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Review papers

Remote sensing, hydrological modeling and in situ observations in snow cover research: A review

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ABSTRACT

Snow is an important component of the hydrological cycle. As a major part of the cryosphere, snow cover also represents a valuable terrestrial water resource. In the context of climate change, the dynamics of snow cover play a crucial role in rebalancing the global energy and water budgets. Remote sensing, hydrological modeling and in situ observations are three techniques frequently utilized for snow cover investigations. However, the uncertainties caused by systematic errors, scale gaps, and complicated snow physics, among other factors, limit the usability of these three approaches in snow studies. In this paper, an overview of the advantages, limitations and recent progress of the three methods is presented, and more effective ways to estimate snow cover properties are evaluated. The possibility of improving remotely sensed snow information using ground-based observations is discussed. As a rapidly growing source of volunteered geographic information (VGI), web-based geotagged photos have great potential to provide ground truth data for remotely sensed products and hydrological models and thus contribute to procedures for cloud removal, correction, validation, forcing and assimilation. Finally, this review proposes a synergistic framework for the future of snow cover research. This framework highlights the cross-scale integration of in situ and remotely sensed snow measurements and the assimilation of improved remote sensing data into hydrological models.

1. Introduction

Snow is precipitation in the form of ice crystals that fall to Earth's surface and become snow cover. The process of snowfall represents the transfer of water from the atmosphere to the ground surface, which is part of the natural water cycle. As a major component of the cryosphere, snow cover plays an important role in the Earth's climate system through its impact on the surface energy budget, water cycle, primary productivity, and surface gas exchange (IPCC, 2013). Snow cover is also an indicator of a changing climate, especially because snow accumulation and ablation are closely related to temperature (Brown and Mote, 2009). In addition, because more than one-sixth of the Earth's population relies on glaciers and seasonal snowpacks for their water supply, the consequences of hydrological changes due to global warming are likely to be severe (Barnett et al., 2005). Thus, it is imperative to decipher the current changes in snow cover at various scales using our knowledge of hydrology and climatology.

According to previous estimations based on observations, reanalysis products, and model simulations (Hirabayashi et al., 2008; Hoinkes, 1967), snowfall accounts for 5–11% of the total global precipitation. The significant disagreement in the estimated fractions of the total precipitation in the form of snow or rain between estimation approaches reveals our insufficient understanding of the spatial distribution of snow. NASA's Global Precipitation Measurement (GPM) is an international satellite mission specifically designed to accurately measure precipitation from space and to provide a new generation of global rainfall and snowfall observations at hourly intervals, with full coverage for latitudes 60°N–60°S and partial coverage for the remaining high-latitude areas up to 90° (Hou et al., 2014; Omranian and Sharif, 2018). Recently, intense warming has led to a general reduction in the fraction of solid precipitation (snow) and an earlier occurrence of snowmelt. Moreover, a shift from spring snowmelt to winter runoff due to climate change is expected to increase risks of winter flooding and summer drought (Arnell, 1999; Feng and Hu, 2007; Knowles et al., 2006; Mote, 2003).

Snow cover in temperate regions (e.g., central and western Europe) is often close to the melting point, and both continental and alpine snow covers are consequently highly sensitive to climate change (Fitzharris, 1996). However, although statistically significant snow recession has been reported since the late 1970s or early 1980s over the

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Northern Hemisphere (Brown, 2000; Brown et al., 2010; Brown and Robinson, 2011; Estilow et al., 2015; IPCC, 2013; Laternser and Schneebeli, 2003), the snow cover dynamics in the spatial and temporal dimensions remain poorly quantified. This situation is due to not only the high heterogeneity of the snow distribution but also by the divergence of different snow data sources. Moreover, measuring the exact impact of changing temperatures and precipitation on snow is difficult due to differences in the impacts over time and in different regions (Serquet et al., 2011). Therefore, considerable effort is required to investigate the spatiotemporal variability of snow cover and snow processes in a changing climate.

This paper introduces the snow cover parameters that are typically first applied by hydrologists. Then, the advantages, shortcomings, and recent progress of the three snow measurement approaches, e.g., in situ monitoring, remote sensing, and hydrological modeling, are reviewed. Finally, a critical appraisal of the potential of integrating the three techniques into snow cover research is provided. Efforts that use ground-based meteorological data to improve remotely sensed snow products are highlighted. The potential contribution of fusing multi-source snow observations to update snow hydrological models with data assimilation schemes is then discussed.

2. Snow cover properties and parameters

Several variables, such as density, albedo, specific surface area, crystal size and shape, thermal conductivity, permeability, diffusivity and shear resistance, are required for a complete physical description of a snowpack (Domine, 2011). Understanding the physical, thermal and optical properties of snow is essential for hydrologic research of snow (Singh and Singh, 2001). Consequently, much attention has been given to snow properties in studies in the literature (e.g., Brucker et al., 2010; Gallet et al., 2009; Jin et al., 2008; Koenig et al., 2007; Montpetit et al., 2011; Warren, 1982).

Due to the special properties of snow, which are summarized by Pomeroy and Brun (2001), snow cover functions as an energy bank, radiation shield, insulator, reservoir and water transport medium in the global climate (eco-) system. In detail, snow cover stores latent heat and crystal bonding forces during its formation and releases energy through fusion and sublimation. Because of its high albedo, fresh snow cover reflects most shortwave radiation, although albedo decreases with snowmelt. As a near black body, cold snow absorbs and re-emits most longwave radiation, but the emission is limited to a snow surface temperature of less than 0 °C, and thus, snow cover hampers rapid warming of the adjacent air relative to a snow-free surface (Street and Melnikov, 1990). Snow cover also acts as an insulator, minimizing the thawing of permafrost and protecting microorganisms and plants from wind and severe winter temperatures. Consequently, snow cover plays an important role in influencing surface radiative exchange and heat transfer. In addition, as a solid water resource, snow directly participates in natural water distribution and redistribution through a series of processes. Environmental factors interact with snow in complex ways, and this makes it difficult to investigate snow processes, e.g., snowfall, snowmelt, sublimation, interception, snowdrift, snow avalanches and rain-on-snow events.

