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Synergistic Use of Remote Sensing for Snow Cover and Snow Water Equivalent Estimation

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

Review Article

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ABSTRACT

An increasing number of satellite sensors operating in the optical and microwave spectral bands represent an opportunity for utilizing multi-sensor fusion and data assimilation techniques for improving the estimation of snowpack properties using remote sensing. In this paper, the strength of a synergistic approach of leveraging optical, active and passive microwave remote sensing measurements to estimate snowpack characteristics is discussed and examples from recent work are given. Observations with each type of sensor have specific technical constraints and limitations. Optical sensor data has high spatial resolution but is limited to cloud free days, whereas passive microwave sensors have coarse spatial resolution and are sensitive to multiple snowpack properties. Multi-source and multi-temporal remote sensing data therefore hold great promise for moving the monitoring and analysis of snow toward estimates of a suite of snow properties at high spatial and temporal resolution.

Keywords: Snow; optical; active; passive; microwave; remote Sensing.

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1. INTRODUCTION

Snow is a key component of Earth's energy balance, climate, environment, and a major source of freshwater in many regions. Seasonal snow typically covers 30% of the total land area of the Northern hemisphere. In the Southern Hemisphere, outside of Antarctica is generally limited to smaller regions in elevated areas, such as the Andes and the mountains of New Zealand. Snow is among the most important earth's surface characteristics and it has a complex interaction with the landscape and different atmospheric conditions. For this reason, monitoring the spatial and temporal variability of snow cover at high resolution provides valuable information for various weather and climate applications [1,2]. Consequently, accurate information about snow characteristics is required to improve the accuracy of existing hydrological and numerical weather models.

The conventional source of acquiring information on snow characteristics are reports from a network of ground-based meteorological stations at which daily observations are performed. However, most of Earth's snow is located in remote and inaccessible areas, where populations are sparse or nonexistent and extreme conditions limit the ability to monitor the snow conditions continuously. As an alternative, satellite remote sensing has been used for mapping snow cover and to estimate snow characteristics for several decades[3–5]. Satellite sensors can provide higher spatial and temporal resolutions than conventional methods. However, the research questions that still are unresolved are: What level of accuracy can be reached using satellite remote sensing, and what direction should be taken to improve existing products?

Despite the success of existing operational snow detection algorithms in mapping snow cover under most conditions, there are limitations in extending these to monitoring snow properties of interest, such as snow depth and snow water equivalent[3,6]. The existing limitations suggest that more attention should be paid on making better use of multi-source and multi-temporal remote sensing data sets. Given that different technical constrains affects each particular sensor, the synergy of satellite observations in the visible and in the microwave spectral bands is an important approach to improve the mapping and monitoring of the snow cover and snowpack properties (Fig.1.). The merging of multiple sensor observations with different spectral bands will lessen the instrumental limitations (e.g. spatial resolution, temporal resolution and all weather capabilities).Moreover the combination of different Spectral Bands adds further independent information about the snow characteristics.

This article reviews various remote sensing techniques for snow studies, such as: optical/infrared, active and passive microwave. However, special attention is given to their synergistic use that can substantially improve snow retrievals.

