Snowpack and runoff generation using AMSR-E passive microwave observations in the Upper Helmand Watershed, Afghanistan

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A B S T R A C T

Passive microwave estimates of snow water equivalent (SWE) were examined to determine their usefulness for evaluating water resources in the remote Upper Helmand Watershed, central Afghanistan. SWE estimates from the Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E) and the Special Sensor Microwave/Imager (SSM/I) passive microwave data were analyzed for six winter seasons, 2004–2009. A second, independent estimate of SWE was calculated for these same time periods using a hydrologic model of the watershed with a temperature index snow model driven using the Tropical Rainfall Measuring Mission (TRMM) gridded estimates of precipitation. The results demonstrate that passive microwave SWE values from SSM/I and AMSR-E are comparable. The AMSR-E sensor had improved performance in the early winter and late spring, which suggests that AMSR-E is better at detecting shallow snowpacks than SSM/I. The timing and magnitude of SWE values from the snow model and the passive microwave observations were sometimes similar with a correlation of 0.53 and accuracy between 55 and 62%. However, the modeled SWE was much lower than the AMSR-E SWE during two winter seasons in which TRMM data estimated lower than normal precipitation. Modeled runoff and reservoir storage predictions improved significantly when peak AMSR-E SWE values were used to update the snow model state during these periods. Rapid decreases in passive microwave SWE during precipitation events were also well aligned with flood flows that increased base flows by 170 and 940%. This finding supports previous northern latitude studies which indicate that the passive microwave signal’s lack of scattering can be used to detect snow melt. The current study’s extension to rain on snow events suggests an opportunity for added value for flood forecasting.

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1. Introduction

Snowmelt is a primary source of water in many mountainous regions of the world, and has a far-reaching influence on areas that rely upon melt water to fill streams and reservoirs and replenish aquifers. In developing countries and very remote regions, ground-based snow data are rarely available due to financial constraints and safety concerns. Thus assessing the volume of water contained in the snowpack can be especially difficult, but is extremely important for water resources management. Without information about the snowpack, these regions are particularly susceptible to flooding or drought which may have broad reaching political and economic implications. Remotely sensed, satellite data can offer a potential source of inexpensive, spatially distributed snow information if the questions of accuracy in these regions can be addressed.

The primary snow data available from satellites are snow covered area (SCA) and snow water equivalent (SWE). Optical sensors provide highly accurate, high-resolution SCA estimates because snow contrasts greatly with its surroundings owing to its high albedo (Gafurov & Bardossy, 2009). Several studies (i.e., Immerzeel et al., 2009; Li & Williams, 2008) have successfully used SCA and a basin-specific snow depletion curve in the Snow Runoff Model (Martinec et al., 2008) to model snowmelt. Other studies have used SCA for data assimilation to improve runoff model accuracy (Andreadis & Lettenmaier, 2006; Nagler et al., 2008). The drawbacks of SCA estimates from optical sensors are that measurements cannot be taken at night or through a cloud cover, and they provide no information about snowpack depth or water volume.

As reviewed by Clifford (2010), passive microwave instruments have a long history of providing SWE estimates beginning with Chang’s seminal work (e.g., Chang et al., 1987, 1976), but at a coarser resolution than the optical sensors. Passive microwave instruments are used to measure microwave radiation (brightness temperature) naturally emitted from the Earth, and can be used to estimate SWE. At wavelengths greater than 20 GHz that signal is attenuated by the presence of a snowpack. Early algorithms used an empirical relationship to estimate SWE based on the signal difference at two different channels: a low frequency that is not scattered by the snow,
at approximately 18 GHz, and a high frequency that is scattered, typically around 37 GHz (Chang et al., 1987).

\[ SWE = c \left( T_{B,18} - T_{B,37} \right) \]  

(1)

where \( SWE \) is in mm; \( T_B \) is the temperature brightness at different channels (K); and \( c \) is a radiative transfer coefficient, given as 4.8 mm/K. Direct calculation of \( SWE \) from passive microwave observations is challenging because it is affected by the liquid water content of the snowpack (Hallikainen et al., 1986; Walker & Goodison, 1993), large snow crystals, or depth hoar (Foster et al., 1999; Hall et al., 1986; Josberger & Mognard, 2002), topology of the ground (Matzler & Standley, 2000) and vegetation (Derksen et al., 2003, 2005). Subsequent algorithms have tried to account for these effects to improve results regionally and seasonally.