Several snow cover parameters are used to study the behavior of snowpack at different spatial and temporal scales. Table 1 shows some of the snow cover parameters that are normally used in hydrological applications (IPCC, 2013; Xie et al., 2015).

Snow-covered area (SCA, %) is an index quantifying the extent of snow cover in a region and is generally derived from snow cover maps and calculated as follows:

$$SCA = (N_s/N_t) \times 100\% \tag{1}$$

where N_s and N_t are the numbers of snow pixels and total cloud-free pixels, respectively, in a snow cover map for the study area or sub-region. Because the SCA only indicates the extent of snow presence in a region, the snow mass or volume information cannot be interpreted based on this index. However, SCA maps have great value for investigating the spatial and temporal variations in snow cover, especially when it is difficult to estimate the snow mass over a large area because of varied topography and inhomogeneous snowfall. In addition, SCA information is essential for studying the coupled land-air system because the extent of snow cover, rather than snow mass, has more influence on the interactions between the snow surface and the atmosphere (Xu and Dirmeyer, 2013). The higher albedo and lower aerodynamic roughness height of snow cover, comparing to the land surface, significantly change the thermal and motion states of the atmosphere through direct and indirect feedbacks.

Table 1
Snow cover parameters investigated in this study.

Parameters	Abbreviation	Unit
Snow covered area	SCA	%
Snow depth	SD	cm
Snow water equivalent	SWE	mm
Snow cover duration	SCD	day
Snow onset date	SOD	Julian day
Snow end date	SED	Julian day

For hydrologists, snow mass and volume parameters are more critical, because the water volume stored in the snowpack and subsequent snowmelt runoff can be estimated. Snow water equivalent (SWE) and snow depth (SD) are normally measured and used for this purpose. The relation between SWE (mm) and SD (cm) is described by the followed equation:

$$SWE = 10 \times SD \times (\rho_s/\rho_w) \tag{2}$$

where ρ_s is the snowpack density ($kg\,m^{-3}$) and ρ_w is the density of liquid water, which is approximately $1 \times 10^3\,kg\,m^{-3}$.

To monitor temporal variations in the snowpack, snow cover duration (SCD, d), snow onset date (SOD) and snow end date (SED) are three indices used to monitor snowpack via seasonal snow cover behavior. The SOD and SED represent the dates of the first and last snowfalls, respectively, during a snow season and are often recorded in Julian dates for hydrological applications. SCD represents the number of days between the SOD and the SED during a snow season. For regions that have persistent snow cover, a hydrological year should be defined in advance, e.g., 1st August to 31st July of the following year. In this case, the SED represents the date of the last snowfall during a hydrological year. For regions that rarely receive snow, it may be more appropriate to calculate Julian dates for both SOD and SED based on a hydrological year beginning on January 1st. Therefore, the SOD and SED may have values higher than 366, which indicate a delayed snow onset or early snow ending.

The six snow cover parameters listed in Table 1 include spatial and temporal snow cover distribution parameters (SCA, SCD, SOD, and SED) and snowpack quantity parameters (SWE and SD). The continuous time series of these six parameters can be utilized to investigate the spatiotemporal dynamics of snow cover and to estimate the water storage in the snowpack, which have crucial significance for climate change assessments and water resource management.

Currently, three approaches are frequently used to derive the above-mentioned snow parameters. One approach is the traditional, ground-based and mostly manual process of monitoring snow characteristics (Fig. 1a), and these data are typically collected in combination with other variables at meteorological stations. However, the sparse distribution of meteorological stations with appropriate snow monitoring protocols hinders the ability to conduct a detailed snow survey at a large spatial scale. As a result, traditional snow measurements cannot provide sufficient snowpack information for water resource management at the basin scale, despite point-scale accuracy. To obtain basin-scale information regarding snow cover, remote sensing may be used as

Fig. 1. Three snow measurement approaches. a. In situ observations; b. remote sensing; c. snow modeling.

a substitute (Fig. 1b). Remotely sensed images have the ability to monitor the near real-time snow cover over large areas. Recently, snow remote sensing has been vigorously developed around the world. An increasing number of sensors aboard multiple platforms (e.g., satellites, drones, and aerial and terrestrial assets) have been used to make snow observations, and they have performed well in measuring snow properties at different scales. However, compared with in situ snow measurements, remotely sensed snow data are limited by the short-term nature of the observations. The longest satellite-based snow dataset, i.e., the NOAA weekly snow cover maps, only dates to 1966 (Robinson et al., 1993), while some climate stations have snow records spanning more than 100 years (e.g., Armstrong, 2001; CDIAC et al., 1991). Remotely sensed snow information is also influenced by cloud obstruction and the large errors. Due to weather influences and the spectral confusion associated with different land surface features, misclassifications frequently occur in remote sensing data (Deems et al., 2013). Hydrological modeling (physically based, conceptual, and black-box models) is another robust approach for snow estimation (Fig. 1c). Based on the input of climatic, geomorphologic and other environmental information, snow cover can be simulated using numerical models. Furthermore, snowpack models are able to predict snow variations in the future under specific climate scenarios. Nevertheless, snow modeling is often restricted by the scarcity of reliable meteorological observations as model inputs (Essery et al., 2013). Moreover, the extremely complicated physics of snow are still not sufficiently understood, which hinders the development of snowpack models.

Therefore, each snow measurement approach, i.e., in situ observations, remote sensing, and hydrological modeling, possesses obvious advantages and shortcomings. It is necessary to compare the usability of the three methods and evaluate the possibility of integrating them in snow cover research. Close relationships exist among the three approaches. In situ observations and remote sensing can both be used to collect snow data, while the data are an essential input for developing hydrological models. Currently, point-based observations are also frequently utilized to improve and validate remote sensing algorithms. As snowpack models are highly dependent on data input, improving the data quality (in situ or remote sensing) is critical for successful simulations.