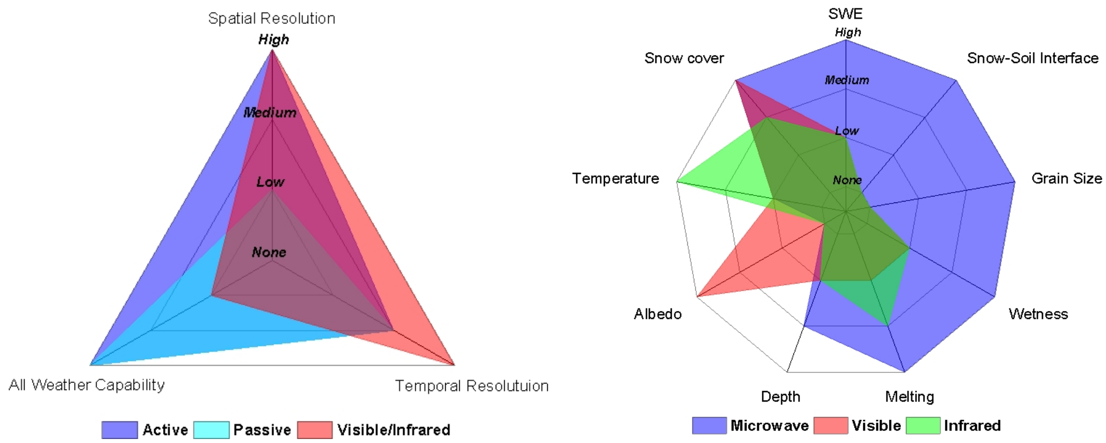

Fig.1. (a) Sensor capabilities in qualitative terms for spatial, temporal resolution and data production and (b) Sensor responses to snowpack properties. Different regions of the electromagnetic spectrum provide useful information about the snow characteristics. Nevertheless, certain regions had better capabilities or responses to measure certain properties. For this reason, the integration of all the available resources could lead to unbiased and better estimations of the snowpack properties

2. REMOTE SENSING OF SNOW

2.1 Optical Remote Sensing

Unique characteristics of snow, like its high reflectance in the visible part of the spectrum and its low reflectance in the mid-infrared is the base for most of the well-known existing techniques for snow detection using the visible (VIS) and infrared (IR) bands [7]. Furthermore, the snow reflectance on these spectral ranges differs from the reflectance of water clouds and soil making possible the foundation for automated and semi-automated snow detection techniques (Fig.2.). Furthermore snow extent is in most cases relatively straightforward to observe using visible imagery because of the high snow albedo (up to 80% or more in the visible part of the electromagnetic spectrum) relative to most land surfaces [8,9]. Overall, visible imagery is better at detecting snow cover extent than at quantifying snow characteristics like snow depth or snow water equivalent. For this reason, the primary use of optical sensors is to provide accurate and spatially detailed information on the snow cover distribution. But, on the negative side, snow mapping with the sensors using visible spectrum is impossible at night and in cloudy conditions. As a result, snow maps generated from the visible imagery can have gaps in the area coverage.

Because surface snow properties and snow cover are rapidly changing phenomena in many regions, there is a need for frequent data. Current optical sensors operated at various spatial and temporal resolutions (Table 1.), providing vital information for monitoring snow. Nevertheless user needs can be compromised, because these methods are limited by a number of factors, such as clouds, forest cover fractions, terrain heterogeneity and different atmospherics phenomena's.

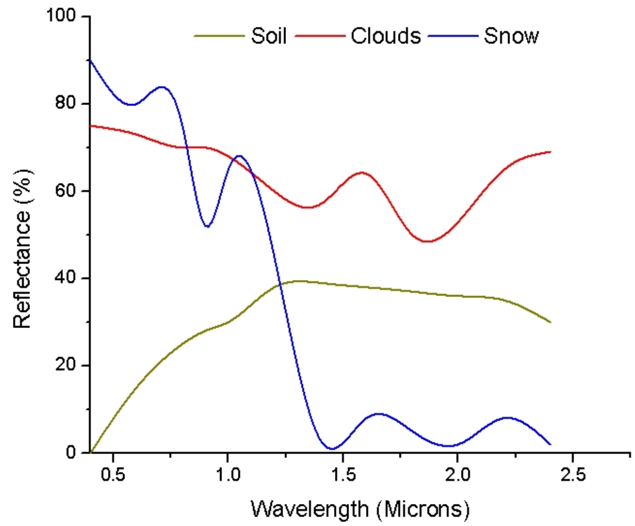

Fig.2. Representative spectral reflectance of snow, vegetation and clouds in the VIS and IR region

Table 1. Typical Sensors used for snow cover mapping

Platform sensor	Spatial resolution	Array dimensions	Temporal resolution
Aircraft (Ortho-photo)	0.5m to 3m	As needed	As needed
Landsat *TM*	28.5 Km	2.5/5	16 days
NOAA-15 (*AVHRR)*	1.1 km	200/500	12 hours
GOES (VISSR)	1.1 km	200/500	As needed
Terra & Aqua (*MODIS)*	500 m	1200	24 hours

Images from satellites have been used for mapping snow cover for several decades; for example, the USA National Oceanic and Atmospheric Administration (NOAA) began mapping snow using satellite-borne instruments in 1966. Satellite sensors such as the Advanced Very High Resolution Radiometer (AVHRR) onboard NOAA and METOP satellites, Moderate Resolution Imaging Spectro-radiometer (MODIS) onboard Earth Observing System (EOS) satellites, Imager instruments onboard Geostationary Operational Environmental Satellites (GOES) and a number of other sensors onboard polar orbiting and geostationary satellites have been used for snow cover mapping. However, most of the optical remote sensing products classify each land pixel into one of three categories, “snow”, “no snow” and “undetermined”, where the latter category includes cloudy pixels and pixels corresponding to night time observations. In the case of NOAA satellites their interactive maps are binary and include pixels of two classes, "snow" and "no snow" (
Fig**3**.).

