Snow products for assimilation and verification

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ABSTRACT

Snow is an important component of the land surface, and the choice of products for assimilation or verification can have a large impact on the surface analysis. This paper introduces the many sources of snow data that are currently available, both in situ and from remote sensing from space, along with some recent developments. Snow extent products are derived from the biggest range of sensors and are the most widely used, while information on snow mass from space is still too error-prone to be used successfully in assimilation schemes.

1 Introduction

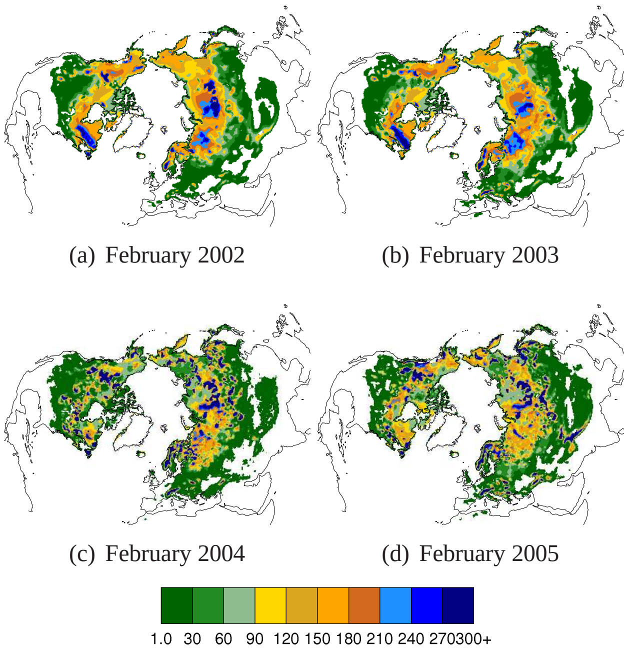
Snow provides important energy and moisture boundary conditions to the atmosphere at the land surface, and long time series of snow extent and mass from reanalysis would be useful for many hydrological and climate applications. For operational use, observations of snow must be available in real time and would ideally be global in extent and come with error estimates. Data not suitable for operational assimilation could be important independent verification of operational forecasts, or for reanalysis.

Ground-based snow measurements have been made at meteorological stations in many parts of the world, but Chang et al. (2005) suggest that to obtain an error of less than 5cm in a 1 degree by 1 degree grid cell, ten measurements are required. This density of measurements is unlikely to be achieved over a wide area. Remote sensing using satellites emerged in the second half of the twentieth century as a means of gathering spatially and temporally continuous datasets of both snow extent and mass, or snow water equivalent (SWE). Snow extent datasets are derived from a range of different instruments and require differing amounts of manual processing. SWE data is only retrieved from microwave instruments. Spaceborne scatterometers are also now being used to monitor snowmelt, while other snow parameters such as albedo and grain size are also beginning to be retrieved from measured reflectances.

2 Current products used at ECMWF

Prior to 2004, and for the ERA40 reanalysis, the analysed snow was relaxed to the Foster and Davy climatology (1988), which used synoptic stations, literature searches and climatological records to reconstruct manually a gridded hemispheric snow depth climatology. However, the authors themselves acknowledge low confidence in data at high latitudes, and systematic biases have been identified, which are particularly problematic over Eurasia (Brown and Frei, 2007). The ERA40 reanalysis also assimilated in situ data from the former USSR snow surveys between 1966 and 1990 and Canadian snow depths from 1946-1995. There is a problem in the ERA40 snow data between 1989 and 1994 and these data should be discarded (Uppala et al., 2005; Clifford et al., 2009).

Since 2004, the operational scheme uses the Northern Hemisphere snow cover product from NOAA/ NESDIS which provides daily data in near real time. The impact of this change in data use can be seen by comparing the snow fields from the ERA Interim reanalysis before and after 2004 (figure 1). Pre-2004, the snow analysis resembles that from ERA40, while after 2004 the distribution of snow is very different.



(a) February 2002 (b) February 2003

(c) February 2004 (d) February 2005

Figure 1: Snow water equivalent (mm), from ERA Interim for February 2002 and 2003 (pre use of NESDIS extent data), and February 2004 and 2005 (with NESDIS extent data assimilated).

3 Ground-based measurements

A number of in situ snow monitoring networks and intensive field campaigns exist that could provide input to or verification for operational snow fields and reanalysis. Since 1980, a network of snow sensors called SNOTEL has been recording data at 730 sites in 11 western US states. Most of the stations are in remote, high-mountain locations, which means the data need to be used carefully to avoid, for instance, elevation biases. Instruments include a pressure sensing snow pillow, a storage precipitation gauge, and air temperature sensors. Soil temperature and moisture measurements are also available at some sites. The network reports in near real time at sub-daily resolution, and longer-term average products are also provided. Information about and access to the data is found at the United States Department of Agriculture's Natural Resources Conservation Service website: http://www.wcc.nrcs.usda.gov/snow/.