3. Measurements of snow cover

3.1. In situ monitoring

Before the development of remote sensing and hydrological modeling, in situ snow monitoring had a long history of being used for snowfall and snow cover measurement. During the 1500–1800 s, modern meteorological observations began in Europe and North America with the invention of meteorological instruments, and the daily SD and new snowfall amounts were observed by various methods in many countries (e.g., Switzerland, USA, and Finland). The national rainfall and snowfall archives of the Qing Dynasty of China date back to 1693 and document systematic records of the rainfall amounts and SD in 268 counties until 1911. Snow depth and SWE measurements became widespread by 1950 in the mountainous regions of western North America and Europe (IPCC, 2007).

With global warming attracting much attention during the second half of the 20th century, large-scale snow studies called for snow observation data exchanges among different countries. The inconsistent monitoring criteria restricted the comparability of snow measurements from various stations and regions. For example, according to the results of the WMO (World Meteorological Organization) Solid Precipitation Measurement Intercomparison project, at a wind speed of 6 m/s, the national gauges (with wind shield) used in Sweden, Norway, and Finland captured less than 40% of the solid precipitation; the instruments used in the USA and Canada captured approximately 75%; and the national gauges (without wind shield) used in Germany, Hungary, Denmark, and Russia captured only 10–20% of the solid precipitation (Goodison et al., 1998). To improve the quality and consistency of in situ snowfall, SD, and SWE observations, several international and national projects have been implemented worldwide and several station-based snow datasets have been established (Table 2). In addition, the global SYNOP (surface synoptic observations) network is sponsored by the WMO and is responsible for the data collection and exchange of coordinated international weather observations from the RBSCN (Regional Basic Synoptic/Climatological Network) stations. In situ SD measurements from the station network are provided by the SYNOP reports in near-real time.

Table 2
Selected international or national projects and datasets including in situ snow observations.

Project/Dataset name	Objectives/Observations	Organizers	Start time	References
Global Cryosphere Watch-CryoNet	Snow, Glaciers, Ice sheets, Sea/lake ice, Permafrost	WMO	2007	WMO (2013)
WMO Solid Precipitation Measurement Intercomparison	Snow	WMO-CIMO	1986	Goodison et al. (1998)
Global Historical Climatology Network (GHCN)	Snow, Temperature, Precipitation	NOAA-NCDC	1992	Menne et al. (2012)
WCRP- Climate and Cryosphere (CliC) International Project	Snow, Glaciers, Sea ice,	ICSU, WMO	2003	Barry (2003)
CMC-Daily Snow Depth Analysis Data	Snow depth, Snow water equivalent	Canada-CMC	1998	Brown and Brasnett (2010)
Historical Soviet Daily Snow Depth (HSDSD)	Snow depth	USA-NSIDC	2001	Armstrong (2001)
Historical Climatology Network (HCN)	Snow, Temperature, Precipitation	USA-CDIAC	1991	CDIAC et al. (1991)
European Climate Assessment & Dataset	Snow depth and other climate elements	ESCN/EUMETNET	1998	Klein Tank et al. (2002)

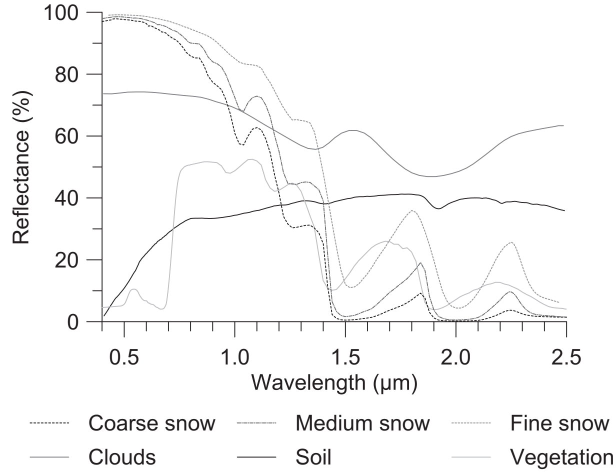

Fig. 2. Observations of snow canopy interception and snow depth using time-lapse photography.

At meteorological stations, SD is generally observed one or two times per day by a surveyor, and the SWE is measured at a very low frequency. In past years, automatic snow stations, e.g., stations equipped with ultrasonic snow height sensors or a SWE weighing system, have been widely used to monitor SD and SWE at high temporal resolutions (e.g., hourly). In addition, time-lapse photography has recently shown the ability to collect SD data (Parajka et al., 2012) and quantify snow canopy interception (Garvelmann et al., 2013). Thus, this technique represents a low-cost and feasible method for monitoring snow processes in remote mountainous areas (Fig. 2). As digital cameras can be easily installed in forested regions to monitor the interactions between snow and vegetation, they are useful supplements to weather stations and manual measurements and serve to collect critical process information for snow models (Dong and Menzel, 2017).

For regions that have an adequate density of point observations, the spatial distribution of snow hydrological variables can be estimated using geostatistical interpolation techniques (Foppa et al., 2007), such as inverse distance weighting (Jarvis and Stuart, 2001), kriging (Carrera-Hernández and Gaskin, 2007) and regression tree models (Molotch et al., 2005). However, estimating the areal spatial distribution of snow cover using point-scale snow monitoring is particularly difficult in mountainous environments given the complex topography, vegetation transition, and scarce meteorological stations. López-Moreno and Nogués-Bravo (2006) evaluated the performance of several local, geostatistical and global interpolation methods for mapping the snowpack distribution on the Iberian Peninsula, and they concluded that local and geostatistical interpolators did not provide satisfactory predictions of SD, whereas generalized additive models (GAMs) performed better but still produced remarkable overestimates for some regions. Meromy et al. (2013) validated the representativeness of the SD and SWE observations at 15 snow stations in the USA, with more than 30,000 field-based snow observations in the surrounding area. These data were interpolated using regression tree models and were then compared with station data. The biases for all sites ranged from 74% overestimated to 77% underestimated, which indicates a poor relationship between the point-scale and regional-scale snow measurements in mountainous regions. Therefore, remote sensing and hydrological simulations possess greater potential to provide accurate predictions of snowpack distributions at large scales.