Early snow cover product using optical remote sensing used threshold-based criteria tests, decision rules and differences between radiances. For example, based on that snow is highly reflective in the visible part of the EM spectrum and highly absorptive in the near-infrared, [10] used the ratio of radiances between 1.6 - 0.754 μm channels and IR band to discriminate between snow and clouds [10]. One decade later, [11] used a more sophisticated normalized difference band ratio (NDSI) of spectral reflectance’s measured with the Landsat Thematic Mapper (equation 1), Where $\rho_2$and ρ_5 is in the range of 0.53- .61 μmand 1.57-1.78 μm respectively. This index is the base of several snow indexes developed in recent years.

$$NDSI = \frac{\rho_2 - \rho_5}{\rho_2 + \rho_5}$$ IfNDSI>4, classified as snow .... (1)

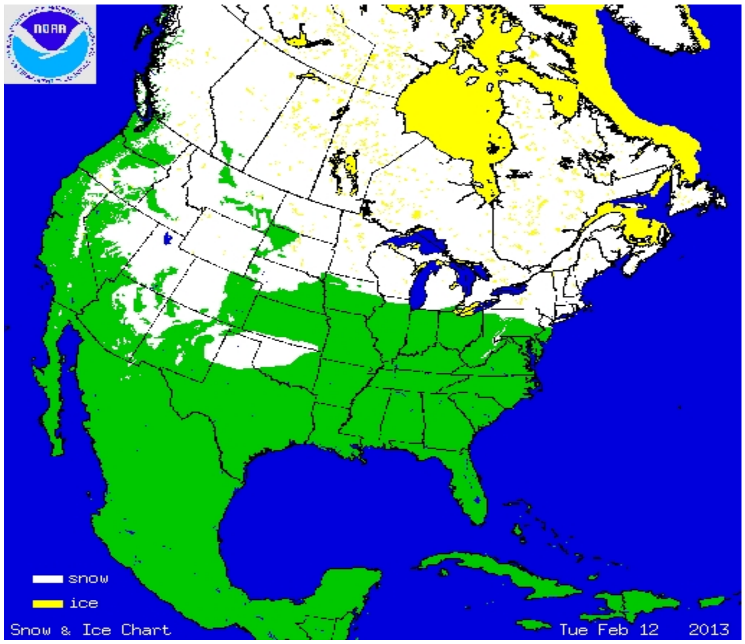

Fig.3. NOAA's interactive multi-sensor snow and ice mapping system (IMS) product shows ice and snow cover extent in the North Hemisphere

Current optical algorithms for the MODIS snow-cover products were improved and enhanced from previous operational products, allowing high resolution, daily availability and the capability to better separate snow and clouds [12]. However, snow mapping using optical wavelengths still requires clear sky conditions and sufficient daylight. For this reason and in order to mitigate these disadvantages, some authors like [7] have suggested the importance of the synergy of satellite optical (visible/infrared) and microwave data to map snow extent (**Fig. 4**.) and monitor its evolution in time and space. Some of the most well know optical snow cover products are summarized in Table 2.

Additionally to the snow cover mapping, other applications for snow studies using optical remote sensors include: derive the snow fraction within the satellite field of view and identifying snow melt using the infrared bands. The importance of fractional snow cover identification is based on the fact that the snow covered area frequently varies at a finer spatial resolution, than the one provided by the remote sensing instrument. This discrepancy, on spatial distribution cause a "mixed pixel" problem, caused byspatial mixture of snow with vegetation, soil and rocky surfaces [13]. Moreover, binary classification can failed in areas that have patchy snow such as near the snow line [14]. Essentially, map snow-covered areas at sub-pixel resolution can provide a better representation of snow distribution for the modeling community.

