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Workshop Report

1st Snow Data Assimilation Workshop in the framework of COST HarmoSnow ESSEM 1404

Jürgen Helmert[1*], Martin Lange[1], Jiarui Dong[2], Patricia de Rosnay[3], David Gustafsson[4], Evgeniy Churulin[5], Ekaterina Kurzeneva[6], Richard Müller[1], Jörg Trentmann[1], Niels Souverijns[7], Roland Koch[8], Uwe Böhm[1], Martin Bartik[9], Marzena Osuch[10], Inna Rozinkina[5], Jean-Marie Bettems[11], Patrick Samuelsson[4], Francesca Marcucci[12] and Massimo Milelli[13]

[1]Deutscher Wetterdienst, Offenbach, Germany
[2]IMSG at NOAA/NCEP/EMC, United States
[3]ECMWF, United Kingdom
[4]SMHI, Sweden
[5]Hydrometcenter of Russia, Russian Federation
[6]FMI, Finland
[7]KU Leuven, Belgium
[8]ZAMG, Austria
[9]Technical University Zvolen, Slovakia
[10]Institute of Geophysics Polish Academy of Sciences, Poland
[11]MeteoSwiss, Switzerland
[12]COMET, Italy
[13]ARPA Piemonte, Italy

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Abstract

The 1st Snow Data Assimilation Workshop, organized under the COST Action ESSEM 1404 HarmoSnow, took place in Offenbach, Germany, on 8–9 March 2017. Of particular relevance for the workshop were thematic sessions on i) data assimilation methods and the use of snow observations, ii) snow observations and evaluation, iii) snow observations and physical snow models, and iv) snow observations and hydrological models. This report summarizes the scientific contributions presented at the workshop. The discussions mainly focused on methods for combining satellite observations with conventional in-situ snow measurements and modeling results, as well as on errors in the spatial and temporal representation of snow measurements for data assimilation in NWP and hydrological models. It has been shown that the assimilation of in-situ and satellite-based snow observations improves the quality of the snow analysis and forecast. However, in order to achieve this positive impact, a thorough quality control of the observational data is necessary, in particular because of the automation of the ground-based networks.

Keywords: snow, data assimilation, COST HarmoSnow

1 Introduction

Due to its unique physical properties, snow on the ground is an essential environmental variable directly affecting the Earth energy balance. Since the representation of the snow coverage is essential for the model radiation budget and the assimilation of radiances over land (e.g. in numerical weather prediction models), it is therefore important to have accurate information on snow and to assimilate it into hydrological, land-surface and meteorological models to address the impact of snow on various phenomena, to predict local snow-water resources and to warn about snow-related natural hazards (Drusch et al., 2004; Viviroli et al., 2011; Fayad et al., 2017; Lafaysse et al., 2017; Etter et al., 2017).

With the implementation of the Global Cryosphere Watch (GCW) in 2011, WMO established a program which satisfies the growing demand for authoritative information on the past, present and future state of the world's snow and ice resources (Key et al., 2015). Although GCW is global in scope, the program needs activities at all scales, including regional, national and local levels, (GCW, 2012) and recognizes the requirements for assimilation, model development and validation. At a European level, the COST Action ESSEM 1404 HarmoSnow (2014–2018) coordinates efforts towards harmonizing the processing and handling of snow data (COST, 2015).

Information about the physical snow properties come from observations (in-situ and remote sensing) and from physical snow models. However, the complexity and heterogeneity of snowpack processes leads to large un-

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*Corresponding author: Jürgen Helmert, Deutscher Wetterdienst, Frankfurter Str. 135, 63067 Offenbach, Germany, e-mail: juergen.helmert@dwd.de

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certainties in the datasets from both, observation and model simulations (Dechant and Moradkhani, 2011).

The aim of this study is to summarize the contributions presented during the workshop. The detailed program of the workshop and PDFs of most of the presentations are available at the following website: http://www.harmosnow.eu/.

In-situ measurements of snow properties are considered in Section 2. In Section 3, the contribution of remote sensing to the estimation of the snow state is discussed. The modeling of snow processes in physical snow models is considered in Section 4 and Section 5 deals with the combination of observations and model data in data assimilation, followed by a summary in Section 6.