3.2. Remote sensing

Remote sensing technology has had a major impact on data collection in the measurement of snow accumulation and ablation (DeWalle and Rango, 2008). During the last several decades, many remotely sensed snow products, including both SCA and SWE data, have been developed to investigate snow cover. In addition, recent satellite products (mainly GPM), provide algorithms to capture solid precipitation (snow) comparing to previous versions which were not able to distinguish between snow and rain (Omranian and Sharif, 2018; Skofronick-Jackson et al., 2017). Snowfall measurement from space is important to understand the global precipitation and hydrologic cycle (Adhikari et al., 2018)

Table 3 shows some optical satellite sensors that have been widely used in snow cover mapping. Optical sensors loaded on satellites or aircraft can distinguish objects on the ground by examining the reflected visible light (VIS, 0.39–0.70 μm) and infrared radiation (IR, 0.70 μm–1.00 mm). Fig. 3 illustrates the spectral reflectances of several land features in the VIS and IR range and shows that snow has a high VIS reflectance and low IR reflectance. Thus, the normalized difference snow index (NDSI) has been developed to detect snow cover in optical remote sensing data. For example, MODIS (Moderate Resolution Imaging Spectroradiometer) band 4 (0.545–0.565 μm) and band 6 (1.628–1.652 μm) are used to calculate the NDSI and map snow cover. This method can discriminate snow from most land cover classes and from water clouds since they have different characteristics on the electromagnetic spectrum. However, ice clouds (upper tropospheric cirrus clouds) have reflection characteristics that are similar to those of snow, and the NDSI is thus prone to incorrectly labeling ice clouds as snow. In mountainous regions where cloud cover is a typical and predominant feature, confusion between snow and clouds is common. In addition, dense cloud cover can seriously block the snow observations of space-based optical sensors.

Table 3
Characteristics of optical sensors used for snow detection.

Satellite	Sensors	Spectral bands	Spectral range /μm	Spatial resolution /m	Temporal resolution/d	Launch time
Landsat 1–3	MSS	4	0.5–1.1	79	18	1972
Landsat 4–5	MSS/TM	4/7	0.5–1.1/0.45–12.5	30/120	16	1982
Landsat 7	ETM+/PAN	7/1	0.45–12.5	15/30/60	16	1999
Landsat 8	OLI/TIRS	9/2	0.43–2.29/10.6–12.51	15/30/100	16	2013
Terra	MODIS	36	0.4–14.4	250/500/1000	1	1999
Aqua	MODIS	36	0.4–14.4	250/500/1000	1	2002
NOAA	AVHRR	4/5/6	0.58–12.5	1090	1	1978
SPOT 1–3	XS/PAN	3/1	0.50–0.89	10/20	26	1986
SPOT 4/5	XS/PAN	4/1	0.48–1.75	2.5/5/10/20	26	1998
SPOT 6/7	XS/PAN	4/1	0.45–0.89	1.5/6	26	2012
IKONOS	XS/PAN	4/1	0.45–0.85	1/4	3	1999
ERS-2	ASTER-2	7	0.55–12.0	1000	2–3	1995
Worldview 2	XS/PAN	8/1	0.40–0.90	0.46/1.84	1	2009
Worldview 3	XS/PAN/SWIR	8/1/8	0.40–2.37	0.31/1.24/3.70	< 1	2014
Quickbird	XS/PAN		0.45–0.90	0.65/2.62	1–3.5	2001
Envisat	AATSR/MERIS	7/15	0.55–12.0/0.39–1.04	1000/300	2–3	2002

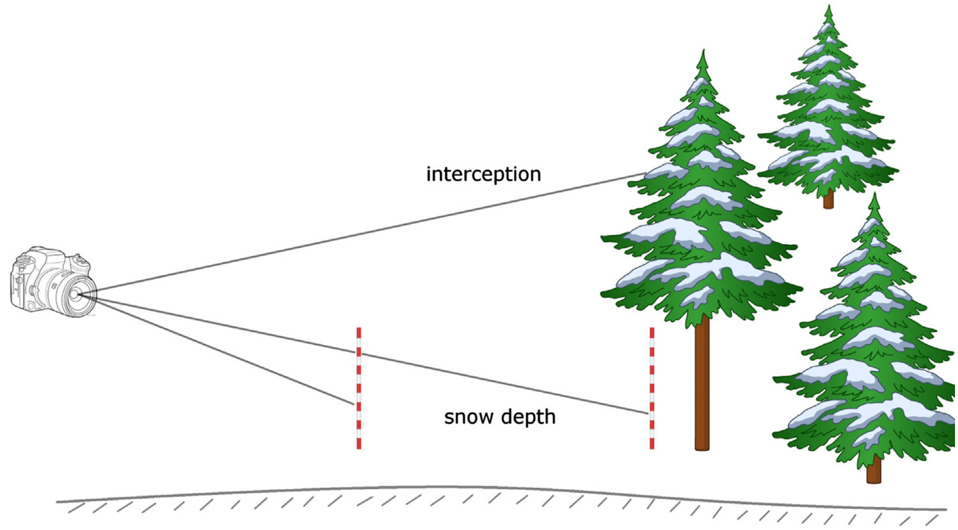

Fig. 3. Representative spectral reflectance of snow, clouds, soil and vegetation in the VIS and IR range.

Table 4
Characteristics of passive (PM) and active (AM) microwave sensors used for snow detection.