The Cold Land Processes Experiment (CLPX) consisted of a series of intensive multi-sensor field campaigns over winter and spring 2002 and 2003 in Colorado, and later Alaska (for CLPX-2). The field sites ranged in size from 1 ha to 160,000 km2 in a nested arrangement, so that the scaling of measurements and processes in cold environments could be investigated. Ground, airborne and spaceborne observations of meteorological and land surface variables were collected, making this dataset a useful resource for the development of techniques to combine data at multiple scales. A journal special issue focussing on the results of the campaign was published in 2008 (Dozier and Melloh, 2008), and data is held at the National Snow and Ice Data Center (NSIDC).

A further technique that may be developed in future is using GPS receivers to infer snow variability. Reflections of GPS signals from snow-covered ground are deliberately minimised, but Larson et al. (2009) showed that there remains a correlation with snow depth that could be exploited. Advantages of this method include an existing network of GPS receivers (many at high latitudes), and a much larger representative area for each measurement than, for instance, a snow pillow (10,000m^2 vs 10 m^2).

4 Remote sensing products

4.1 Snow extent and duration

Snow extent data is usually provided by visible band instruments, as snow has high albedo in the visible part of the spectrum so shows up clearly next to the (low albedo) snow-free surface. Careful discrimination is required between snow cover and cloud cover, and it is estimated that more than a third of the northern parts of both continents is obscured by clouds during the winter months. The data is also affected by low solar illumination in winter, making the satellite pictures harder to interpret (Frei et al., 2003). Masking of the snow due to vegetation can also be a problem for visible band sensors.

Active instruments such as NSCAT and QuikSCAT have been used to detect melting snow through the change in radar backscatter and hence derive a snow line (Nghiem and Tsai, 2001). Snow onset and melt datasets have also been derived from these scatterometers; Wang et al. (2008) found significant correlations with snow-off dates derived from station data although melt was difficult to detect in dense forest or where snow cover is very shallow, such as across the tundra. A dataset of snow-off dates has been compiled by the Canadian Centre for Remote Sensing for 1982-2004 (Zhao and Fernandes, 2009). It is based on the daily 5km Equal Area Scalable Extent (EASE)-Grid product from AVHRR and uses a new snow cover fraction algorithm that takes account of cloud cover. Snow-off date is defined as the date when a pixel has no snow for at least three continuous days during the spring melting season.

A widley-used snow extent product is that from the National Oceanic and Atmospheric Administration (NOAA)/National Environmental Satellite, Data, and Information Service (NESDIS). Weekly snow extent data goes back to 1966, but from 1997 onwards a daily product known as the Interactive Multisensor Snow and Ice Mapping System (IMS) became operational. Snow cover is interpreted by analysts using primarily data from Polar Operational Environmental Satellites (POES) and Geostationary Orbiting Environmental Satellites (GOES), but also other visible and microwave imagers, with a pixel designated as snow-covered when more than 50% is covered with snow.

The MODIS instrument, launched in 2000, has a fully automated algorithm for determining snow extent, unlike the IMS, and daily products at 500m resolution are available. The MODIS snow products also make use of an automatic cloud mask, which is conservative (more likely to identify clear sky as clouds than vice versa). Masking by vegetation can be a problem; Hall et al. (2001) assess errors in the MODIS snow cover retrieval due to land cover type by assigning percentage errors for each of seven land cover classes, plus additional errors due to mixed pixel effects. They estimate that the Northern hemisphere snow extent mapping error is 8%, largely due to the amount of forest cover north of the snowline.

Other large scale snow extent products include a North America-only 1km dataset from the National Operational Hydrologic Remote Sensing Center (NOHRSC), also based on AVHRR and GOES data, and products derived from microwave radiometers such as the Special Sensor Microwave/Imager (SSM/I) and the Scanning Multichannel Microwave Radiometer (SMMR). The detection of snow cover using microwave frequencies has a number of advantages over using visible-band imagery. Data can be obtained during darkness or when the sky is overcast, as clouds are fairly transparent at microwave frequencies. However, the microwave measurements are not sensitive to thin snow, so will underestimate the total extent.

A number of large-scale comparisons of snow extent data have been performed. A comparison of data from MODIS, NOHRSC and SSM/I was undertaken by Hall et al. (2002). They found that MODIS and NOHRSC often agree well, although MODIS nearly always maps a larger area as snow-covered. As expected, SSM/I shows the lowest snow-covered area although agreement between MODIS and SSM/I increases as the snow season progresses. Armstrong and Brodzik (2001) found that data from visible and passive microwave sensors showed similar interannual variability, but that the microwave measurements underestimated the extent by up to eight million square kilometres, compared to the visible data. The largest differences were found in autumn with some improvement in winter and the most agreement in spring. A comparison of snow-off dates from QuikSCAT, MODIS and the IMS shows agreement is good over Siberia but in the Canadian Arctic the IMS shows snow for several days longer than the other data sources. It is suggested that the high concentration of ice-covered lakes in the Canadian Arctic hinders the manual determination of the snowline in the IMS product (Chris Derksen, pers comm 2009).

