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Assessing uncertainty and sensor biases in passive microwave data across High Mountain Asia

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ABSTRACT

Snowfall comprises a significant percentage of the annual water budget in High Mountain Asia (HMA), but snow-water equivalent (SWE) is poorly constrained due to lack of in-situ measurements and complex terrain that limits the efficacy of modeling and observations. Over the past few decades, SWE has been estimated with passive microwave (PM) sensors with generally good results in wide, flat, terrain, and lower reliability in densely forested, complex, or high-elevation areas.

In this study, we use raw swath data from five satellite sensors — the Special Sensor Microwave/Imager (SSMI) and Special Sensor Microwave Imager/Sounder (SSMIS) (1987–2015, F08, F11, F13, F17), Advanced Microwave Scanning Radiometer — Earth Observing System (AMSR-E, 2002–2011), AMSR2 (2012–2015), and the Global Precipitation Measurement (GPM, 2014–2015) — in order to understand the spatial and temporal structure of native sensor, topographic, and land cover biases in SWE estimates in HMA. We develop a thorough understanding of the uncertainties in our SWE estimates by examining the impacts of topographic parameters (aspect, relief, hillslope angle, and elevation), land cover, native sensor biases, and climate parameters (precipitation, temperature, and wind speed). HMA, with its high seasonality, large topographic gradients and low relief at high elevations provides an excellent context to examine a wide range of climatic, land-cover, and topographic settings to better constrain SWE uncertainties and potential sensor bias.

Using a multi-parameter regression, we compare long-term SWE variability to forest fraction, maximal multi-year snow depth, topographic parameters, and long-term average wind speed across both individual sensor time series and a merged multi-sensor dataset. In regions where forest cover is extensive, it is the strongest control on SWE variability. In those regions where forest density is low (<5%), maximal snow depth dominates the uncertainty signal. In our regression across HMA, we find that forest fraction is the strongest control on SWE variability (75.8%), followed by maximal multi-year snow depth (7.82%), 90th percentile 10-m wind speed of a 10-year December-January-February (DJF) time series (5.64%), 25th percentile DJF 10-m wind speed (5.44%), and hillslope angle (5.24%). Elevation, relief, and terrain aspect show very low influence on SWE variability (<1%). We find that the GPM sensor provides the most robust regression results, and can be reliably used to estimate SWE in our study region.

While forest cover and elevation have been integrated into many SWE algorithms, wind speed and long-term maximal snow depth have not. Our results show that wind redistribution of snow can have impacts on SWE, especially over large, flat, areas. Using our regression results, we have developed an understanding of sensor-specific SWE uncertainties and their spatial patterns. The uncertainty maps developed in this study provide a first-order approximation of SWE-estimate reliability for much of HMA, and imply that high-fidelity SWE estimates can be produced for many high-elevation areas.

1. Introduction

Tracking the accumulation and melt of snow is essential for weather forecasting, climate modeling, and water management applications. Estimates of snow depth (SD) and snow-water equivalent (SWE) provide additional information on the volume of water stored and released from snowpack, which is critical for managing flood risk, irrigation systems, and hydropower (Armstrong & Brodzik, 2002), (Tedesco & Narvekar, 2010). Several methods have been used to estimate SD and SWE over large areas, such as modeling based on snow covered area (SCA) and a conversion factor (Bookhagen & Burbank, 2010), (Immerzeel, Droogers, De Jong, & Bierkens, 2009), estimating melt volume by backward calculation of snow clearance dates (Molotch & Margulis, 2008; Guan et al., 2013), direct measurements of SWE with in-situ climate stations, and SWE estimation with passive microwave (PM) data (Chang, Foster, Hall, Rango, & Hartline, 1982; Chang, Foster,

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& Hall, 1987; Clifford, 2010; Daly et al., 2012; Pulliainen, 2006; Takala, Pulliainen, Metsämäki, & Koskinen, 2009; Takala et al., 2011; Tedesco, Derksen, Deems, & Foster, 2015). SWE estimation with PM data is the only method which can estimate SWE over large areas, across all terrain types, and provide high-temporal resolution SWE estimates based on empirical relationships. High temporal-resolution data is imperative for accurately guaging snowmelt and downstream runoff (Anderton, White, & Alvera, 2002; Dozier, Painter, Rittger, & Frew, 2008; Painter et al., 2009).

Beginning in 1978 with the Scanning Multichannel Microwave Radiometer (SMMR) system, PM data has been used to measure snow parameters (Knowles, Njoku, Armstrong, & Brodzik, 2002; Chang et al., 1982). PM data has several significant advantages over optical remote sensing data for the collection of snow data, including cloud penetration, night-time data collection, and high sensitivity to water content in snowpack. For many snow-covered regions, winter storms can drastically limit optical data collection due to cloud cover. The Special Sensor Microwave/Imager (SSMI) (Wentz, 2013), Special Sensor Microwave Imager/Sounder (SSMIS) (Sun & Weng, 2008), Advanced Microwave Scanning Radiometer — Earth Observing System (AMSR-E) (Ashcroft & Wentz, 2013), AMSR2 (Imaoka et al., 2010), and Global Precipitation Measurement (GPM) (GPM Science Team, 2014) sensors each collect data at several microwave spectra, and can be used for the evaluation of snowpack at daily or greater resolution.