Previous research suggests that remotely sensed \( SWE \) may be able to enhance snowpack prediction skill and improve quantification of available water resources in remote regions (Yang et al., 2009, 2007). However, other studies have found poor or no relationship between passive microwave \( SWE \) and stream runoff (Rawlins et al., 2007). The performance may decrease when the snowpack depth exceeds a critical depth, of approximately 240 mm, and the microwave signal saturates (Andreadis & Lettenmaier, 2006). These results indicate that the value of remotely sensed \( SWE \) for runoff predictions may differ by location and requires further investigation.

For this study, we examine the evolution of the snowpack and snowmelt runoff in the mountainous, Upper Helmand Watershed of Afghanistan using a 1 km distributed snow hydrology model. Model results are compared to remotely sensed data to determine if passive microwave estimates of \( SWE \) can be used to characterize the snowpack and estimate runoff from snowmelt in the Helmand River. Because ground-based snow measurements are non-existent, validation is conducted using a suite of satellite observations, model results and runoff observations. This research addresses the following questions for this study region, 1) How do estimates of \( SWE \) from two different passive microwave sensors compare? 2) How does the \( SWE \) from a snow hydrology model differ from that estimated directly from passive microwave sensors? 3) Is the relative magnitude of spring runoff predictions from the snow model improved using remotely sensed \( SWE \) updates?

## 2. Methodology

### 2.1. Site location

The study region is the Upper Helmand Watershed in central Afghanistan. The watershed is approximately 47,000 km² and extends from the Hindu Kush Mountains in the northeast to the Kajakai Reservoir in the southwest (Fig. 1). Elevations range from 4085 m at the divide to 1000 m at the dam. The Helmand River, the longest river in Afghanistan, originates in the Upper Helmand Watershed and flows approximately 500 km to the Kajakai Reservoir, and then another 610 km until it reaches the Sistan Delta on the border with Iran. The Helmand River is a main source of water for the southern region of Afghanistan.

Snowmelt contributes a significant portion of the total runoff to the Helmand River. According to the Watershed Atlas of Afghanistan (Favre & Kamal, 2004), 80% of Afghanistan's water resources come in the form of snow. Snowmelt and spring rainfall provide the water necessary to sustain crops and irrigation during the summer, when streamflows decrease significantly. The Kajakai dam regulates the Helmand River for irrigation and flood control and supplies electricity to southern Afghanistan. This project is economically important to the region with future increases to capacity being investigated recently (USACE, 2007).

### 2.2. Data

Ground data are scarce in all of Afghanistan, including the Upper Helmand Watershed. A system of stream gages along the Helmand River routinely recorded discharge data beginning in the 1940s until being discontinued during the Soviet invasion in 1979 (Williams-Sether, 2008). Meteorological data were limited and unreliable prior to 1980. Since 2003, a limited number of Afghan Meteorological stations have been reestablished to record temperature and precipitation. Because the terrain is rugged and has limited access, no ground-based snow data are available for Afghanistan.

#### 2.2.1. Hydrologic data

Several streamflow gages were operational in Afghanistan prior to 1980 (USGS, 1979). There is an ongoing effort to reinstall these gages to monitor flow, but as of this report, the Helmand River has no operational gages. Historical data are available until 1980 from three

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Fig. 1. The study region in the Upper Helmand Watershed in central Afghanistan shown with the temperature gage network and the Kajakai Reservoir watershed outlet.
stations above the Kajakai Reservoir and one just downstream of the dam. These flow records show a snowmelt-fed system with the highest flows occurring during the spring runoff (Fig. 2).

Model runoff validation was conducted using monthly water surface elevations from 1998 to present and daily elevation data from 2006 to 2007 and 2008 to 2009. Inflows \( I(t) \) to the Kajakai Reservoir were estimated for periods having daily elevation data using a reservoir water balance model.

\[
I(t) = \frac{ds}{dt} + O(t.)
\]

where \( S \) is the reservoir storage at a given time, \( t \); and \( O \) is outflow. Storage was estimated from observed elevations using a USGS elevation–storage relationship (Vining & Vecchia, 2007). Outflow was estimated using an elevation–discharge rating curve based on the spillway geometry, power production at the hydropower plant, and irrigation withdrawals (John Hazelton, USACE, 2009, personal communication 2009). Monthly precipitation and evaporation account for 5% in the calculated daily inflow, with the greatest differences occurring during low flow periods. Because these data are not available at the reservoir during the entire time period, they were not included in the water balance calculations. To evaluate the results, the Nash–Sutcliffe efficiency, \( E \), was used which can range from 1 to \( -\infty \), with 1 signifying a strong fit between modeled and observed values, and a negative value indicating that the average observed value would lead to a better result than the model (Nash & Sutcliffe, 1970).