2 In-situ measurements

Snow depth observations from the SYNOP (synoptic) station network are used by a number of operational NWP and hydrological centers. They provide very valuable information, which is used to initialize prediction models. The SYNOP snow depth network is relatively dense in Europe, but in some regions with low population density it can be very sparse. SYNOP observations are made available by each country via the WMO Global Telecommunication System (GTS), which is a dedicated observation exchange network for NWP. M. Lange showed in his presentation that it is imperative to monitor SYNOP station snow depth reports to detect problems in the snow analysis based on SYNOP reports, as they could have a negative impact on the NWP forecast. This monitoring becomes even more important because of the automation of the ground-based networks.

In addition to the SYNOP networks, some countries have national networks for snow depth measurements, which are not reported via GTS. Making these extra snow measurements available on the GTS is potentially very valuable for NWP applications. The presentation by de Rosnay et al. showed the currently available in-situ data and discussed the gaps in the GTS reporting of snow depth in relation to ongoing actions, carried out by the World Meteorological Organization Global Cryosphere Watch (GCW) SnowWatch initiative and the Harmosnow COST action. These initiatives contribute to improving the availability of snow depth reports on the GTS (de Rosnay et al., 2015, 2016).

In field experiments, it is possible to gather more snow information for a limited time period. Using snow water equivalent (SWE) and snow depth (SD) measurements, which had been analyzed over several winter seasons for a mountainous region with open forests, open meadows, living forests and dead forests, M. Bartik and T. Šatala showed that the main influences on SWE in forests are vegetation type and state, altitude, and exposition. Considering the effects of vegetation on snow could improve the forecasts of water supply in catchment areas with forests.

The presentation by M. Osuch et al. showed the results of a study carried out for the small unglaciated catchment area of Fuglebekken, located near the Polish Polar Station Hornsund on Spitsbergen. During the hydrological years 2013–2014 and 2014–2015 a number of hydro-meteorological measurements were carried out in order to calibrate and validate the conceptual rainfall-runoff model Hydrologiska Byråns Vattenbalansavdelning (HBV) (Wawrzyniak et al., 2017). The outcomes indicate that the calibration results depend on the data time step and the data averaging. Good calibration and validation results were obtained, which will allow the use of the model for other years and an assessment of the actual state as well as a simulation of future changes.

Considering changes in seasonality of snow depth, air temperature and precipitation in western Spitsbergen, the presentation by M. Osuch and T. Wawrzyniak focused on the analysis of their variability, using the recently proposed tool 'Moving Average over Shifting Horizon (MASH)' (Anghileri et al., 2014), based on time series for 32 snow seasons between 1984 and 2016 at four stations in Spitsbergen. It was shown that the MASH method combined with the Mann-Kendall test can be successfully applied for estimating trends of daily snow depth, air temperature and precipitation (Osuch and Wawrzyniak, 2017a,b). Given that in-situ measurements of snow depth in Spitsbergen are rare and data are only available from a few sites, there are still not enough homogeneous data and further investigations and snowpack modeling are required.

3 Remote sensing

Remote-sensing data have the potential to provide estimates of the snow state (de Lannoy et al., 2012) in regions with sparse in-situ snow measurements. In the visible (VIS) and near infrared (NIR) spectral range, spaceborne remote sensing can determine the snow cover area (SCA) and snow cover fraction (SCF) at a high spatial resolution (MODIS, AVHRR, Sentinel-2). Passive microwave remote-sensing data allow an estimation of snow depth and SWE by relating the microwave brightness temperature to snow parameters without any impact from clouds (Pulliainen, 2006; Pulliainen and Hallikainen, 2001). However, the resolution of these products is typically coarser than that of remote-sensing products from VIS and NIR spectral bands, and their accuracy is sensitive to the assumptions used and to the properties of the snowpack (Foster et al., 2005; Dong et al., 2005; Leppänen et al., 2015; Kontu et al., 2017). Alternatively, active microwave sensors can determine snow depth from space with a higher resolution, but they require spaceborne measurements at appropriate frequencies (de Lannoy et al., 2012).

Furthermore, a number of blended satellite products have been developed, which merge visible, near-infrared and passive microwave observations (Kongoli et al., 2007; Gao et al., 2010; Foster et al., 2011) and which could be used for data assimilation. For SWE however, most of these products are research products and are only generated for a limited time period and area (de Lannoy et al., 2012). For SCA, a number of combined and operational products exist, which also include in-situ measurements (Ramsay, 1998).