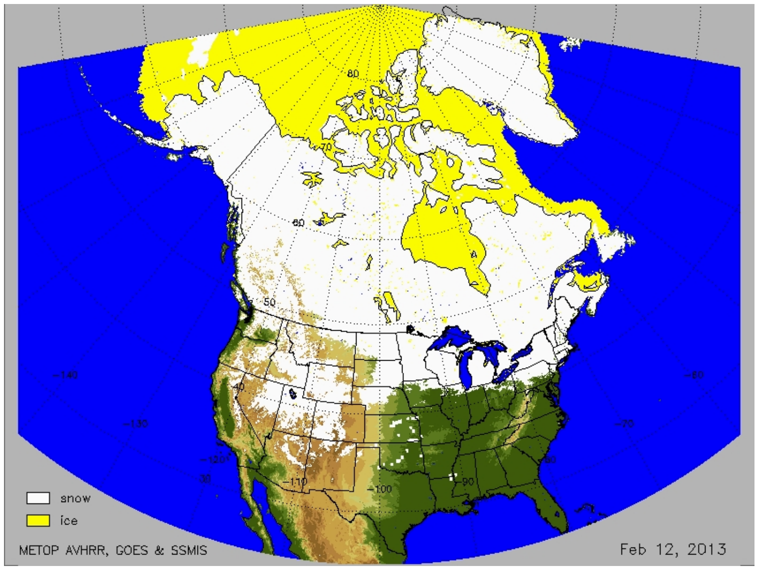

Fig. 4. Automated snow cover product for northern hemisphere [7].

Table 2. Snow covers products with their respective accuracies.

Snow cover product	Spatial resolution	Temporal resolution	Primary uses	Reference	Accuracy
IMSSystem	4km	Daily	Input to operational atmospheric forecast models.	[5]	≈ 90% to Stations
Automated snow mapping system*	4-km	Daily	Input to numerical weather models, Support IMS.	[3]	≈ 85- 90% to IMS
MODIS	500m	Daily, 8 Days & monthly	Modeling at hemispherical and regional scale.	[12]	>80% to IMS

**Synergistic product from optical and microwave observations*

2.2 Microwave Remote Sensing

Satellite observations in the microwave spectral range have also been used for the global monitoring of snow cover and surface snow properties for more than three decades. For example, the remote sensing community uses several data sets from the following sensors: the Electrically Scanning Microwave Radiometer (ESMR) (1973–1976), Scanning Multichannel Microwave Radiometer (SMMR) (1978–1987), Special Sensor Microwave/Imager (SSMI/S) (1978–Present) and Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E) (2002–2011).

Also, it has been demonstrated that active microwave have similar potential as passive microwave for snowpack properties studies [15–17]. Advantages like a finer spatial resolution and more frequent data holds promise. However, the complexity of the data and the effect of surface characteristics like soils complicate its applicability at global scale. Active microwave remote sensing instruments like RADARSAT-1, QuickSCAT, CryoSAT and CryoSAT-2 are currently operational. In general, both active and passive techniques have brought new products with some advantages over counterpart's instruments in other regions of the EM spectrum.

2.2.1 Passive microwave remote sensing

Passive microwave sensors detect the weak microwave radiation that is constantly emitted from the surface and atmosphere of the Earth. In the field of microwave radiometry, the microwave radiance is mostly expressed in terms of brightness temperature, Tb at the measured frequency (Fig.5.). In the case of the snow the upwelling microwave radiation is emitted by the sub-snow surface and altered by the snowpack and consequently it carries information on the physical properties of the snowpack. Furthermore, the radiation emitted by the snowpack strongly depends on the physical properties of the snowpack, including liquid water content, snow density, grain size, vertical temperature profile and often, on the state of the ground surface beneath the snowpack [18–20].