Several algorithms have been developed to estimate SD and SWE from PM data (e.g., (Chang et al., 1987; Kelly, Chang, Tsang, & Foster, 2003; Pulliainen, 2006; Kelly, 2009; Tedesco & Narvekar, 2010; Takala et al., 2011). The majority of these algorithms exploit the difference between the brightness temperatures (Tb) at the ~18 and ~36 GHz channels. However, more recent algorithms, such as those proposed by (Kelly, 2009), also exploit the ~10, ~23, and ~89 GHz channels available on AMSR-E/2 and GPM, which can better resolve shallow snow conditions and are less sensitive to saturation of the PM signal at the ~18 GHz band (Derksen, 2008). Improvements on SWE estimation have also been made by tuning the original equations proposed by (Chang et al., 1987) to specific regional conditions (Mizukami & Perica, 2012), correcting for elevation (Savoie, Armstrong, Brodzik, & Wang, 2009), and by introducing a forest cover correction (Foster et al., 2005). While these methods have improved upon SWE estimation, they remain unreliable in complex topography (Tedesco et al., 2015).

Topographic relief can have strong impacts on sensed Tb values (Mätzler & Standley, 2000;Dozier & Warren, 1982). First, the path between the ground surface and the PM sensor is determined by the ground elevation, which can introduce a height-dependent bias (Savoie et al., 2009). Second, complex terrain can interact constructively, where the sensed Tb values are not only the PM radiation emitted by a flat surface, but the combination of interacting microwave signals from hillslopes which face each other. Third, topography can shadow parts of the satellite field of view, which preferentially samples those hillslopes which face the satellite. Last, land surface slope changes the relative look angle of the satellite, which can preferentially enhance or degrade the microwave signal from different areas of the same field of view, and modify the relative signal strengths of horizontally and vertically polarized Tb data (Dozier & Warren, 1982). In addition to topographic impacts, forest cover can significantly reduce the Tb difference term used by SWE algorithms (Chang, Foster, & Hall, 1996; Foster et al., 2005). This is due to the attenuation of microwave signals as they pass through dense vegetation, which can reduce SWE estimates by as much as 50% (Brown, 1996; Vander Jagt et al., 2013).

While studies have examined the reliability of SWE data from several satellite platforms (i.e. Imaoka et al., 2010; Armstrong & Brodzik, 2001; Armstrong & Brodzik, 2002; Brown, 1996; Chang et al., 1996; Dai, Che, & Ding, 2015; Foster et al., 2005; Langlois et al., 2011;Mizukami & Perica, 2012; Sun & Weng, 2008; Tedesco & Narvekar, 2010; Wang & Tedesco, 2007; Savoie et al., 2009; Dong, Walker, & Houser, 2005), few large-scale analyses of SWE have been undertaken in High Mountain Asia (HMA), and none have examined the impacts of long-term maximal snow depth and wind redistribution on SWE variability.

As HMA lacks an extensive and reliable ground-weather station network, particularly at elevations above 3000 m, we do not rely on in-situ data to compare our satellite-based SWE estimates to those of any snow-monitoring stations. Instead, we focus on understanding the utility and limitations of satellite-based PM data – especially those factors which may reduce the reliability of SWE estimates – by examining a multi-frequency time series of PM data across a range of topographic, land cover, and climate settings.

2. Materials and methods

In this study we use a multi-instrument time series of SSMI, SSMIS, AMSR-E, AMSR2, and GPM PM data from 2000–2015 in combination with topographic, land-cover, and climatic data.

2.1. Study area

Our study area encompasses a wide range of climatic seasonality, elevation, topographic relief and hillslope angles. It includes not only high relief and high complexity areas typical of many mountain ranges, but also large areas of low relief at high elevation (i.e., the Tibetan Plateau). Low but variable forest density across the study region, in combination with the range of topographic characteristics, allows us to examine a range of factors which impact SWE estimation with PM data. We randomly generated 5000 points within our study area, and removed those close to major bodies of water. From this subset, we choose 2500 sample points which cover a wide range of elevation, relief, slope, and aspect settings (Fig. 1).

2.2. Topographic, land cover, and climate data

The 2000 Shuttle Radar Topography Mission V4.1 (SRTM) Digital Elevation Model (DEM) (~90-m, void-filled) was leveraged to provide elevation, hillslope angle, aspect, and 5-km radius relief (Jarvis, Reuter, Nelson, Guevara, et al., 2008) (Fig. 1). We then apply an averaging filter over a 20-km radius to the hillslope, elevation, and relief surfaces to minimize spatial-resolution differences and PM location uncertainties when comparing between 90-m and ~25-km resolution data (Fig. 2A, B).

High Asia Reanalysis (HAR) (2000–2014) provides 10-km resolution land-surface temperature at 2-m heights (product t2) at both daily and 3-hourly temporal resolution over 98% of the study area for the period 2000 to 2014 (Maussion et al., 2014). For those points which fall outside of the 10-km HAR domain, we use the 30-km product instead. We use the hourly product to create average daily daytime and nighttime temperatures, as well as bi-daily deviation values from the long-term average monthly temperatures. In addition to the HAR temperature product, we leverage the 10-m surface wind speed dataset (product ws10) to assess the impact of high-wind areas on SWE variability (Fig. 2C). We treat the HAR wind product as a 'static' dataset in our analysis by using long-term statistics derived from the 14-year time series of wind speed data, such as the long-term December-January-February (DJF) median, 25th and 90th percentile wind speeds at each pixel. By using percentiles as proxies for long-term trends in the climate data, we can more accurately compare trends in wind speed with trends in SWE and SWE variability over the whole time series instead of on a daily or hourly basis.

TRMM product 3B42 V7 (1997–2014) provides daily rainfall estimates at $0.25^\circ \times 0.25^\circ$ resolution (Huffman et al., 2007). This data is used to isolate precipitation-free days and multi-day periods from the larger time series, with a sensed precipitation threshold of 0.1 mm/h.

Fractional forest cover is derived from MODIS MOD12Q1 yearly data (2001 — 2012), following the Boston University IGBP classification