	Satellite	Sensor	Bands	Frequencies /GHz	Spatial resolution /km/m	Temporal resolution /d	Launch time
PM	Nimbus-7	SMMR	5	6.6/10.7/18.0/21.0/37.0	30–160 km	1	1978
	DMSP	SSM/I, SSMIS	4	19.3/22.2/37.0/85.5	13–70 km	1	1987
	Aqua	AMSR-E	6	6.9/10.7/18.7/23.8/36.5/89.0	5–50 km	1	2002
	ADEOS-II	AMSR	8	6.9/10.7/18.7/23.8/36.5/89.0/50.3/52.8	5–50 km	1	2002
	GCOM-W1	AMSR2	7	6.9/7.3/10.7/18.7/23.8/36.5/89.0	5–50 km	1	2012
AM	ADEOS I	NSCAT	Ku	14	50 km	2	1996
	ADEOS II	Seadwinds	Ku	13.4	25 km	1	2002
	QuickSCAT	Seadwinds	Ku	13.4	25 km	1	1999
	MetOp	ASCAT	C	5.3	25/50 km	2	2005
	RADARSAT	SAR	C	5.3	8–100 m	24	1995
	RADARSAT-2	SAR	C	5.4	3–100 m	24	2007
	ERS 1–2	AMI	C	5.3	30 m	35	1991
	Envisat	ASAR	C	5.3	30/150/1000 m	35	2001
	JERS-1	SAR	L	1.275	18 m	44	1992
	Terra	SAR-X	X	9.6	1/3/18 m	11	2007

Microwave remote sensing is an appropriate substitute in this situation. The emitted microwave radiation (with a wavelength of 0.1–100 cm) from the underlying surface is attenuated by snow cover, and a passive microwave (PM) sensor on a remote sensing platform can quantify the snow mass (e.g., SWE) of a snowpack by analyzing the characteristics of the received microwave signal. Since 1978, space-borne passive microwave sensors (e.g., SMMR) have made it possible to globally monitor snow cover, SD and SWE without being affected by cloud cover and winter darkness (IPCC, 2007). The parameters of five representative satellite-based passive microwave sensors are provided in Table 4. Since the microwave radiation emitted from the Earth's surface itself is at a low level, passive microwave sensors cannot provide snow parameters at a fine scale, although a high temporal resolution can be achieved. Thus, active microwave (AM) remote sensing has advantages over passive microwave sensing. By continuously transmitting a microwave signal to the ground surface and receiving the reflected signal, an AM instrument can map snow properties at high spatial resolution but at the expense of the repeat-pass interval (Table 4). However, microwave reflectivity and scattering characteristics of snow depend on many different factors, such as SD, SWE, grain size, crystal shape, liquid water content, impurities, temperature, stratification, ice content and the terrain located beneath the snow cover (Dietz et al., 2012; Foster et al., 2005; Hall and Martinec, 1985; Kelly et al., 2003; Painter et al., 2009). The multiple influences of the snowpack on the microwave signal lead to a large degree of uncertainty and a low accuracy in SWE measurements using microwave remote sensing. Therefore, microwave remote sensing of snow needs further improvement of the algorithms used to quantify the relations between snow cover parameters and microwave signals.

Since optical sensor data have a high spatial resolution (e.g., 1–10 m) but is limited to cloud-free days whereas passive microwave sensors have a coarse spatial resolution (e.g., 5–50 km) but are sensitive to multiple snowpack properties, the synergistic application of optical and microwave spectral bands with multi-sensor fusion techniques provides an opportunity to improve snowpack property estimations (Muñoz et al., 2013). In addition, some state-of-the-art remote sensing techniques have recently been developed to obtain snow measurements, including GPS-reflectometry (e.g., Jin et al., 2016; Larson, 2016; McCreight et al., 2014) and airborne LiDAR (Deems et al., 2013; Kirchner et al., 2014). To derive SD, GPS-reflectometry utilizes active microwave reflectometry with a bistatic geometry rather than a monostatic geometry, which is typically used in satellite-based remote sensing (McCreight et al., 2014). This technique has an intermediate spatial scale of $\sim 1000\ m^2$ and is therefore considered a complementary snow measurement to those of in situ sensors ($< 1\ m^2$) and satellites images ($> 100\ km^2$) (Larson, 2016). In addition, this technique can be used for other navigation constellations, e.g., GLONASS, Galileo, and Beidou, and thus, it may potentially provide new SD data for thousands of sites around the world (Larson, 2016). Airborne LiDAR uses a laser scanning system to detect SD by analyzing changes in the signal return

Table 5
Selected snow hydrological models (Rutter et al., 2009; Slater et al., 2001).

Type	Snow Model	Identifier	References
Conceptual models	COSERO	COSERO	Frey and Holzmann (2015)
	GSM-SOCONT	SOCONT	Schaefli et al. (2005)
	HBV	HBV	Bergström (1976, 1992)
	MIKE SHE	SHE	Bøggild et al. (1999)
	PDM	PDM	Moore (2007)
	SNOW-17	S17	Anderson (1973, 1976), Raleigh and Lundquist (2012)
	SRM	SRM	Abudu et al. (2012), Martinec (1975)
	TRAIN	TRAIN	Menzel et al. (2009), Wimmer et al. (2009)
	UBC	UBC	Quick and Pipes (1976, 1977), Morrison et al. (2002)
	VIC	VIC	Cherkauer et al. (2003)
Physically-based models	2LM	2LM	Yamazaki (2001), Yamazaki et al. (2004)
	ACASA	ACA	Pyles et al. (2000)
	BATS	BATS	Dickinson et al. (1993), Yang et al. (1997)
	CLASS	CLA	Bartlett et al. (2006), Verseghy (1991)
	CLM2-TOP	CLI	Bonan et al. (2002), Niu and Yang (2003)
	CLM3	CL3	Lewis et al. (2004), Oleson et al. (2004)
	CRHM	CRH	Hedstrom et al. (2001); Pomeroy et al. (2007)
	CROCUS	CROCUS	Brun et al. (1989, 1992)
	ESCIMO	ESC	Strasser et al. (2002, 2008)
	ISBA-ES	ISE	Boone and Etchevers (2001)
	JULES	JUL	Blyth et al. (2006)
	MATSIRO	MAT	Takata et al. (2003)
	MOSES	MOS	Cox et al. (1999), Essery et al. (2003)
	NCEP	NCEP	Koren et al. (1999)
	NOAH-LSM	NOH	Ek et al. (2003)
	PLACE	PLACE	Wetzel and Boone (1995)
	RCA	RCA	Kjellström et al. (2005), Samuelsson et al., (2006)
	SAST	SAS	Jin et al., (1999a, 1999b)
	SRGM	SRG	Gelfan et al., (2004)
	SNOWCAN	SNO	Tribbeck (2002), Tribbeck et al., (2004, 2006)
	SLAM	SLAM	Desborough (1999)
	SNOWPACK	SNP	Bartelt and Lehning (2002), Lehning et al., (2002)
	SSiB3	SSI	Xue et al., (2003)
	SWAP	SWAP	Gusev and Nasonova (1998)