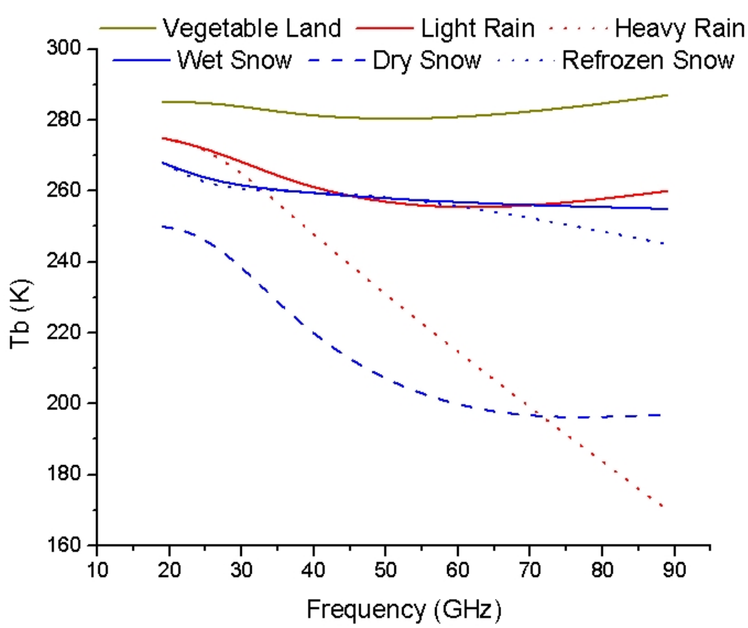

Fig.5. Microwave spectral responses at different frequencies to snow and land parameters

Currently, there are many satellite sensors measuring brightness temperature in different microwave bands. These multi-frequency observations can be used to classify snow conditions, to estimate the water equivalent of dry snow and to determine the start of the melting period. With the results of several years of ground-based microwave observations along with the experience gained with satellite-borne microwave radiometers, several microwave emission models have been developed. Many of these physically based models have been proposed to describe the relationships between the microwave emission and snowpack parameters such as the mean snow grain size, density and depth [19,21–23] (Table **3**.). These microwave emission models may be based on physical principles as well as observations and they can be classified as empirical, semi-empirical or theoretical. The objective of microwave models that are capable of predicting the measured radiation, facilitate the use of inversion techniques to estimate snow parameters. However, proper characterization of the behavior of snow-emitted microwave radiation throughout winter season remains a challenge and it is still a subject of study. Additionally, numerous research studies have used emission models along with brightness temperature at 19, 37 and 85/89 GHz microwave frequencies from satellite-mounted instruments, including AMSR-E and SSM/I (Fig. 6.), for estimation of the snow cover extent, snow depth and snow water equivalent [4,7,21,24,25].

Table 3. Characteristics of commonly used microwave emission models for snowpack property retrieval

Model	Model type	Characteristics	References
Grody	Empirical	Decision tree algorithm for global snow covers mapping from spectral gradients in SSM/I data.	Grody & Basist [4]
HUT	Semi-Empirical	Considers homogeneous snow or multiple layers. Includes the atmosphere, soil and vegetation.	Pulliainen et al.[22]
MEMLS	Semi-Empirical	Considers a layered structure of the snowpack. Classical RT with Empirical scattering and absorption properties.	Wiesmann & Mätzler [23]
DMRT	Theoretical	Based on scattering theory. Considers snowpack as a medium consisting of scattering particles.	Tsang et al.[30] & Tsang & Kong [31]

