of those 4 TWh would have become available for hydropower planning purposes. This is of course not realistic, since the spill is due to a number of factors, where only a part is the uncertainty of the predicted filling rates. If we moderate this calculation by assuming only 10 % of the spill in that period was due to the uncertainty of the forecast of the filling rates (400 GWh), we then find 300 GWh could have been saved using the SNODDAS methodology, and expressed as 300 GWh/ 27 years = 11 GWh per year. This compares to ca 3.5 Mkr in gained production per year for that period using the average normal energy price for Umeälven.

WP5 Deliverance

This work package is the dissemination of our results, including scientific publications, dissemination and discussion of our results with the scientific society and the hydropower industry as well as our reporting to Energimyndigheten. government research environment. Selected parts of our collected data and results will be open to the public in open archives. Active data that contains information about the current year's production will not be open to the public.

<u>Dissemination</u>

We have disseminated our work in a number of different ways, that can be grouped within these four items: a) internal meetings within the consortia, b) external meetings with the industry through our reference group and with HUVA, c) direct contacts with the industry on specific tasks, c) attending international conferences and workshops.

a) Internal meetings: We have had totally 25 meetings to discuss our progress and following our goals and deliverables for the project. Björn Norrell from Vattenregleringsföretagen have been integrated in SNODDAS, and such the hydropower industry has been present in these meetings, and granted the industry perspective in the development and implementation of the project.

b) External meetings: We had an ambition with SNODDAS to disseminate and discuss the progress and results with the hydropower industry. This was done in two different ways: i) forming a reference group with members from both industry and science, and having an annual workshop with them to present our results and plans, and, ii) presenting our results in the wider forum HUVA (Hydrologiskt utvecklingsarbete) run by Energiforsk. We had one workshop with our reference group per year (the first organized by Statkraft in Oslo, to bring a good start-up of our project, and to set the scene), and we were asked to have three presentations to HUVA. Both these activities were important to us to test our ideas and results, and to communicate them. See further details in Appendix 5.

c) Direct industrial contacts: We got material from our industrial partners of their snow taxation campaigns we used to test our models. The data from Vattenregleringsföretagen from Överuman was included in our plan, but in addition we got data from Uniper and Vattenfall. We have not, yet, been able to work on the data from Vattenfall, but with our satellite module we were able to produce results similar to Figure 9 of Ankarvattnet/Blåsjön for Uniper. We were further co-supervising two master students from Chalmers with Uniper to test how to use different SWE products to reconstruct the SWE distribution in one of their catchments.

d) International scientific meetings. 1. The International Glaciological Society (IGS) Nordic Branch Meeting, Rovaniemi, October 2018; 2. AGU Fall meeting, San Francisco, December 2019; 3. Northern Research Basins Symposium and Workshop, Yellowknife, Canada, August 2019; 4. International Conference on Snow Hydrology, Bolzano, Italy, January 2020; 5. 9th EARSeL workshop on Land Ice and Snow, Bern, Switzerland, February 2020; 6. Virtual IGS Nordic Branch Meeting, November 2020.

<u>Deliverance</u>

Our deliverance is so far included in the bullets a-d above, the annual reports to Energimyndigheten, including this report, and two scientific publications, Zhang et al, in press, Appendix 6, and Clemenzi et al, and Gustavsson et al, in prep, with the preliminary title “Evaluating a snow modelling approach to predict snowmelt runoff” to be submitted to Hydrology Research. We are further planning for a manuscript describing the general work flow of SNODDAS, to be submitted to Water Resources Research, or similar outlet.

Diskussion

The overall results of the project show that consistent improvements of hydropower reservoir inflow forecasting down to about 5% or better is possible by assimilating the snow observations and distributed snow water equivalent estimates based on the methods and models developed in the project. As such, our suggested improvements in methodology show a good potential to contribute to the development of an improved sustainable energy system. Figure 4 show an example. The average uncertainty of estimating the inflow using HBV model with no snow correction is ca 10% over the period 2001-2020. Our methodology would half that uncertainty, and in the period 2013-2020 cut the uncertainty by ca 2/3, and such increase the potential to use that water for planning purposes in hydropower production. The uncertainties with the estimation are larger during years with anomalous snow amounts.