The different snow covered area datasets see different amounts of snow, but the interannual variability in extent show good agreement once datasets are normalised. In much the same way as ensemble means of climate forecasts, the average snow cover anomaly from multiple datasets seems to do better than any one dataset. Interestingly, the multi-dataset mean mean snow cover extent anomaly series was almost identical to the snow cover anomaly series derived from ERA-40 snow depths (manuscript in prep, Ross Brown 2009).

MODIS reflectance measurements have also been used to derive surface grain size and albedo using a variety of methods. Most recently, Painter et al. (2009) demonstrate the simultaneous retrieval of the snow fraction, albedo and grain size of each MODIS pixel using linear spectral mixture analysis. The retrieval is physically-based and because both the grain size and snow covered fraction are retrieved simultaneously, neither relies on an assumed value of the other. The method can also estimate the pixel-by-pixel uncertainty in snow fraction, which would be of particular use in data assimilation schemes.

4.2 Snow water equivalent

Snow water equivalent (or mass, or depth) is derived from measurements at microwave frequencies, although to date no instrument has been flown specifically for this purpose. Microwave imagers with channels that have been used for snow measurements include SMMR (1978-1987), SSM/I (1987-present) and AMSR-E (2003-present). Retrievals are generally based on the work of Chang et al. (1987), where the linearized difference between two frequency channels is used to infer the mass of snow on the ground:

$$\text{SWE (mm)} = c(T_B 18H - T_B 37H) \tag{1}$$

where H refers to the horizontally polarized channel, T_B is brightness temperature in degrees Kelvin and the gradient of the linear fit, c, is generally derived from radiative transfer models based on an assumed grain size. This regression-based retrieval method is sensitive to this grain size assumption, and the frequency difference saturates in deep snowpacks and is insensitive to very shallow ones. The Tibetan plateau is a problematic area for microwave imagers: the atmosphere is very dry so the area is often snow-free, although it is often misclassified by passive microwave brightness temperatures as snow-covered as it is so cold (Armstrong et al., 2004). Most operational retrievals, including that described above, use a 'static' approach, where the algorithm uses a constant linear coefficient c both spatially and throughout the season.

The longest-term global SWE product based entirely on observations is the Global Snow Water Equivalent Climatology, provided by the NSIDC (Armstrong et al., 2005). The climatology is produced from a combination of SMMR, SSM/I and visible data, with the passive microwave data providing the SWE information, and visible data is used to fill in any pixels that were seen to be snow covered but not detected by the microwave radiometer. Only data from the 37GHz and 19GHz channels are used, gridded to the 25km EASE grid. The dataset comprises monthly means from November 1978 to May 2007 (as of late 2009). To account for the masking effect of vegetation, the algorithm is adjusted by a forest factor using MODIS land cover. This factor increases on a linear scale with forest cover percentage, up to a maximum value for forest cover fraction of 50% or above. A similar product based entirely on AMSR-E observations is also now available from NSIDC.

Foster et al. (2005) propose a modified version of the original Chang algorithm (eqn. 1) to investigate the errors due to the effect of vegetation cover and the assumption of constant grain size. The new algorithm now uses seasonally- and spatially-varying regression coefficients, relating to climatological forest cover and grain size variability. The new algorithm is an improvement during the melting phase, however there are still problems observed in dense maritime forests and alpine regions around the Great Lakes. 'Dynamic' approaches, where the grain size used evolves with time and is dependent on, for example, the temperature history of the pixel, have also been developed. Tedesco et al. (2010) have recently compared the following approaches for real time SWE retrieval:

Static retrieval The retrieval of Foster et al. (2005) described above. This is the benchmark to which all the other methods are compared.

Dynamic retrieval Retrieval coefficients are recalibrated every few days or weeks according to ancillary in situ snow depth data

Forward modelling with an EM model 'Effective grain size' parameter in the forward model recalibrated every few days or weeks according to ancillary in situ snow depths

Land surface model Forcing comes from the Global Land Data Assimilation System which provides meteorological forcing at 2x2.5 degrees resolution at 3 hourly intervals. These forcing data are derived from observed data at global scales.