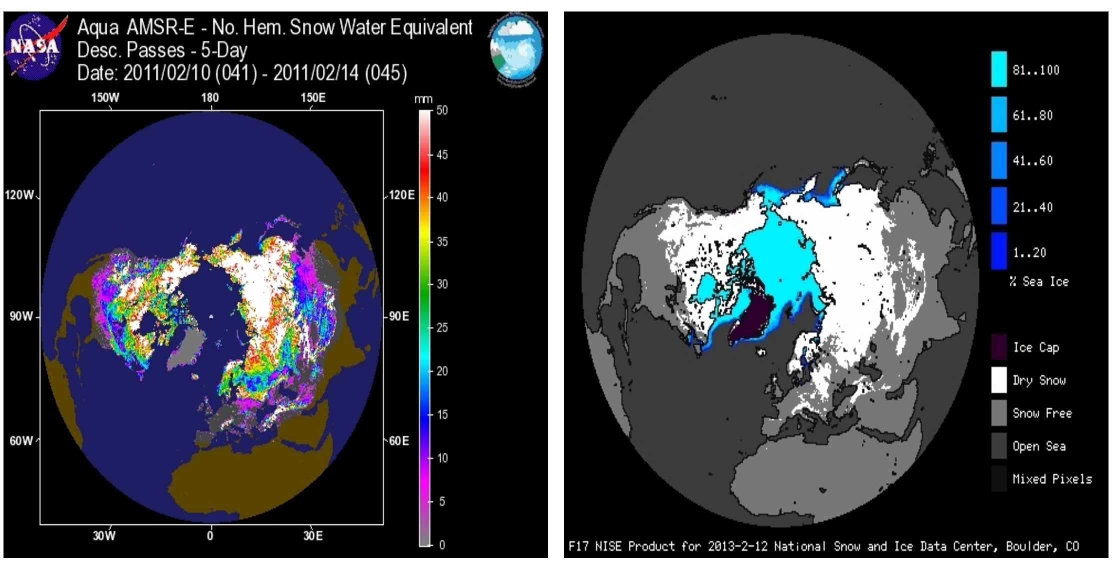

Fig. 6. (Left) AMSR-E/Aqua 5-day products of global snow water equivalent on EASE-Grids format for northern hemisphere. (Right) The Near-Real-Time SSM/I-SSMIS EASE-Grid Daily Global Ice Concentration and Snow Extent product for northern hemisphere (Source: http://nsidc.org)

The spectral gradient(difference between microwave bands) is used in most algorithms for snow cover detection [26]. Kunzi et al. [27] Used the spectral gradient method on SMMR data to map snow cover extent and found that the resulting line delimiting the snow cover corresponded to 5 cm snow depth. In addition, earlier snow depth retrieval algorithms [28,29] provided an "instantaneous" daily snow depth estimate based on differences in brightness temperature between microwave frequencies [28,29]. The same multi-frequency approach has been used for many years to retrieve SWE (Table 4.). Currently, AMSR-E (Fig. 6.) global SWE product(http://www.ghcc.msfc.nasa.gov/AMSR/) has been most frequently used by researchers.

Table 4. Basic algorithms to retrieve snow properties using microwave remote sensing

Snow depth	SWE	Snow cover
SD = A[$\Delta(Tb)$] Where: $\Delta(Tb)$ is the difference in brightness temperature between 19H GHz and 37H GHz channels, (A= 1.59 cm)	SWE = A + B $\frac{[\Delta(Tb)]}{f2-f1}$ Where: A and B are the offset and the slope of the regression of $f_1 = $37H GHz and f_2=19H GHz	[$\Delta(Tb)$] > 3.8 K Where: 3.7 is the threshold for snow cover detection.

In terms of the accuracy of existing algorithms,[32] compared several passive microwave snow products including [4,26,33]. They reported that all of them underestimate snow in comparison with the NOAA Northern Hemisphere snow charts derived from manual interpretation of visible satellite data. Generally, they concluded that the microwave data indicates less snow-covered areas than the visible data throughout the year. The mean difference during the winter months (November-April) was about 4 million square kilometers, decreasing from 8 million square kilometers in November to about 0.3 million square kilometers (approximate 1% of the snow covered areas) in April [32]. The underestimation and the large difference in snow extent in early winter can be explained due to the thin snow cover, the inability of present microwave products to detect shallow (< 5cm) and discontinuous snow cover. In contrast, they explain that there is no reason to suppose that the optical data would overestimate.

Following a similar path [8], compared different snow products, including IMS and MODIS (visible), AMSR (Microwave) and the Canadian Meteorological Center Snow Product (CMC) which is a hybrid model/observational dataset, on a global basis. They conclude that there is a significant concordance among products during clear skies and non-melting conditions but large discrepancies in the presence of wet, thin and sporadic snow. Similar conclusions were drawn by [32,34]. These results suggest that the synergy of optical and microwave data can minimize the inconsistency between data sets. Visible imagery can help diagnose several of the sources of error in estimating snow depth and SWE using microwave remote sensing, including heterogeneity and variability in snow cover, grain size, snow density and snow liquid water content within the microwave sensor footprint through land cover change, patchy snow fall and/or melting snow.

2.2.2 Active microwave remote sensing

Active Microwave remote sensing, known as radar or Synthetic Aperture Radar (SAR) is based on actively transmitting a powerful pulse of microwave radiation and measuring its backscatter from the target surface. Several authors have proven that, in theory, active microwave remote sensing has similar sensitivity to snow properties as passive microwave remote sensing [35,36] and enables more precise retrievals because the output power is known. Moreover, active retrievals typically achieve much better spatial resolution than passive sensors due to their higher signal-to-noise ratio, even though this also depends on the antenna size. Active microwave measurements are very promising for snow remote sensing, but retrievals are complicated because the backscattered energy is influenced by the soil type and soil moisture as well as the geometry of the microwave beam and receiver. Moreover, SAR is very sensitive to snow melting or wet snow, providing the ability to adequately distinguish or discriminate between bare soil and wet or melting snow [37].