If similar snow monitoring systems were implemented for all major hydropower reservoirs situated in similar high mountain catchment areas we could add as much as 35/350/1000 GWh of hydropower production a normal/ anomalous/ extreme year, on basis of course estimations made by use of historic discharges during the spring flood in Umeälven. That is a substantial addendum of green/blue power and contributes to a fossil-free national energy production. A more elaborated cost-benefit analysis comparing the cost of implementing such snow monitoring program in a larger scale to the potential gain in hydropower production and water use efficiency accumulated over multiple years would be needed to do a full assessment of this question. We had in mind doing so within SNODDAS WP4, but we did not manage to satisfy this ambition fully. The reason for this was firstly that we used more time for the hydrological modeling/assimilation in WP 2 and WP3 than anticipated. Secondly, and more important, is that we made a choice to contribute to a comparison of the two models HBV and HYPE requested by the hydropower hydrology reference group at the Swedish energy research and knowledge institute Energiforsk, which was not initially planned (Table 2). This work brought us closer to the objective in WP3 to test our methodologies with both the HBV and the HYPE model, to better understand the differences and similarities of these two models, and to reach out to the hydropower industry with our findings in WP5, since the HBV model is the favored model in industrial production.

We have shown the potential to reduce the uncertainties of the inflow into a hydropower reservoir to be below 5% in mountain regions where the volumes of the snow water storages generally pose a problem to make prognostic work of the water routing. In our methodology we use ground observations of snow properties as a reference material, which we distribute over the catchment using satellite images or wind distribution models as input for assimilation into our routing model. The reference data from the ground observation is labor intensive, but probably cost effective when finding the large reduction in inflow model uncertainty. Although, with the use of drones as tested one of the years, we believe we can cut the costs substantially by implementing drone measurements to replace / complement the manual ground truthing part of our methodology. This, we hope, will be the focus of a forthcoming study, and a further development of our SNODDAS methodology.

Publikationslista

Clemenzi, I., Gustafsson, D., Zhang, J., Norell, B., Marchand, W.D., Pettersson, R., Pohjola, V., in prep. Evaluating a snow modelling approach to predict snowmelt runoff. Manuscript in advanced stage, to be submitted to Hydrology Research.

Zhang, J., Pohjola, V., Pettersson, R., Norell, B., Marchand, W.D., Clemenzi, I., Gustafsson, D., 2021. Improving the snowpack monitoring in the mountainous areas of Sweden from space: a machine learning approach. Environmental Research Letters, in press. (Appendix 7).

<u>Planned publications:</u>

Gustafsson, D., Clemenzi, I., Zhang, J., Norell, B., Marchand, W.D., Pettersson, R., Pohjola, V., in prep. Snow data assimilation for improved spring flood runoff predictions. To be submitted by the end of 2021.

Gustafsson, D., Clemenzi, I., Zhang, J., Norell, B., Marchand, W.D., Pettersson, R., Pohjola, V., in prep. Economical assessment of hydropower reservoir inflow seasonal forecasting. To be submitted by the end of 2021.

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Bilagor

- *Administrativ bilaga*

1. Measured snow depths along the eight snowlines at Överuman 2017-2020.
2. Calculated SWE along the eight snowlines at Överuman 2017-2021 (mm SWE)
3. Improved characterization of snow dynamics in Sweden using Google Earth Engine (This work has been presented at 2020 IGS Nordic Branch Meeting).
4. Spatial heterogeneity of AMSR2 brightness temperature for characterizing snow depth across Sweden (This work has been presented at 9th EARSeL Workshop on Land Ice and Snow).
5. List of SNODDAS workshops, HUVA presentations and our reference group.
6. Snow courses and bulk density observations points.
7. Tables snow courses snow statistics.
8. The publication in press, Zhang et al 2021.