\[
E = 1 - \frac{\sum_{i=1}^{n} (O_i - M_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}.
\]

Applying this reservoir model to the historical period, 1953 to 1979, when discharge data upstream of the reservoir were available, resulted in a Nash–Sutcliffe efficiency of 0.78 with observed values.

2.2.2. Precipitation

Because gage precipitation data in this region are sparse and unreliable during the period of interest, this study used remotely sensed precipitation data from the Tropical Rainfall Measuring Mission (TRMM) obtained from NASA's Goddard Earth Sciences Data and Information Services Center. The TRMM Multi-satellite Precipitation Analysis (TMPA) data are available from January 1998 through the present at a spatial resolution of 0.25 × 0.25° for the area between latitudes 50° S to 50° N. The TMPA 3B42 research-grade product is produced by combining estimates from multiple passive microwave (PM) and infrared (IR) sensors, and adjusted with ground-based gage measurements (Huffman et al., 2007). PM sensors can detect ice particles in the clouds at 89 and 150 GHz, with additional channels used to detect a ground snow cover. IR sensors are not as accurate as PM at estimating precipitation, but are available at a much higher temporal resolution. These data are calibrated to the PM data and used to fill in when PM is not available or where ground snow cover impacts the PM signal. Monthly gage measurements are compared to monthly satellite precipitation and used to retroactively adjust the 3-hour and daily data to remove any biases.

Comparisons of TMPA data to gage data have shown that the results are generally reasonable. For the gage-corrected product, Huffman et al. (2007) report a correlation of about 0.9 with a 9% bias over Australia. Xie et al.'s (2006) comparison of distributed gage data to satellite precipitation in China had a correlation of 0.756 and a bias of \(-0.06 \text{ mm} \). A simple comparison of monthly TMPA data to available gage data in Afghanistan gave a much poorer correlation (0.247). However, the quality of the Afghanistan gage data is relatively unknown. Additionally, a better comparison would account for orographic effects and require additional gage data that are spatially distributed.

2.2.3. Temperature

Since 2003, the Afghan Agricultural Research Department–Meteorological Department has maintained several daily temperature stations (Fig. 1). However, none of the stations are in the study watershed. Daily temperature 1 km grids were generated for the basin by interpolating the station data near the study region using inverse distance weighting and adjusting for elevation using a temperature lapse rate. Monthly lapse rates were determined from monthly average temperatures (2003 to 2009) and station elevation. Because the lapse rate did not vary by the month or location, a single average value of \(-5.6 \text{ °C/km} \) was used.

Fig. 2. Historical stream flow (1952–1979) and climatology data (NCDC, 2010).
2.2.4. Snow covered area

Biweekly SCA images, created for operational snow assessments of Afghanistan (Daly et al., 2006–2010), were available during the 2006 to 2009 winter seasons. The majority of the images were created using an automated algorithm to process Advanced Very High Resolution Radiometer (AVHRR) imagery (Rosenthal, 1996). When AVHRR data were not available Moderate Resolution Imaging Spectroradiometer (MODIS) imagery was manually processed using ERDAS Imagine software to extract the snow covered area and cloud cover. The resulting SCA grids have a 1-km resolution. Pixels with at least 20% snow coverage are classified as “snow”, otherwise they are classified as “no snow”. Cloud covered pixels were not included in the analysis.

2.2.5. Snow water equivalent

Daily passive microwave SWE data were available from two sources; the Special Sensor Microwave/Imager (SSM/I) and the Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E). The SSM/I sensor was launched in 1987 on the Defense Meteorological Satellite Program (DMSP) satellite. SWE estimates are derived from the SSM/I brightness temperatures measured at frequencies 19 and 37 GHz, and have a spatial resolution of 69 × 43 km (19.4 GHz) and 37 × 29 km (37 GHz) (Armstrong & Brodzik, 2001). SWE estimations from SSM/I are based on the original algorithm developed by Chang et al. (1987), with an adjustment made to use the 19 GHz channel rather than the 18 GHz channel.