Instruments such as the QuikSCAT active microwave scatterometer has been used to estimate the timing of snow melt across Greenland [38] and Arctic lands [39] with fairly accurate results. Both studies were based in the backscattering's signature difference (Fig. 7) between the dry snow and wet snow. Furthermore, a product developed by [40] for mapping wet snow in mountainous terrain showed very good correlation with existing snow cover retrievals. This product used comparisons between images from consecutive passes of the Synthetic Aperture Radar (SAR). Then, filtering was performed over the measured backscattering using a high precision Digital Elevation Model (DEM) and a reference image.

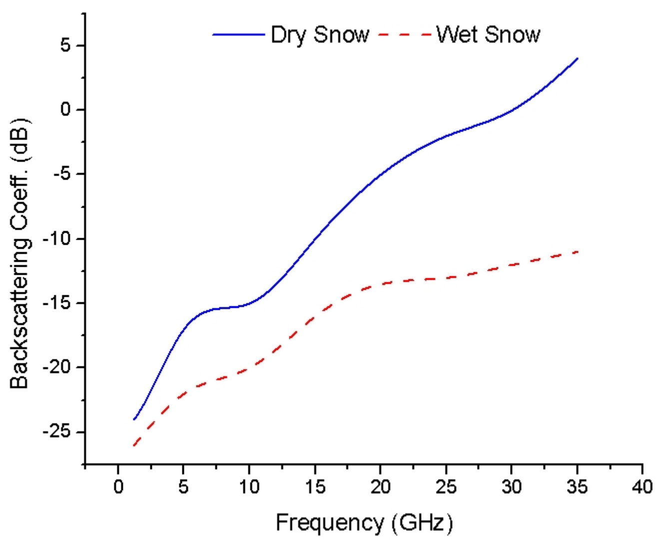

Fig. 7. Response to active microwave sensors by dry and wet snowpack conditions at different frequencies

Additionally, different methods based on active microwave sensors have been used for retrieving snow properties. Such properties are snow melting, snow depth and snow cover, which have been tested in different situations and regions around the world [21,41,42]. In some cases these products provided accurate results; however in other cases they offered poor to fair correlation when compared to in-situ measurements. For instance, [42] study compared the melt duration derived from passive microwave SSM/I's Brightness Temperature (TB) and QuikSCAT's backscattering signal time series, by making use of threshold-based processing methods. The estimation of snow depth were compared using two approaches, first a simple static approach based on radiative transfer models and second, a dynamic approach which assumes that snowpack properties are temporally and spatially variable [21]. The most important outcome from this study is that the static approach underestimated the snow depth more than the dynamic algorithms. As well, in active microwave remote sensing there are other possibilities that are being explored. For instance, P-band has been used for sea-ice detection and the X-band that has been used experimentally for high resolution mapping.

In general, it can be concluded that for the proper implementation of active microwave in snow studies, additional factors need to be considered. One example is, taking in account that the snowpack is a combination of several parameters that are continuously changing in time and space. Finally, research on active microwave remote sensing of snow illustrates a peculiar situation. It has been studied for more than three decades, including multiple field studies, theoretical models and additionally large data sets are available. However, active microwave retrievals still are not widely used on operational products.

3. SYNERGISTIC APPROACH

While standalone approaches for snow estimation using individual satellite instruments have made significant progress in recent years, many of the products currently used are still based on empirical or semi-empirical relationships and are accurate only over a limited range of snow properties [6]. For this reason, some studies have explored the possibility of improving snow retrievals by incorporating the use of multi-source and multi-temporal remote sensing data. Given the technical constraints and limitations previously discussed, the synergy of satellite observations in the visible and in the microwave spectral bands is an important approach to improve the mapping and monitoring of the snow cover and snow pack properties.