An overview of the spectral properties of snow and their consideration in remote-sensing retrievals was given by R. Müller et al., whose presentation focused on snow cover products from LSA-SAF (Siljamo and Hyvärinen, 2011) and the interactive multisensor snow and ice mapping system (IMS), (Ramsay, 1998). Both data sources provide daily values. However, for many applications intra-daily updates of the snow cover information would be most appropriate. Different snow cover update options have been discussed. While the spectral behavior of snow and clouds differs, clouds covering land-surface areas with snow for a long time remain a problem for daily and intra-daily updates of the remote-sensing products. However, it is desirable for climate data records (CDRs) to cover time periods as long as possible. Therefore, using "first generation satellites" is also of high interest for the generation of CDRs. It is difficult to distinguish between clouds and snow-covered surfaces when working with measurements by early satellite instruments (e.g. MVIRI: Meteosat Visible Infra-Red Imager) or with their replacements. In climatological time series of remote-sensing data in particular, snow coverage is often wrongly classified as clouds, which results in a systematic underestimation of the derived surface radiation in snow covered situations. Due to the limited spectral resolution of the early satellite sensors, historic remote-sensing data often does not allow for a separation of snow cover and clouds when using current retrieval algorithms, as the latter require multi-spectral information. It is however possible to separate clouds from snow coverage by analyzing motion vectors (HELSNOW method), using consecutive satellite images (visible channel only) from geostationary satellites and modern image recognition software, as shown in the presentation by J. Trentmann.

Cloud cover, which most often occurs during winter storms, can also impede the detection of wind-blown snow. Wind-blown snow impacts on the surface mass balance of a snowpack and ice sheet by transport and sublimation. Its importance has been recognized for large regions covered by snow and ice such as Antarctica. It is possible to detect wind-blown snow using satellite data (Palm et al., 2011). The near-surface layers of wind-blown snow are apparent in lidar backscatter profiles (532 nm attenuated backscatter). These data are processed from CALIPSO (Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations) at a high resolution (1×1 km), using a new algorithm, which was developed by A. Gossart and which is designed to detect wind-blown snow from a ground-based remote-sensing ceilometer at Princess Elisabeth station (Dronning Maud Land, East Antarctica, 72° S, 23° E) (Gossart et al., 2017). When the 910 nm attenuated backscatter profiles were processed with a temporal resolution of 15 s using this algorithm, a strong signal for wind-blown snow signal could be detected for the first time from layers thicker than 15 m. The newly developed algorithm has the added value that it also detects wind-blown snow events mixed with snowfall, thus even during overcast conditions. Those events are not detected by satellites, but represent the majority of wind-blown snow events at the Princess Elisabeth station.

4 Physical snow models

Numerical model predictions are able to provide continuous estimates of the snow state. However, the accuracy of the predictions is limited due to uncertainties in meteorological forcing data and structural problems in land-surface models regarding snow processes (de Lannoy et al., 2012; Slater et al., 2001; Rutter et al., 2009; Dutra et al., 2010; Raleigh et al., 2015). Three major classes of snowpack models are used for various applications (Armstrong and Brun, 2008): single-layer snow schemes (see, e.g., Tarboton and Luce 1996; Jansson and Karlberg 2004; De Michele et al. 2013), schemes of intermediate complexity (Marks et al., 1998; Koivusalo et al., 2001) and detailed snowpack models, which differ in the description and parameterization of the properties inside the snowpack and the related processes (see e.g. Anderson 1976; Jordan 1991; Bartelt and Lehning 2002; Rutter et al. 2008; Vionnet et al. 2012). The model to be applied (single-layer vs. multi-layer) should be chosen according to the problem addressed. When a detailed description of the snowpack is needed, for example, for the modeling of avalanches, a multi-layer model is to be prefered. On the other hand, when a general description is sufficient, for example for the evaluation of the water stored within the snowpack, a single-layer model can be satisfactory. Single-layer representations of snow thermodynamics are still used in operational NWP models (Essery, 2013). In more advanced land-surface schemes used in operational models, there are multi-layer snow options with fixed or variable numbers of layers available (Essery, 2013), e.g. in HTESSEL at ECMWF (Dutra et al., 2012), JULES at the Met Office (Best et al., 2011), ISBA-ES in SURFEX (Boone, 2002), and TERRA in the ICON model at DWD (Zängl et al., 2015). Detailed snowpack models also include state variables for the microstructure of snow grains in different layers (Essery, 2013).