AMSR-E was launched on NASA’s Aqua satellite in 2002. SWE is calculated from its brightness temperature observations at frequencies 18.7 and 36.5 GHz, with a spatial resolution of 28 × 16 km (19.7 GHz) and 14 × 8 km (36.5 GHz) (Kelly et al., 2004). The AMSR-E algorithm uses different thresholds to check for deep snow and shallow snow. Shallow snow is assigned a nominal snow depth of 5 cm, while deeper snowpack depths (cm) are calculated to account for forest fraction and density (Kelly, 2009). The estimated snow depths are then converted to SWE by estimating a seasonal snow density and adjusting for location based on the snow classification work of Sturm et al. (1995).

Though AMSR-E samples at a higher resolution than SSM/I, both SWE datasets are published as 25 km grids and available from the National Snow and Ice Data Center (NSIDC) in an EASE-grid projection. SSM/I and AMSR-E global SWE products are available twice daily from ascending passes which occur in the afternoon and descending passes which occur in the early morning. For this study, only descending SWE data were used to reduce the potential effects of wet snow in the afternoons. Every 3 to 4 days the satellite swath does not completely cover the region of interest due to the low latitude of the site, resulting in a one to two day observation gap. This study only used days when the complete watershed was included in the satellite swath. The SSM/I and AMSR-E gridded SWE data were converted to geoTiff format and re-projected to an Albers Equal Area projection. The grids were resampled to 1-km grid cells using the nearest neighbor method which assigns the same value to the pixel as the data layer in that location without any interpolation. The basin-average SWE was calculated over the Upper Helmand Watershed for each day on which no grid cell values were missing. To reduce the scatter present in the daily data, the maximum weekly values were extracted.

2.3. Snow hydrology model

A snow hydrology model of the Upper Helmand Watershed and subbasins was developed and validated using historical data and recent measurements at the Kajakai Reservoir. For this study, the Hydrologic Engineering Center’s Hydrologic Modeling System (HEC-HMS) model was used. HEC-HMS uses a water balance approach to estimate streamflow and a temperature index approach to model snow in the basin (USACE, 2009). For this study, a 1 km spatially-distributed HEC-HMS model was developed. Model parameters for baseflow and routing were developed using historical discharge data from three stream gages on the upper Helmand River during dry, non-snowmelt periods. Unit hydrograph parameters were estimated using the basin physical characteristics. Initial soil infiltration parameters were based on limited soil information and adjusted during calibration.

The model estimates daily SWE given temperature and precipitation data and an initial SWE value. A base temperature, typically 0 °C, is used to discriminate between snow and rain precipitation. Snow melt is a function of air temperature and a given melt rate, which can be adjusted based on the time of year or during rain events. As a stand-alone model, outside HMS, the temperature index snow algorithm has been successfully used to model the Red River of the North (Hu et al., 2006) and the Sacramento and San Joaquin basins (Daly et al., 2000). Additional model details are available in Vuyovich (2011).

The model was run for the study region from October through June for six winter seasons, 2004 to 2009, to capture the entire snow accumulation and ablation period. Daily precipitation grids from TRMM data and temperature grids from interpolated gage data were the primary model input. The modeled snow extent was compared to high-resolution SCA imagery to confirm that the model was correctly simulating snow accumulation and melt throughout the season. The hydrologic model was calibrated during Spring 2007 when daily reservoir data were available, then run for the remaining 5 years.

3. Results

The following sections compare the remotely sensed data to independent modeled data and reservoir observations. First, the snow model snow extent is compared to the high-resolution SCA images. Then the passive microwave SWE estimates of SWE are examined for six winter seasons (2004 to 2009). Finally, the passive microwave estimates of SWE were used to initialize the runoff model at maximum SWE for each winter.

3.1. SCA comparison

The total SCA estimated by the model was compared to the SCA imagery at approximately bi-weekly intervals throughout the 2007, 2008, and 2009 winter seasons, when processed images were available. The high-resolution SCA imagery is considered to be the reference dataset, or “observation,” of the snow extent because of its relatively high accuracy. An error matrix spatial analysis (Congalton, 1991) was performed to determine if the location of modeled snow matched the observed snow for each date when SCA images were available. Each pixel within the watershed was classified based on whether the imagery and the model both had snow, both had no snow, or one contained snow but not the other. Any pixels classified as clouds in the SCA image were excluded from the analysis. The overall accuracy is the percentage of pixels that were correctly classified by the model.