3.1 Snow Cover

Snow has a high reflectivity ratio in the optical range of the electromagnetic spectrum; this characteristic makes its detection very easy using different combinations of visible and infrared wavelengths. At the same time, visible and infrared bands have the well-known limitation of allowing only clear day detection, as neither of them can penetrate clouds. Also snowpack properties such as the snow water content can't be derived from VIS/IR wavelengths. A solution to the cloud problem and to inferring properties beyond snow cover is incorporating microwave data either passive or active that can be acquired during night or day. Although the cloud problem is removed, interpretation of microwave imagery is much more difficult compared to optical-based indices [1,43].An automatic system of snow mapping with a spatial resolution of 5 km using GOES visible and infrared data and SSM/I microwave data was developed[7,44]. This method was shown to be as precise as the IMS (Interactive Multi sensor Snow and Ice Mapping System) products if not better especially on the level of the consistency of the time series. In general they showed the utility of the multi-sensor techniques for the improvement of the snow detection. Others, have gone further, combining visible (MODIS), active (QuickSCAT) and passive (AMSR-E) microwave [45]. They demonstrate that this combination was able to distinguish between dry and wet snow using MODIS, areas where melting was at initial stages using AMSR-E and areas with heavy melting using QuickSCAT. In general these result shows that synergistic products are more accurate in determining the snow covered areas.

Future works, included: downscaling to achieve better spatial resolutions (<500m), the use of multiple instruments in different orbits to have better temporal resolution and validation. As snow cover is currently showing rapid changes because of the climate change, hydrologists and climatologist are very interested on better techniques using remote sensing for snow mapping.

3.2 Snow Water Equivalent

Passive microwave data at 19 and 37 GHz (or similar frequencies) have been historically used to retrieve snow parameters such as snow water equivalent (SWE) and snow depth. Nevertheless, the numbers of parameters that influence brightness temperatures in the microwave range make it very difficult to accurate estimate SWE. Validation studies shows that the accuracy of the AMSR-E SWE products is around 68.5% [46] and they tend to overestimate SWE [8].

There are two different approaches that can be used to increase the accuracy of existing SWE products. First approach, merging visible and microwave data with ground observations. The second approach is to explicitly combine active and passive microwave remote sensing data. Most of the studies using active microwave data have concentrated on the separation between wet and dry snow. However, the sensitivity of active microwave also exists to other parameters such as snow grain size and SWE [18].

The first approach is used by [46] to create a new SWE product with better spatial resolution (5km) and less overestimation using combination of MODIS data with the AMSR-E SWE product [46]. In their analysis of the product they conclude that the synergy produced slightly better SWE accuracy with respect to ground measurements. However, AMSR-E is no longer operational, but the same principle can be used to merge other optical data sets like GOES-R with SSM/I, AMSU or the next generation in the family the Advanced Technology Microwave Sounder (ATMS).

The second approach proposed by [36], combined active (QuikSCAT/Sea Winds) and passive (SSMI) data for monitoring key snow parameters in Finland [37]. Data from 21 test sites were used to validate their study. In general the results show that combined active and passive microwave sensors provide useful information on diurnal and seasonal variability and increase the accuracy of SWE by approximate 6%. Additionally, Azar et al. [47] demonstrate that combining SSM/I with QuikSCAT and NDVI produce improved and more accurate SWE estimates than those obtained by only using SSM/I [47]. Furthermore, both active and passive microwave are very sensitive to snow wetness. Given the complexity of the relationship between this parameter and the microwave emission is unrealistic the accurate estimation of SWE, based on the existing microwaves models. Consequentially the assimilation of surface temperature using visible and infrared bands can be used to estimate the snow wetness, resulting in better SWE estimates. Overall, there is evidence that the combination of visible, active and passive microwave data to retrieve SWE may improve the results from those obtained just using passive microwave.

4. SUMMARY

Unbiased estimates of snow properties could lead to much better understanding of hydrological processes in snow covered watersheds. This understanding is important not only for seasonal-scale processes such as the snowmelt contribution to water supply systems and snow-atmosphere interactions, but for predicting flash floods caused by rapid snowmelt. Specific future improvements and challenges for using synergistic approaches include refinement of snow-cover extent estimates with better spatial-temporal resolutions, minimizing SWE retrieval errors, and improving our ability to ingest remote sensing data into land-surface models.

To conclude, several snow characteristics can be measured using different remote sensing techniques based on different parts of the electromagnetic spectrum. The accuracy and/or sensitivity of retrievals will depend on the parameter being measured and instrument used for the snowpack estimation. Future efforts towards improving snow retrievals should therefore seek to merge various of the existing products into one capable of compensating the disadvantages of any one retrieval method, and to better understand the underlying physics of the snowpack in order to make more robust operational products, compared to current ones that are based on empirical relationships between sensor data and snow extent and properties.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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