

## Using SSM/I to Validate Continental-Scale Modelled Snow Water Equivalent

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### ABSTRACT

This paper assesses the retrieval of snow water equivalent (SWE) from the Special Sensor Microwave/Imager, through comparisons with ground observations of SWE and runoff, model output and empirical orthogonal functions (EOFs). A static difference algorithm is used, with a correction for forest cover. Most validation studies of SSM/I retrieved SWE concentrate on the catchment scale, where the large pixel size and sensitivity of the retrieval to land cover type can be important. This study attempts to validate the retrieval on the hemispheric scale where these local effects are minimised. A ten year average of Northern Hemisphere monthly means is presented and compared to a ten year HadCM3 model run. There are significant differences between the two, particularly over Siberia where the satellite data shows high values (~150mm) and the model shows low values (~50mm). Runoff data from Siberian rivers is shown to support higher values than in the model, though the observations may be subject to some overestimation due to depth hoar. The EOF method is used to establish patterns in northern hemisphere SWE. Results are shown for the Northern Hemisphere, North American continent and Eurasian continent. They show that the seasonal cycle is the highly dominant pattern, with some significant low frequency variability captured in some higher EOFs. The patterns of SWE from SSM/I appear robust at the hemispheric scale. This dataset is a better basis for hemispheric-scale estimates of snow distribution than GCMs, or sparse in situ data.

**Keywords:** SWE, SSM/I, HadCM3, runoff, Siberia

### INTRODUCTION

Snow is a useful variable for climate model validation, as it requires both precipitation and temperature regimes to be correct (Foster *et al*, 1996). However, it is difficult to verify snow depth or water equivalent (SWE) at large scales as in situ data is sparse. SWE retrieved from passive microwave instruments on satellites is the only way to obtain spatially and temporally complete coverage at the continental scale, but the retrieval is subject to certain biases due to factors such as forest cover and grain size. If passive microwave data is going to be used as a validation dataset it should be robust, and the effect of these biases at each scale must be understood. This study examines SWE data over Eurasia from the Special Sensor Microwave/Imager, first using empirical orthogonal functions to assess the amount of noise in the data, and then comparing the distribution to that generated by the HadCM3 general circulation model. Runoff data is then used to investigate the differences between the two datasets. Eurasia has been chosen an area of interest as Siberian snow is thought to modulate climate across the Northern Hemisphere (Gong and Entekhabi, 2002, 2003), and in situ data in the region is particularly sparse.

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## DATA

### SSM/I

The dataset used is the Global Monthly Snow Water Equivalent Climatology, provided by the National Snow and Ice Data Center (Armstrong and Brodzik, 2005). The data are gridded to the 25km Equal Area Scalable Earth grid (EASE-grid). The SWE is derived from passive microwave measurements from the SMMR and SSM/I radiometers, and the entire dataset runs from November 1978 to June 2003. The final product has been supplemented with NOAA's snow extent charts, to provide information in areas where the passive microwave data underestimates snow cover (Greenland is masked out as a permanent ice sheet). For this study, it was decided to use only the data from the SSM/I radiometers, which starts from August 1987, due to the systematic biases found between the data from the SMMR and SSM/I instruments. It was also decided to remove the visible data from the dataset. Firstly this allows the monthly data to be easily averaged, as all the data is provided in the same units, and secondly it allows conclusions to be drawn about the quality of the passive microwave data and retrieval algorithm.

The retrieval algorithm used in this dataset is (Chang *et al* 1987, Armstrong and Brodzik 2001):

$$SWE = 4.77(T_{B19H} - T_{B37H})$$

where  $SWE$  is snow water equivalent,  $T_B$  is brightness temperature in degrees Kelvin, 18 and 37 are the frequencies used in GHz (where  $H$  refers to horizontal polarization), and 4.77 is a constant, derived using a grain size assumption of 0.3mm.

### HadCM3 and HiGEM

HadCM3 is a general circulation model from the Hadley Centre, and has been used in the Atmospheric Model Intercomparison Project (Frei *et al* 2003). HiGEM is a high resolution GCM also from the Hadley Centre, (with updated physics from those in HadCM3), included to illustrate the effect of more realistic topography on model snow distribution.

### ERA-40

ERA40 is a 40 year reanalysis product from the ECMWF. Meteorological observations from many sources are assimilated into a general circulation model to produce global reanalysis fields. Snow data from the former USSR have been assimilated into this product.

### Runoff data

Runoff data for the Lena River comes from the Global Runoff Data Centre (Dumenil Gates *et al* 2000). The data is a fifty year average (1935-1984) from the Kusun station.