Fig. 3 shows the SCA comparison during the 2006–07 winter. The model is under-predicting the snow extent at the beginning and end of the winter season, and minor differences are also evident along the edge of snow extent throughout the season. The model appears to overestimate the snow in January, though the actual SWE values in the lower elevation area are quite low. The blocky effect in the modeled snow covered area is caused by the TRMM data grid size. This effect disappears as the snow cover reaches its maximum extent. In general, the SCA agrees quite well between the model and the imagery, with an average overall accuracy of 87.3% during the 2006–07 winter and 87.0% during both the 2008 and 2009 winter seasons. The average and peak season values exceed 85% accuracy level generally required to validate the use of spatially distributed data (Congalton & Green, 2009) and indicate that the model is adequately representing
snow extent throughout the winter season. The model results are quite promising given the region’s limited data.

3.2. SWE comparisons

For the Upper Helmand Watershed, two SWE comparisons were conducted using data from 2003 to 2009. The first comparison was between the two passive microwave SWE observations. The second comparison was between the AMSR-E passive microwave SWE observations and the HEC-HMS SWE estimates.

Weekly basin average SWE depths were computed using SSM/I and AMSR-E. Fig. 4 shows that the two instruments provide similar SWE estimates in the Upper Helmand Watershed, with a correlation of 0.94 and a Nash–Sutcliffe efficiency of 0.92. Both SWE estimates consistently increase during the snow accumulation period and display more scatter during the snowmelt period. The AMSR-E algorithm detects SWE earlier in the winter, which may indicate that AMSR-E is better at detecting shallow snowpacks than the SSM/I sensor. However, at least in the Fall of 2007, the SCA from AVHRR agrees better with SSM/I showing no snow until later in the season, suggesting that AMSR-E is detecting something other than snow early in the winter. Because the values are comparable, studies requiring a longer historical record of SSM/I SWE may be paired with the AMSR-E SWE to analyze snowpack trends in the basin. While both datasets give nearly identical results for the study watershed, for the remainder of this study, AMSR-E was used because it has a slightly higher native spatial resolution.

AMSR-E and model SWE estimates were compared from 2003 to 2009 for the entire Upper Helmand Watershed and also at the 25 km grid scale. At the watershed scale, the timing and magnitude of SWE are similar for both datasets in most years (Fig. 5). However in other years the comparison is poor. In the 2003–2004 and 2005–2006 winter seasons, the model SWE was much lower than the AMSR-E SWE. These 2 years also had lower than normal precipitation based on the TRMM and gage precipitation data. In contrast, the AMSR-E data are relatively consistent year to year. AMSR-E frequently detects snow earlier than the model predicts a snowpack, which agrees better with SSM/I during the early winter. Annual correlations range from 0.5 to 0.8, while Nash–Sutcliffe efficiencies range from 0.8 in 2007–08 to −13.0 in 2003–04. Table 1 summarizes the evaluation statistics for the passive microwave and model SWE comparison.
A spatial comparison was conducted for each winter month to show general locations in the basin where the model and AMSR-E SWE agree. Model SWE grids were selected on a day in the middle of each month when no AMSR-E data were missing, and aggregated to match the 25-km² AMSR-E grids. An error matrix, similar to that used in the SCA comparison, was computed for each monthly comparison by classifying each pixel into 50-mm SWE bins. An overall match was computed by calculating the percentage of pixels that agree between the two datasets (shown as a dashed line in Fig. 5). In the early and late winter seasons, when the snowpack is thinner, the model and AMSR-E estimates of SWE are similar throughout the basin, and the overall match is near 100%. In mid-winter, the AMSR-E sensor detects increasingly more SWE than the model at higher elevations. The average monthly accuracy from January to March ranges between 55 and 62%.

3.3. Hydrologic results

Predicted runoff values were validated by comparing simulated runoff to reservoir measurements at the basin outlet. The runoff from snowmelt was first predicted using only the HEC-HMS model, then with the model snow state updated with the remotely sensed SWE. For the latter approach, the model was updated with the maximum SWE before melt to minimize further accumulations of snow and because passive microwave SWE is less reliable during the melt period.