time for snow-covered and snow-free conditions. Due to the significant volumetric scattering component of snow, more work is needed in terms of error estimation when LiDAR is applied to the retrieval of snowpack parameters. Nevertheless, both GPS-reflectometry and LiDAR have the potential to provide accurate SD and SWE information at high spatial resolutions in the future.

3.3. Hydrological modeling

Since the 1960s, the application of digital computers has allowed hydrologists to simulate snow accumulation and ablation processes using numerical models, i.e., a set of equations depicting the relationships between various environmental elements (Armstrong and Brun, 2008). Hydrological models have developed from lumped conceptual models (e.g., Snow-17 model) to physically based distributed models (e.g., NOAH-LSM model). Table 5 lists some selected hydrological models that include a snow module. Due to the sparse observation network of meteorological stations, snowpack models have made great contributions to the estimation of seasonal snow cover distribution and snowmelt runoff. In addition, an increasing number of snow parameters can be simulated using hydrological models, including SWE (e.g., TRAIN), SD (e.g., CRHM), snow-covered fraction (e.g., JULES), snow interception (e.g., SWAP), snow albedo (e.g., NCEP) and snowmelt runoff (e.g., VIC).

However, using hydrological models to investigate seasonal snow cover and snow processes is a challenging task. For example, complicated topography and consequent high variability in snow cover, frequent alternations between rain and snow in some regions, complicated relationships between the vegetation canopy and snow, and wind-driven snow redistribution (snow drift) significantly add to the difficulty of modeling snow processes. Slater et al. (2001) compared snow simulations for a grassland catchment in Valdai, Russia, using 21 different land surface models as part of the Project for the Intercomparison of Land Surface Parameterization Schemes (PILPS) Phase 2(d). Systematic differences between the simulations from each model were found, such as in simulations of early season ablation events, although the models captured the broad features of the snow regime at both intra- and interannual scales (Slater et al., 2001). Model differences were evident in the vapor exchange and energy budgets, which are closely related to snow albedo, fractional snow cover, and the interplay of these parameters (Slater et al., 2001). Rutter et al. (2009) conducted a similar project (SnowMIP2) that was more focused on forest snow processes, and the simulations of 33 snowpack models were evaluated across a wide range of hydrometeorological and forest canopy conditions at five Northern Hemisphere locations. Precipitation phase and duration of above-freezing air temperatures are largely responsible for the divergence and convergence of sub-canopy snow modeling, and the SWE estimates showed lower performances at forested sites than open sites (Rutter et al., 2009). In addition, the calibration of models contributed to decreasing errors, although the benefits of calibration did not translate across years, models, or forested/open conditions (Rutter et al., 2009). Rutter et al. (2009) concluded that there was no universal "best" model for all sites or locations because of the high complexity of snow processes in forest environments, and the model performance showed large differences between individual models, as well as between forested and open sites.

4. Integration and difficulties of different approaches

As discussed above, each approach of in situ monitoring, remote sensing and hydrological modeling has specific advantages and disadvantages for snow cover measurements. Sturm (2015) compared these three approaches in a paper (Fig. 4). Field measurements have the greatest reliability and are essential to successful modeling, but they often fail to capture the local heterogeneity due to either a sparse network or the wrong observing locations. Remote sensing products have optimal coverage in space but also have fewer snow parameters, outright errors, and sometimes, coarse resolutions. Snow modeling can partly offset the shortcomings of the above two methods, but errors frequently arise from the numerical simplifications of the complicated physics of snow-covered areas and from our insufficient understanding of the boundary conditions and forcing functions.

The best solution for this issue is to integrate the three techniques, which can strengthen our ability to monitor, estimate and predict snow cover variation and snow-related processes in future hydrological research. In situ and remote sensing snow observation data can be independently or jointly applied in the calibration process in hydrologic modeling (e.g., Ahl et al., 2008; Franz and Karsten, 2013). In situ monitoring data are frequently used as ground truth data to support the algorithm development of remote sensing products (e.g., Gafurov et al., 2015). Additionally, remotely sensed data are useful in extending the point-based station measurements to areal scales (e.g., Takala et al., 2011). Sturm (2015) regarded the three methods used in snow research as a system with three legs (Fig. 4), and he described how to combine them to obtain an accurate understanding of snow. In addition, the three snow measuring techniques can be connected for confirmation