## EOF ANALYSIS

Empirical orthogonal function analysis was used to decompose this dataset from a monthly time series into spatial patterns (EOFs) with an associated time-varying pattern (principal component or PCs). The EOFs are ordered by how much variance of the original dataset they explain. The method produces as many EOFs (with associated PCs and eigenvalues) as there are timesteps in the original dataset. No rotation of the EOFs was performed, as this procedure can favour local modes of variability at the expense of global modes which are the focus of this study (Dommenget and Latif 2002).

Figure 1 shows the eigenvalues of the dataset, which represent the amount of variance explained by each EOF. It is clear that the dataset is dominated by the first EOF, with a value of over 80%. Figure 2 shows the first four EOF patterns and associated principal component time series and eigenvalues for the original SWE dataset. The first EOF shows the main annual component of variability, as expected. The pattern shows highs across most of Russia and northern Canada, and

the PC shows one maximum a year in February. There is some inter-year variability in the amplitude of the maxima.

EOF2 and EOF3 show 'dipole' structures accounting for accumulation and melt in the seasonal cycle, as shown by the frequencies present in the time series. EOF3 shows clearly the areas that accumulate snow early in the season and retain snow until late. This is also borne out by the peaks occurring in winter and late spring in the time series.

EOF4 is the first anomaly pattern, occurring positively in some winters and negatively in others. By EOF5 the patterns are starting to lose coherence, and the PC becomes very noisy (not shown). However all the eigenvalues by now are very close together, and represent only 12% of the variance in the dataset.

The EOF analysis suggests that the SSM/I dataset has a high signal to noise ratio and is not subject to any obvious contamination.

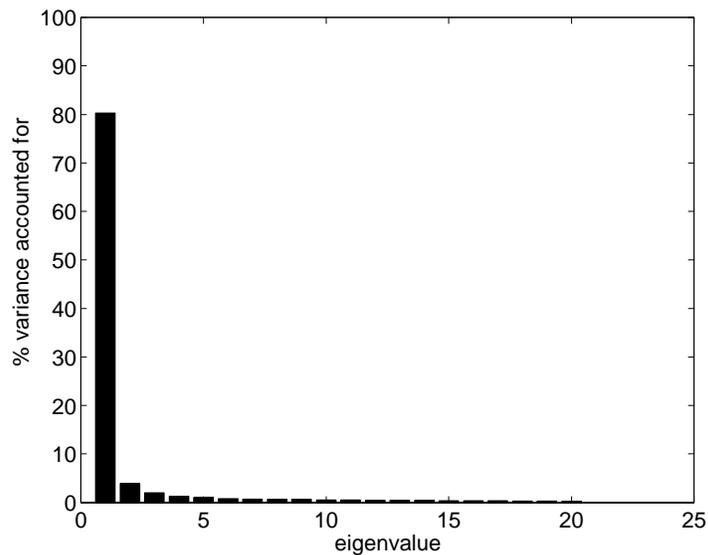


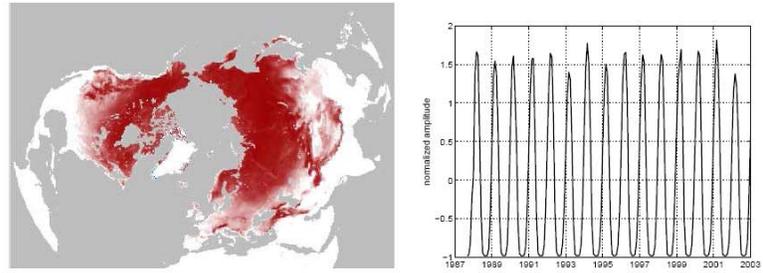
Figure 1. Eigenvalues of SSM/I data.

## EURASIAN SWE DISTRIBUTION

Figure 3 shows Eurasian February SWE distribution from a 10 year average for SSM/I, HadCM3, HiGEM and ERA-40. The model produces much more snow over western Eurasia and very little (<60mm) over Siberia, whereas in contrast the satellite observations show the deepest snow in Siberia (>150mm) and shallower snow in western Eurasia. HiGEM has a very similar distribution to HadCM3, so this snow distribution is most likely driven by model circulation rather than the representation of topography. ERA-40 is more similar to the SSM/I retrievals than the model, although the maximum is located further west than in the SSM/I data.