Fig. 6 compares the predicted monthly reservoir levels to the observed levels. Overall, the monthly results improved when AMSR-E SWE was used to initialize the model. Significant improvements are evident in 2003 to 2004 and 2005 to 2006, when the water levels modeled using only meteorological data were much lower than the observed. In no case does the use of passive microwave SWE data reduce the performance. For all years, the average correlation between the average monthly storage determined using AMSR-E SWE and observed is 0.83, and the Nash–Sutcliffe efficiency is 0.81 (Table 1). This is a significant improvement over the model results that did not use the initial AMSR-E SWE, which had a correlation of 0.40 and a Nash–Sutcliffe efficiency of −3.35 over the same time period. With respect to water supply, Fig. 7 shows that model results with AMSR-E input consistently provide accurate estimates of the reservoir storage, while the model alone could significantly underestimate the available water.
Table 1
Evaluation statistics comparing AMSR-E SWE to snow model results, entire basin.

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4. Anomalous AMSR-E observations

The success of passive microwave observations to estimate SWE depends on snowpack characteristics. It is well established that the passive microwave signal does not scatter through water present in wet snow because wet snow acts as a blackbody emitter (Hallikainen et al., 1986; Walker & Goodison, 1993), so the difference in temperature brightness at two different frequencies becomes minimal, thus reducing the estimate of SWE. This reduction can cause an underestimation of SWE. However, this reduction may provide valuable insight into the snow pack state if used in combination with other observations.

For our study watershed, the passive microwave SWE values typically increase steadily during the accumulation period, and then become increasingly sporadic in the spring when liquid water in the snow, via melt or rainfall, impacts the signal. Occasionally, the daily basin average SWE will rapidly decrease to near zero, then return to approximately the original value over several days. This phenomenon is evident in the weekly maximum SWE data (Fig. 4).

During the study period, five rapid decreases in daily SWE were observed during or shortly after a precipitation event. The rain on snow appears to temporarily reduce the SWE signal over a large portion of the watershed. As rain and any snowmelt runs off, and the remaining snowpack dries or refreezes, the SWE signal returns. The time series of AMSR-E SWE was compared to modeled reservoir inflows (2004 to 2009) and observed daily inflows (2007 and 2009). For each notable decrease in the AMSR-E data, an inflow increase between 170 and 940% was observed (Table 2).

The time lag between the AMSR-E anomaly and the inflow increase was approximately 4 days. In the upper subbasins of the watershed, the time of concentration is between 0.5 and 1 day and the river routing time is approximately 3 days. Thus, the observed time lag is reasonable in light of the estimated travel time for the rainfall and snowmelt to reach the reservoir. The 2007 event between 16 March and the inflow increase on 22 March had the greatest SWE decrease (98%) and the largest discharge increase (2132 m³/s). This event was also noted for widespread flooding and evacuations in the region (Dartmouth Flood Observatory, accessed 2009). Thus for this region, these passive microwave anomalies may have value for detecting snow melt and could serve as a flood warning tool (Table 3).

5. Discussion

Studies assessing the accuracy of passive microwave SWE using point ground measurements have reported a range of results. Mote et al. (2003) compared observed snow depths in the US Midwest to SSM/I SWE and found generally good agreement with differences ranging from 2 to 22 mm. Derksen et al. (2003) analyzed 18 years of passive microwave data over Canada and found that performance was strongly linked to land cover, with estimates in open areas showing strong agreement. In contrast, Tekeli (2008) compared ground measurements to passive microwave estimates of SWE in the mountainous regions of Turkey and found differences ranging from −218 to +93 mm. However, Chang et al. (2005) suggest that at least 10 stations are needed within a 1×1° area to accurately compare point measurements to the large passive microwave pixel area. This sort of ground coverage is difficult to obtain without a dedicated field campaign and unlikely to occur in data-scarce countries. While the current comparison of model SWE to passive microwave SWE in the Upper Helmand Watershed was not supported by ground observations, the results demonstrate that over a large area both estimates often give a similar magnitude of snow mass. Challenges due to the lack of ground data to validate SWE estimates are particularly noticeable in winters of 2003 to 2004 and 2005 to 2006 when the model was negatively affected by low precipitation data.