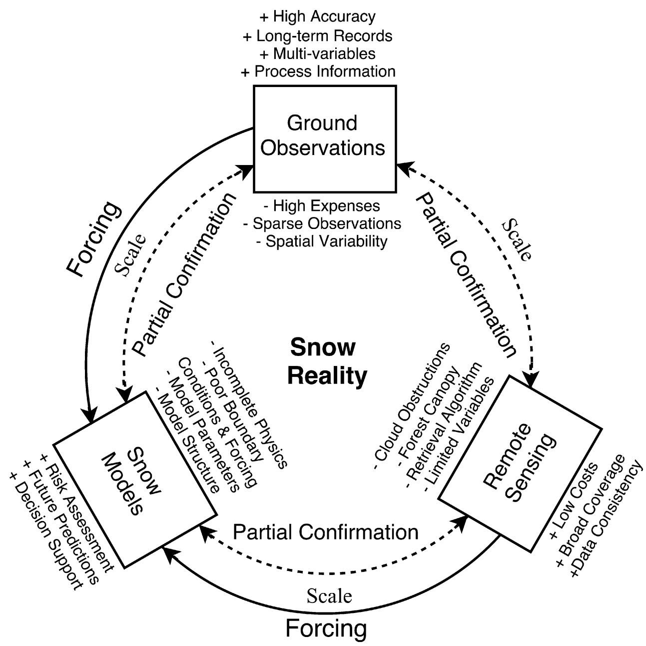

Fig. 4. Relations between ground snow observations, hydrological modeling, and remote sensing suggested by Sturm (2015). Redrawn by the author.

purposes, and both ground observations and remotely sensed snow data can be applied to force snow models (Sturm, 2015). Within the snow modeling, measuring, and remote sensing communities, a consensus has been building that modeling ultimately achieves its best results (and greatest accuracy) when it is paired with the other two approaches (Sturm, 2015). During the past two decades, remote sensing has experienced the most rapid progress. Many snow research groups are working on better satellite-based and airborne sensors and algorithms to derive more precise SCA, SD and SWE products. Besides, the field observation technology is developing quickly. More and more cheap but effective instruments (e.g. sonic sounder, time-lapse camera) have been applied to observe snow dynamics in remote and unattended regions. These field-based data will contribute to the development of both remote sensing algorithms and snowpack models (calibration, data assimilation, and validation). However, scale transformation should be considered when using any two of the three methods. In snow water research, as in other aspects of hydrology, we either must upscale from too few measurements or downscale from measurements that are too coarse and imprecise (i.e., remote sensing products) (Sturm, 2015). When the strengths of one leg are used to compensate for the weaknesses of the other legs, snow researchers should be able to achieve more realistic snow measurements.

Recently, data assimilation (DA) has provided an outstanding solution for improving hydrological modeling by synchronously integrating observations from in situ stations or remote sensors. An ensemble Kalman filter (EnKF) was applied by Slater and Clark (2006) to assimilate in situ SWE data into the SNOW-17 model, and evident improvements in the resulting SWE were achieved during the accumulation and melt periods. Thirel et al. (2013) successfully improved the modeled SCA and discharges by assimilating MODIS snow cover products into a distributed hydrological model using a particle filter (PF). Liu et al. (2013) assimilated satellite-based snow products into the Noah land surface model, which includes the standard MODIS SCA and AMSR-E SD data, as well as bias-adjusted versions compared to in situ observations. Those authors concluded that the assimilation of bias-corrected snow data consistently improved the snow and streamflow predictions. Therefore, it is essential to improve the snow observation data quality before assimilation into hydrological models; otherwise, the model performance will deteriorate, as evidenced in the study by Molotch and Margulis (2008).

There are still few studies about the integration of field measurements and remote sensing products in snow hydrology, although some researchers have recently made attempts. Gafurov et al. (2015) provided a novel approach that utilized in situ snow measurements to extrapolate cloud-covered pixels on MODIS snow maps based on the conditional probability between pixels. Dong and Menzel (2016a,b) introduced a similar method to generate cloud-free MODIS snow cover products, and they also used in situ snow observations to reject overestimated snow in satellite data. At present, due to the scale gap between the two observation approaches, the sparse in situ station network has hindered the fusion of these two approaches. Adding more stations might be helpful, but the benefits would be offset by the enormous expense. Time-lapse photography has inspired us to utilize another data source: internet-based digital pictures that are shared voluntarily by individuals. As suggested by Goodchild (2007), volunteered geographic information (VGI) has the potential to provide geographers with a significant source of information on the Earth's surface. Today, citizens and travelers worldwide are sharing an increasing number of digital photos with geotags derived from their personal devices, such as cameras, cell phones, and driving recorders, and in the future, drones and driverless automobiles will also likely contribute such data (Fig. 5). In many countries, a large number of weather cameras and traffic monitoring cameras have been connected to the internet and thus can provide real-time photos. All these web-based photos provide valuable geographic information that can be extracted using pattern recognition techniques (Giuliani et al., 2016; Yuan et al., 2010). Moreover, some government agencies have already set up platforms to make use of VGI for weather observation purposes. For example, NOAA's Citizen Weather Observer Program (CWOP, http://wxqa.com/) invites volunteers to collect and share weather data using their private instruments, and NOAA provides technical support to ensure data quality. The Australian Weather Observations Website (WOW, http://bom-wow.metoffice.gov.uk/) also provides the public with the ability to share their weather observations, information and photos. By being fused with these new ground-based observations, e.g., snow presence or absence, the remotely sensed snow cover products can be significantly improved, which could help enable retrieval of cloud-obstructed pixels and eliminate cloud/snow confusion. Therefore, the "three leg system" proposed by Sturm (2015, Fig. 4) might be modified

Fig. 5. Available sensors (a) and websites (b) that can provide digital photos for snow observations.

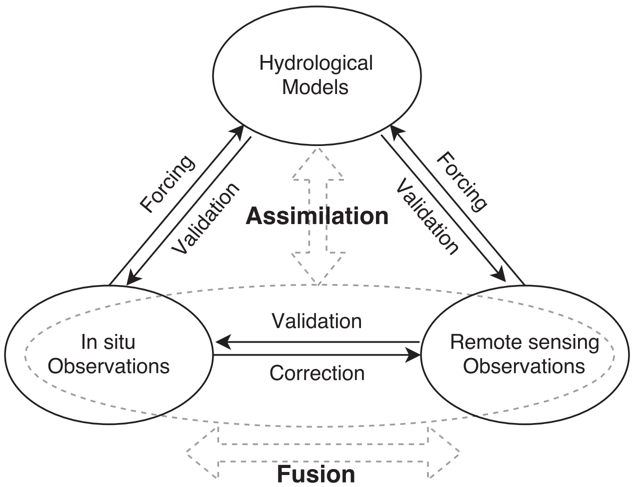

Fig. 6. Relations between in situ observations, hydrological models, and remote sensing.

as shown in Fig. 6, i.e., the arrow from "in situ observations" to "remote sensing observations" indicates the "correction" function of the former for the latter. The fused ground-based and remotely sensed snow observations would better serve hydrological models as data sources for forcing, validation and assimilation data due to their increased accuracy and reliability, and the resulting models would better approximate the extremely complicated snow physics.