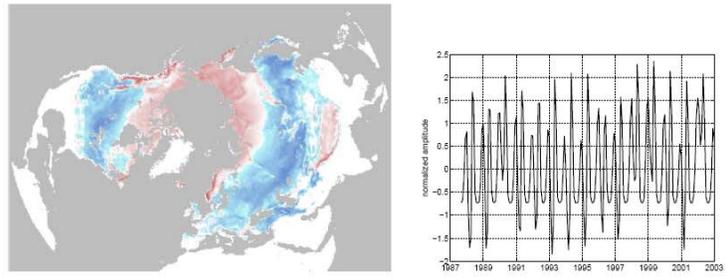
The SSM/I retrieval algorithm used in this study contains an assumption of constant grain size, which is a source of bias in the SWE retrievals (Foster *et al* 2005). Grain size varies hugely in snow packs, in both time and space, but Sturm *et al* (1995) have attempted to derive a classification system for snowpacks. Siberian snow is shown to be a mixture of tundra and taiga snow, which have significant amount of depth hoar. These large depth hoar crystals scatter microwave radiation more heavily, leading to an overestimation of the depth of the snowpack. But is this effect enough to explain the difference between the modelled snow and the satellite observations of Siberia? Foster *et al* (2005) attempt to quantify the error in the retrieval due to the assumption of constant grain size. The maximum overestimation, from their estimate, is 30%.

Taking 180mm as a representative value of the satellite-derived SWE in Siberia in February, a revised estimate would be 120mm, which is still twice the modelled SWE in that area. An



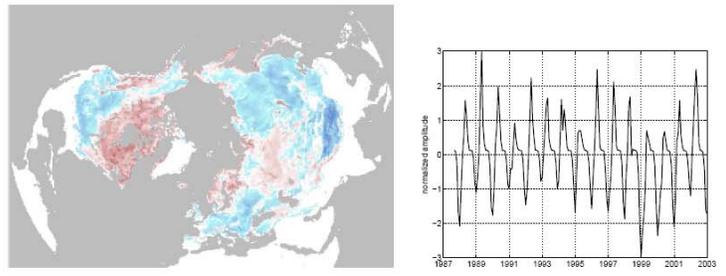
(a) EOF1

(b) PC1



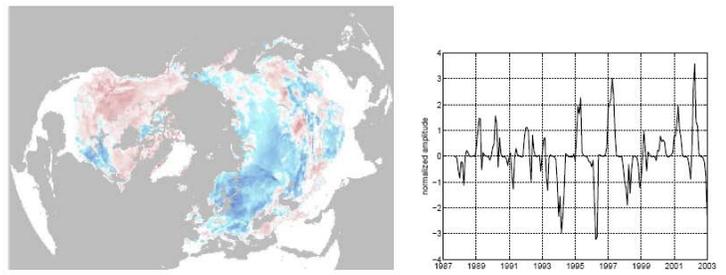
(c) EOF2

(d) PC2



(e) EOF3

(f) PC3



(g) EOF4

(h) PC4

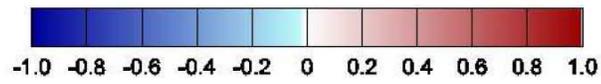


Figure 2. EOFs 1-4 and PCs 1-4 of SSM/I dataset.

investigation of passive microwave retrievals in the Kuparuk River Watershed, a snowpack that is dominated by depth hoar, found that the Chang algorithm produced estimates within 30mm of the spatially averaged SWE for the watershed (Koenig *et al* 2004).

In situ data from Siberia (as distributed by the NSIDC (Krenke, 2004) and discussed in Kripalani and Kulkarni (1999)) also suggest that depths of over 60cm in winter are not uncommon, supporting the proposal that the SSM/I data are more representative of the ground truth in Siberia than HadCM3.

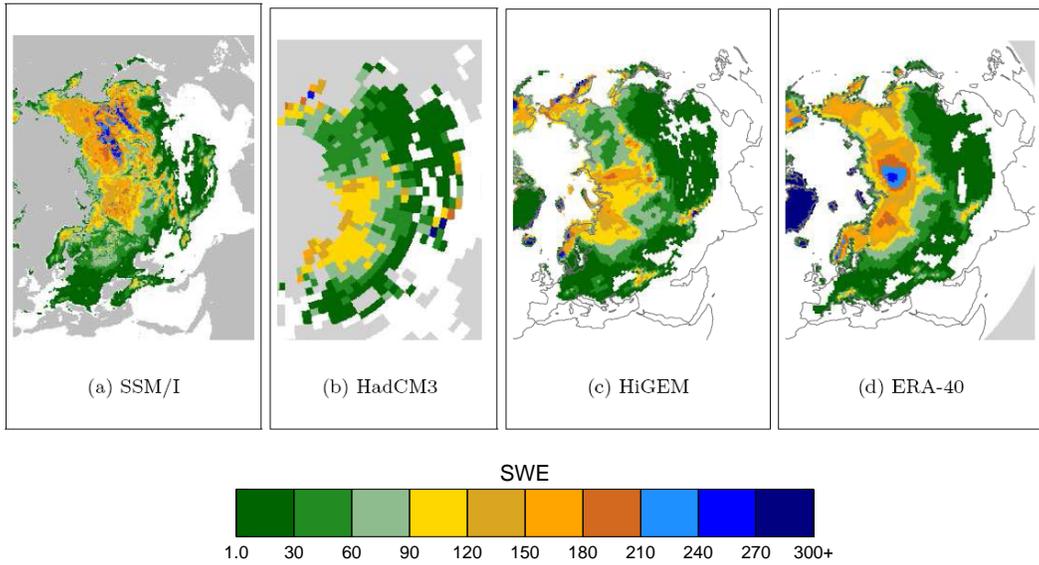


Figure 3. February SWE distribution from a 10-year average.