Several studies have tried to correlate satellite estimates of SWE to stream runoff with mixed results. A correlation analysis between remotely sensed SWE and streamflow data from three major Siberian watersheds (Yang et al., 2007) and in the Yukon River basin (Yang...
et al., 2009) found statistically significant relationships between the data. These studies found relatively consistent annual SWE volumes at the watershed scale, as was the case in this study. Rawlins et al. (2007) compared mid-winter SWE from SSM/I to total spring runoff in 179 Arctic basins and found poor and even negative correlations. This was attributed to vegetation effects in some regions and saturation of the passive microwave signal. For the Upper Helmand Watershed, such comparisons are difficult to make because of the limited streamflow data and the short historical overlap between data sets.

This study demonstrated success when using passive microwave SWE to initialize the HEC-HMS model. This finding agrees with that from Wilson et al. (1999) who developed a distributed snow hydrology model of the Rio Grande River in Colorado, and used SSM/I SWE to periodically update the snow parameters through inversion. Their modeled SWE better matched observed data when updated with passive microwave data. Andreadis and Lettenmaier (2006) also assimilated passive microwave SWE into a hydrologic model of the Snake River basin in the western U.S. They found that passive microwave data only improved model results for shallower snowpacks, and introduced error when a snowpack deeper than 240 mm was present, again attributed to saturation of the signal. Their findings regarding snowpack depth are supported by this study because the Helmand watershed average SWE values rarely exceed 120 mm.

The use of passive microwave observations to initialize the model removed some of the uncertainty in the precipitation estimates. Error in the passive microwave signal caused by vegetation or saturation limit is likely minimal given that there is little vegetation and the snow does not reach significant depths. However, topography may still be a concern. Given the resolution of the passive microwave data, the large size of the watershed may average out some of the local data uncertainty. Andreadis et al. (2008) similarly found a reduction in snow model error at a larger spatial scale as the heterogeneity in local snow processes was averaged out. For this region, AMSR-E and SSM/I give similar estimates of SWE, except in the early season. As snow accumulation is beginning, AMSR-E typically detects snow earlier than SSM/I. Model results and SCA imagery both support SSM/I results showing no snow during this early period, which may indicate that AMSR-E shallow snow algorithms are being impacted by other processes.

The sensitivity of the passive microwave data to wet snow has been investigated as a potential source of hydrologic information in studies that exploit the diurnal amplitude variation (DAV) (Kopczynski et al., 2008; Ramage et al., 2006; Yan et al., 2009). DAV analysis compares the brightness temperature during the morning and evening overpasses to identify when the snowpack is affected by daytime melt, which may indicate the onset of melt (Ramage & Isacks, 2002; Tedesco, 2007). This study also confirmed the impact of liquid precipitation on the SWE signal over a large basin area, but differed from the earlier DAV studies in that the identified periods occurred when the SWE signal rapidly decreased during mid-winter precipitation events. The observed flow increases to the reservoir provide support for microwave sensors' ability to detect melt patterns and runoff in this region. Further investigations and ground data are needed to determine if these anomalies can quantify runoff predictions.

6. Conclusion

Passive microwave estimates of SWE were successfully used to characterize water available from snow in the Upper Helmand Watershed, central Afghanistan. Based on results from six winter seasons, 2004 to 2009, AMSR-E and SSM/I SWE estimates are equally valuable data sources for this remote region. The HMS model, initialized with AMSR-E SWE demonstrated that passive microwave is a reasonable source of snow mass data in the Upper Helmand Watershed for spring runoff predictions and an improvement over the simple temperature index snow model alone.

Differences between the modeled SWE and the AMSR-E SWE during the two winter seasons with less snow highlight the challenges of obtaining model input data in remote regions. That modeled runoff and reservoir storage predictions improved significantly when peak AMSR-E SWE values were used to update the snow model state during these periods further supports the use of AMSR-E SWE estimates for this region.

The sensitivity of the passive microwave data to wet snow is just beginning to be seen as a potential source of valuable hydrologic information which may be used to predict runoff due to rapid snowmelt. This study found that strong agreement between the rapidly decreasing SWE signal during precipitation events and lagged flood flows into the reservoir. Further investigations using the DAV approach and expanded ground data may provide a better understanding of the microwave SWE's potential value to runoff predictions.

In summary, passive microwave SWE has potential value for forecasting reservoir inflows including seasonal forecasting in conjunction with the hydrologic model and event-based forecasting using the wet snow signal. This study found that passive microwave SWE provides valuable water resource information in this data-scarce region of central Afghanistan. The next step for this region is to better understand the skill added by the AMSR-E SWE for water management. This will require longer term records that capture a range of snow packs and additional validation data.

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