5. Discussion and conclusions

Blöschl (2011) emphasized the scale issues in hydrology, but these issues are also very important in snow studies. As two kinds of snow observations, in situ monitoring and remote sensing can provide snowpack information at the point scale (1-D data) and areal scale (2-D data), respectively. With the high reliability and accuracy of modern meteorological instruments, field measurements can partly achieve "what you see is what you get" at the point scale. However, such accuracy is never achieved at the areal scale (e.g., basin scale) because of the large heterogeneity in the hydrological variables. Due to frequent errors, remotely sensed data are often "what you see is not what you get", even at the areal scale. To improve the remote sensing data to "what you see is what you get", one potential solution involves incorporating ground observations, and the applicability of this technique has been proven by several studies (Dong and Menzel, 2016b; Gafurov et al., 2015). However, remote sensing cannot provide the snow information most important to hydrologists, e.g., snowmelt runoff, surface energy balance and snow prediction, whereas snow models can, i.e., their major advantage is that they provide "what you want". Due to the ability to offer large-scale spatially distributed observations, remote sensing has opened new opportunities for the development of fully distributed hydrologic and land surface models (Xu et al., 2014). Moreover, it is more appropriate to update the model output by assimilating remote sensing observations instead of point-based ground measurements. Zhang et al. (2014) utilized only remotely sensed data to force, calibrate, and update a hydrologic model towards streamflow simulations in an ungauged basin, and promising results were achieved. As great uncertainty still exists in the inversion algorithms of remote sensing for snow parameters, considerable potential improvements remain in the development of remotely sensed snow products.

More optimization is also needed for snow hydrological models, as they are currently unlikely to produce a snow model corresponding to "reality" due to the lack of local input, boundary data and calibration (Sturm, 2015). In situ observations and remote sensing do not easily reveal the snow "reality" because distinct "realities" exist at different scales. For example, a station located within a city may not observe the snowfall that occurred in the surrounding mountains. The station record of "snow-free" was the "reality" in the city but not in the mountainous area. A satellite-based sensor might capture the snow cover by labeling a coarse pixel as "snow-covered", despite the absence of snow in the city. The snow "reality" for a citizen is "snow-free", while the "snow-covered" conditions in the adjacent mountains is very important for a hydrologist because the subsequent snowmelt will add to rivers through runoff. Therefore, hydrologists can find the best approximation of the snow "reality" with the full utilization of the "three leg system" containing in situ observations, remote sensing, and hydrological modeling. NOAA's National Operational Hydrologic Remote Sensing Center (NOHRSC) has made some progress in this direction by providing Snow Data Assimilation System (SNODAS) data products, which estimate daily SD, SWE and other parameters based on the assimilation of satellite-derived, airborne, and ground-based observations of snow using Numerical Weather Prediction (NWP) models (NOHRSC, 2004). As snow cover plays an important role at both local and continental scales, data assimilation is useful in bridging the scale gap between local observations and hydrological models. For example, Javaheri et al. (2018) have assimilated catchment-scale water level observations into National Water Model for flood forecasting at the continental scale, and they significantly improved the model predictions. Thus, similar data assimilation schemes can also be applied to increase the accuracy of snow simulations at both local and larger (continental) scales. However, as data assimilation highly depends on accurate observations, continuous monitoring of snow characteristics is critical for improving model performance, especially in mountainous areas where snow plays a key role in the hydrological cycle.

In alpine and polar regions, glaciers have also been remarkably influenced by climate change (e.g., Immerzeel et al., 2010; Yao et al., 2007). As this review mainly focuses on the measurements of seasonal snow cover, approaches for glacier monitoring are not discussed above. Traditionally, glacier mass balance was measured with the in situ glaciological method, which involves placing a network of stakes and pits on the glacier surface and measuring the surface changes (Kaser et al., 2002). Recently, remote sensing has become a powerful and efficient approach for studying glaciers, which are usually located in remote and inaccessible environments (Gao and Liu, 2001). Optical remote sensing data have been used to map glaciers (e.g., Paul et al., 2004). However, cloud obstruction remains a challenge for optical sensors aboard aircraft or satellites (Veettil and Kamp, 2017). Unmanned aerial vehicle (UAV) photogrammetry and microwave remote sensing have performed well in mapping cloud-covered glaciers (e.g., Wigmore and Bryan, 2017; Winsvold et al., 2018). Furthermore, non-imaging radar systems, such as airborne laser altimeter (ALA) and radio echo sounding, offer great potential for remote sensing of glacier microtopography, ice thickness, and glacier temperature (Gao and Liu, 2001; MacGregor et al., 2015). Moreover, the modeling approach is a powerful tool in studying glacier dynamics, and it can be used for avalanche forecasting, glacier melt estimation, and assessing the response of glaciers to climate change (Stahl et al., 2008). Thus, the three-leg integration system (Fig. 6) for snow research can also be applied to glacier studies.

As a concluding remark, the author wishes to emphasize the significance of improving the quality of remotely sensed hydrological datasets using ground observations. Although the different scales lead to a great gap between the two data sources, in situ meteorological records still have the potential to contribute to error minimization and cloud removal in remote sensing data. The assimilation of remotely sensed observations is an effective technique for relieving the uncertainty of hydrological models, but inferior observations may weaken the performance of a model. Therefore, the fusion of ground-based and remotely sensed observations is indispensable for achieving superior data assimilation in hydrological research.

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