5 Snow data assimilation

Data assimilation can improve the snow properties simulated by numerical models by combining data sets from observations with numerical model predictions and by taking into account the uncertainties of observed and modeled variables (Liston and Hiemstra, 2008).

Therefore, efforts have been made to merge snow observations and snow modeling using the data assimilation method (e.g., Andreadis and Lettenmaier 2006; de Lannoy et al. 2012). Recently, increasing attention is given to investigating how data assimilation (DA) schemes can consistently improve the model simulations by assimilating ground-based measurements or remotely sensed snow-related observations (Bergeron et al., 2016; Dziubanski and Franz, 2016; Alvarado Montero et al., 2016; Charrois et al., 2016; Piazzi et al., in review). For this purpose, several DA methodologies have been developed (Evensen, 2009; Bannister, 2017). Their performances differ depending on their degree of complexity (Piazzi et al., in review). For real-time applications, sequential DA techniques are widely used. They sequentially update the model state, using observational data as they become available (Piazzi et al., in review). Basic approaches use direct insertion (DI) methods (Liston et al., 1999; Malik et al., 2012), or Cressman interpolation (Cressman, 1959). Other approaches include optimal interpolation (OI) schemes (Brasnett, 1999; de Rosnay et al., 2014) and nudging methods (Stauffer and Seaman, 1990; Boni et al., 2010). However, for complex, multi-layered snow models the application of conceptually simple DA schemes is not straightforward due to possible spin-up behavior by the model, resulting from physical inconsistencies between the state variables (Magnusson et al., 2017). The presentation by R. Koch and M. Olefs showed results from a study, in which maps of the daily fractional snow-covered area product from the Moderate Resolution Imaging Spectroradiometer (MODIS) during the winter season of 2015–2016 were used to correct modeled quantities (snow depth, snow water equivalent) at a very high resolution, which had been produced by the operational snow cover model (SNOWGRID) for Austria. When MODIS data are available, the snow cover fraction for this model time step is taken into account, when determining whether or not snow is present in the modeled SNOWGRID fields. As a measure of the impact of MODIS observations on the modeled snow quantities, the differences are analyzed between model runs with and without the use of MODIS for correcting SNOWGRID fields. While taking into account the uncertainties in satellite data for mountainous regions, it is the aim of the qualitative and quantitative comparison to gain further understanding of how the SNOWGRID forecast skill could potentially be improved by using remote-sensing data from the moderate-resolution satellite observations in model domains which include areas of low as well as high altitude.

The presentation by U. Böhm et al. focused on combining ground-based measurements with remote-sensing snow observations within the grid-based physical model SNOW4 for the analysis and short-term forecasting (up to 72 hours) of snow water supply. This is the total amount of runoff from snow melt and precipitation and constitutes an important parameter for flood warning and forecasting. When analyzing the past 30 hours, the model is forced by hourly surface measurements of 2 m-temperature, wet bulb temperature, wind speed, sunshine duration and precipitation. Ground-based daily snow observations at 06 UTC are interpolated to the model grid once a day, including a quality control. The chosen interpolation algorithm contains a method based upon optimal interpolation (Gandin, 1963). Similarly to External Drift Kriging, remote-sensing data may in addition be used to estimate the spatial structure of the snow cover in regions with sparse or no surface observations. It was found that the use of satellite observations as a supplementary source of information had a positive impact on the result of the gridding algorithm of ground observations. IMS data provide added value compared to Land-SAF data in terms of coverage due to a multisensor approach. For operational use in SNOW4, a selection-based approach will be implemented (use of IMS product if available, otherwise use of LAND-SAF product). The frequency of data provision remains a problem as well as the question of how to update the daily IMS product sub-daily.

For sequential DA techniques, Kalman filters (Kalman, 1960) are among the most commonly used methods (Piazzi et al., in review). The basic version of the Kalman Filter (KF) (Gelb, 1974) still uses the assumption of system linearity (Piazzi et al., in review). The Extended Kalman Filter (EKF) (Miller et al., 1994) makes it possible to consider nonlinear dynamic models using a linearizing approach (Dong et al., 2007). With the Ensemble Kalman Filter (EnKF), the inaccuracy of the linearization procedure can be avoided (Evensen, 1994), which affects the filter performance due to possible strong model nonlinearities (Moradkhani, 2008). In order to obtain error estimates instead of a model linearization, an ensemble of possible model realizations is needed, based on the Monte Carlo approach (Evensen, 2003).