### LENA CATCHMENT RUNOFF

As in situ data in the region of interest is sparse, it is difficult to verify the overall SWE distribution. However, the main area of discrepancy is coincident with the Lena catchment (shown in figure 4 so summer runoff data from this river could be used as an integrated measurement of winter precipitation).

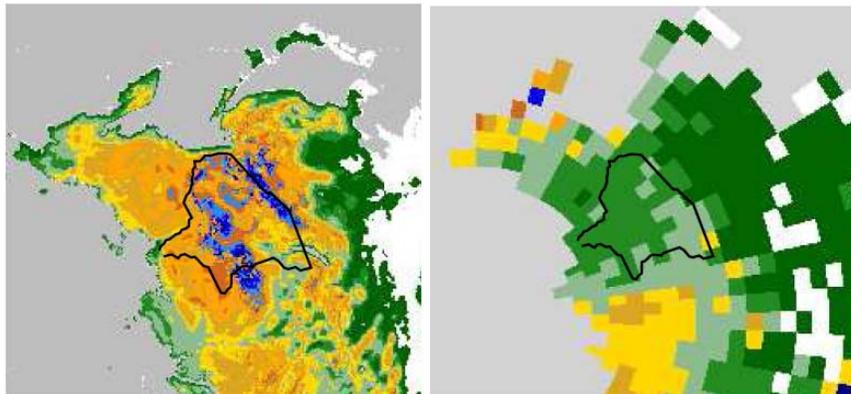


Figure 4. Location of Lena catchment in SSM/I and HadCM3 datasets (key as for Figure 3).

Figure 5, taken from Dumenil Gates *et al* (2000), shows measured discharge from the Lena River. Summing the values for May, June and July and dividing by the catchment area gives 130mm: the equivalent depth of water required across the catchment to provide the runoff

measured in summer. From this runoff data alone it appears that the SSM/I data provides a more reasonable estimate of the SWE in the Lena catchment. This could be a misleading result, however, as much of the Lena catchment contains ground ice: layers of sediment containing up to 80% ice which can collapse in summer and release large amounts of water into rivers. Furthermore, Yang *et al* (2002) suggest that summer discharge in the Lena River is only weakly correlated to snow depth, suggesting that other factors may contribute more strongly to discharge in this catchment.

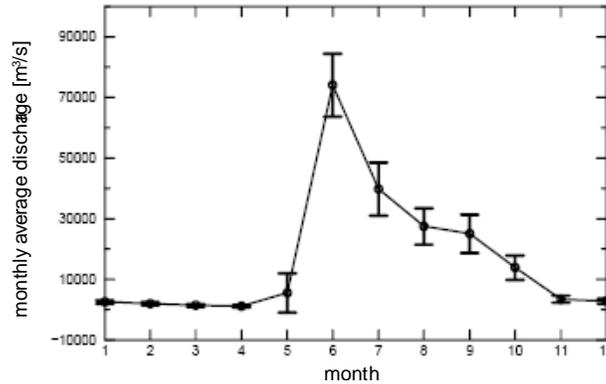


Figure 5. Monthly average discharge from the Lena catchment.

## CONCLUSION

Eurasian SWE distribution from passive microwave observations and the HadCM3 general circulation model have been compared for the Eurasian continent. The main area of disagreement is over the Lena catchment in Siberia, where HadCM3 shows very low values (<60mm) whereas the satellite retrievals suggest maximum values for the continent (>200mm in places). Discharge from the Lena River is high enough to suggest that the SSM/I values are more realistic, though the catchment also contains ground ice which could be contributing significantly to the runoff. It is possible that the satellite retrievals are overestimates, although known biases in the retrieval alone are unlikely to account for this large discrepancy. Alternatively, if the SSM/I values really are more representative of the ground conditions, there must be deficiencies in the model leading to a lack of winter precipitation in the area. This suggestion is supported by the higher values present in the ERA40 reanalysis product, though without further investigation with ground data it will be difficult to resolve these differences. As the snow extent and depth in this area are believed to have important connections with events such as the Indian monsoon, it is essential that the differences between these continental-scale datasets are understood.

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