These different approaches are evaluated with 3 years of in situ data at 37 WMO stations. The biggest improvements are seen with the dynamic retrieval, which show a 50-90% reduction in RMSE compared to ground-measured snow depth. The EM model also offers improvements but not so much, and at some stations performs significantly worse. This could be due to the neglect of snow stratification in the model, and soil properties not being calibrated for the different sites. The highest RMSE for the benchmark retrieval and the forward model is for heavily forested stations. RMSE at these stations for the novel approaches is lower: dynamic approaches have no need to take account of the vegetation explicitly as this is included implicitly through the updated retrieval coefficient. Estimates of SWE using the land surface model come out equal to the dynamic retrieval in terms of RMSE, and as the best in terms of a correlation coefficient. Using the microwave data adds no information to the model estimates: high frequency noise in the brightness temperatures degrades the model estimates, and signal saturation prevents information retrieval for deep snowpacks.

Similarly, recent attempts to assimilate retrieved SWE with a land surface model and meteorological forcing data and have not been very successful. A Kalman filter approach was used to assimilate remotely sensed SWE data into a macroscale hydrology model by Andreadis and Lettenmaier (2006), but the output appeared to be dominated by retrieval errors. Simulation of ground-measured brightness temperatures using forward models driven by snow pit measurements can improve snow depth estimates (Durand et al., 2009) but scaling up to satellite pixels is a problem. The land surface model requires several snow layers and model melt-refreeze layers for good estimates of brightness temperatures (Durand et al., 2008), and deriving suitable input parameters such as grain size at global scales is troublesome.

5 Multi-source products

Several products are available that use a mixture of data sources to produce global products. The ESA Globsnow project aims to produce two fundamental climate data records, one for snow extent and one for SWE. The project team includes agencies and companies from Finland, Norway, Austria, Switzerland and Canada. Snow extent data will be provided from 1995 onwards, based on medium resolution optical imagery. The basic product will be available weekly and monthly, with 1km resolution globally, 250 and 500m for complex terrain. The SWE data will be obtained from a mixture of active and passive, optical and microwave-based spaceborne sensors combined with ground-based weather station observations, with the retrieval based on Pulliainen (2006). This retrieval uses a Bayesian approach within a data assimilation framework to compare the brightness temperature spectral difference with station data, based on prior error estimates. The estimated accuracy of the output is 25-40mm for areas with less than 150mm of SWE, with daily output at a resolution of 25km, and excluding the mountainous areas, Greenland, the glaciers and snow on ice.

Another blended product is the Air Force Weather Agency/NASA Snow Algorithm (ANSA), at 25km resolution (Foster et al, in press). It combines data on snow extent, SWE, fractional snow cover, snow-pack ripening, onset of snowmelt and actively melting areas in all weathers. MODIS is the default data source for cloud-free snow cover data and as a quality check on SWE retrievals from AMSR-E. The SWE algorithm first checks brightness temperature thresholds to ensure the presence of snow, then subsequently for whether the snow is shallow, medium or deep. Then the retrieval algorithm of Kelly (2009) is used along with 500m resolution forest data to retrieve snow depth. This is converted to SWE using Sturm classes (Sturm et al., 1995). AMSR-E is also used to detect wet snow (incipient melt) prior to active melting. The QSCAT diurnal difference (relative backscatter between morning and afternoon passes) is used to identify active snowmelt.

6 Final remarks

Recently there has been an increase in the number and variety of snow data products available, particularly at global scales. The longest-term datasets from remote sensing are now several decades long, providing an important observational record of interannual variability. The range of methods for obtaining snow extent data allows much inter-comparison, although care must still be taken over the discrimination of cloud-covered and snow-covered scenes. New techniques using active microwave sensors will add to the range and resolution of remotely sensed data over the coming years.

Nevertheless, there are still many questions about the reliability and utility of SWE retrievals from passive microwave sensors. Several studies have shown that SWE estimates from good land surface models are actually degraded by the introduction of passive microwave data (Andreadis and Lettenmaier, 2006; Tedesco et al., 2010), and in some cases by assimilating in situ data (Ross Brown, pers comm). Assimilation of in situ snow depth and/or SWE observations is successful where the observations are both dense enough to properly sample the terrain, and are unbiased estimates of the snow cover. These two conditions are rarely met. It is also important to note, however, that much of the algorithm development and calibration for remote sensing has taken place in North America, and that application of these retrievals over Siberia is relatively untested, due to a paucity of ground data and good quality forcing for land surface models.

A snow property that appears repeatedly in remote sensing retrievals is the grain size. Care must be taken over the interpretation of this parameter, as it is not clear that the grain size that is measured in the field or laboratory is easily related to the bulk parameter that controls the scattering over a satellite pixel at optical or at microwave frequencies. With the development of active remote sensing techniques there now exists the opporunity to study the scattering properties of snow from space at finer scales. The combination of data from different sources, used to maximise their particular strengths and minimise the number of assumptions inbuilt into retrievals, is surely the next step in measuring and understanding snow across the globe.

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