In snow hydrology, an increasing number of studies confirms that the EnKF is a well-performing method, which improves the accuracy of hydrological simulations through the assimilation of snow-related observations (Andreadis and Lettenmaier, 2006; Slater and Clark, 2006; de Lannoy et al., 2012; Magnusson et al., 2014; Piazzi et al., in review).

The presentation by D. Gustafsson et al. showed the application of data assimilation methods such as the Ensemble Kalman filter for updating the simulated water storages in snow and soil during the initialization period before issuing forecasts at different times through the winter and the snow melt season. The aim was to make a systematic evaluation of the improvement in seasonal spring melt forecasting skill by assimilating various types of snow data for a number of hydropower reservoir basins in Sweden. Using different methods for updating hydrological models from in-situ measurements and remote-sensing data, it was shown that the assimilation of snow information improved spring melt forecasts in most of the study areas and study years. The main factors for improving the forecasts were manual observations of snow water equivalent and satellite-based data on fractional snow cover area. However, updating the model with snow data does not always lead to improved simulations of river discharge and reservoir inflow. This could be due to a dominant uncertainty in the weather forecast/climatological forecast, uncertainties in snow observations (sparse in-situ measurements, errors of satellite data in mountainous regions), or underestimation of systematic representation errors in the assimilated snow information.

Compared to the state of the art in data assimilation, the methods used for snow analyses in numerical weather prediction are much simpler (Essery, 2013) and lag behind the level of sophistication used for the initialization of other surface variables (e.g. soil moisture). The presentation by E. Kourzeneva et al. addressed the existing gap between rapidly developing remote-sensing snow observations and the simple methods which are used to assimilate them into NWP models. When assimilating remote-sensing Snow Extent (SE) observations, the main problem is that SE is a categorical variable (yes/no), and statistical methods have not yet been developed for such a type of data. It is not known how the observational error of SE could be represented qualitatively. Also, the impact of observations is dominating, since there are no objective statistical methods which could be used to combine observations from different satellites. A comparison of SE observations from two satellites (METEOSAT and METOP) with SYNOP data and with simulations produced by the NWP model HARMONIE showed good overall agreement between all data sources suitable for data assimilation purposes. However, all types of data have errors that need to be accounted for in data assimilation systems. Satellite data mainly overestimate snow due to cloud contamination; they may also contain situations where snow has not been detected. METOP may give an ‘added value’ to products from METEOSAT, especially for Nordic countries, which means that it is worth combining the products of the two satellites. The comparison of SE from two satellites should also be used to derive information on the observational error of categorical SE data.

ECMWF’s snow analysis uses a 2D OI method to assimilate the IMS snow cover information, in addition to the snow depth measurements (de Rosnay et al., 2015). In the presentation by P. de Rosnay et al., the relative impact of different types of observations from a set of Observing System Experiments (OSEs) on the analysis of snow depth was evaluated and it could be shown that forecasts of both surface fields and low-level atmospheric variables are highly sensitive to the snow initialisation. Combined assimilation of both types of observations, in-situ snow depth and IMS snow cover, significantly improves near-surface weather forecasts, compared to experiments without snow data assimilation or experiments using only a partial snow observing system.

In current operational NWP systems, snow depth from in-situ ground measurements and satellite-derived snow extent are assimilated (Drusch et al., 2004; de Rosnay et al., 2015; Pullen et al., 2011), but SWE is not considered during the assimilation cycle (Essery, 2013).

In the presentation by Kuzmina et al., results from the SNOWE technology were shown, which uses SYNOP snow depth observations together with a satellite snow mask in order to correct the SWE values from global data assimilation systems at a local scale with a stand-alone system. The aim is to obtain more realistic daily SWE values at the location of the SYNOP station, since the history of previous weather situations is taken into account. This product provides reliable SWE, which has been shown to have a positive impact on limited-area NWP forecasts produced by the COSMO model, and can be used in hydrological forecasts. By using SNOWE technology to correct the initial fields of COSMO-RU, the RMSE of T2m forecasts near the snow boundary in the spring time could be reduced by 0.5–1.5 K, and in some places by up to 7 K. SNOWE data and technology have been used for forecasting spring floods in 2015/2016 for the northeastern part of the Russian Federation, where the observing network is sparse. Pre-operational runs of SNOWE with COSMO-RU technology for the winters of 2014/2015 and 2015/2016 have resulted in more realistic values of SWE than the ones obtained from the global NWP data assimilation system (in comparison with direct hydrological snow measurements).

Ensemble Kalman Filters have been used in many studies for processing snow observation data in the data assimilation for snow models (Andreadis and Lettenmaier, 2006; Durand and Margulis, 2006; Durand et al., 2009; Kumar et al., 2008; Slater and Clark, 2006; Su et al., 2008; Dechant and Moradkhani, 2011), however, they are not applied operationally to snow information in NWP assimilation systems.

The presentation by Dong et al. focused on the new NASA Land Information System (LIS), which combines NOAA operational land-surface and hydrological models, high-resolution satellite and observational data, and land data assimilation tools. The existing land data assimilation capabilities in LIS have been extended to also support NCEP’s land-surface assimilation of satellite-based soil moisture and snow observations. A set of offline numerical experiments, driven by the GFS forecast forcing, has been conducted to evaluate the impact of assimilating snow information with daily values from the Global Historical Climatology Network (GHCN). The results show that the statistics of the LIS EnKF data assimilation system with 20 members are better than those of an assimilation with direct insertion, LIS control run, operational GFS/GDAS product and U.S. Air Force Weather Agency (AFWA) SNODEP product.

6 Summary

The workshop emphasized the valuable collaboration between research and operational services regarding the use of snow observations for data assimilation in numerical weather prediction models, hydrological models, and physical snow models. These applications have common objectives, methods, and challenges when it comes to combining in-situ and satellite data for usage in a model and for validation. There is a demand for more combined products, retrievals and flow-dependent approaches for data assimilation systems, but in the long term, the aim is to assimilate radiances from spaceborn instruments.

Current snow data products from satellites are typically based on the specific spectral properties of snow. They are used to force land-surface models within a data assimilation framework. However, the remote-sensing data which are most often used are snow cover and fractional snow cover, whilst satellite products such as snow water equivalent and snow depth are only rarely used in data assimilation. New approaches are investigated in order to be able to make use of early satellite images for long-term records in reanalysis applications.

In-situ measurements provide an essential data source for snow depth. However, their sparse coverage in some regions is problematic. They do provide valuable additional information especially in mountainous areas, where satellite data, which are also influenced by clouds and snow below vegetation (e.g. forest), have large uncertainties due to snow conditions varying in a very small area. Therefore it is important to improve the availability of snow depth reports on the GTS, which is being supported by WMO GCW and COST Harmosnow. Satellite data have great advantages in regions with only few in-situ measurements, compared to interpolated station data. The workshop therefore discussed the great potential of a combined assimilation of both types of observations, in-situ snow depth and remote-sensing data (e.g., IMS snow cover), which had been confirmed by results demonstrating the significant improvement of the forecast of near-surface weather variables when using this method.

Applying the SNOWE technology at SYNOP stations represents an approach that takes into account the history of the snowpack for initialising limited areas NWP forecasts and is available to the operational COSMO NWP consortium. For hydrological models, the assimilation of snow information improves spring melt forecasts. Manual observations of snow water equivalent and satellite-based data on fractional snow cover area are considered as most useful in these models. The sensitivity of these model results to data time steps and to data averaging is currently investigated using long-term measurements.

There was a discussion of the existing problems in snow analysis products related to data assimilation methods. For example, snow water equivalent increments that correct the model trajectory to compensate for snow melting processes issues result in a water budget value that is potentially disadvantageous for hydrological forecasts. A combined snow and soil moisture data assimilation can be useful to keep consistency in the water budget. Since observation errors matter in snow data assimilation, the relationship between MODIS snow product errors and temperature was discussed in a study carried out by Dong et al. (2014).

It is important to capture the interaction processes between vegetation and snow in models, since large areas with seasonal snow in the northern hemisphere are regions with forests. Depending on vegetation type and state, altitude and exposition, snow depth and snow water equivalent can differ significantly, which has implications for hydrological forecasts. For climatological applications, the importance of investigating the seasonality of snow and of analyzing potential sources of change in snow depth has been recognized.

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