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Globally scalable alpine snow metrics

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ABSTRACT

Horizontal and altitudinal redistribution of snow by wind transport and avalanches can be important controls on small- and large-scale snow accumulation patterns that control meltwater supply in alpine environments. Redistribution processes control the spatial variability of snow accumulation, which not only controls meltwater supply, but also regulates snowmelt timing, duration, and rates, as well as snow-covered area depletion and the variable contributing area for meltwater runoff generation. However, most hydrological models and land surface schemes do not consider snow redistribution processes, and those that do are difficult to verify without spatially distributed snow depth measurements. These are rarely available in both high resolution and covering large scales. As an increased number of hydrological models include snow redistribution processes there is a need for additional snowcover metrics to verify snow redistribution schemes over large areas using readily available data.

This study develops novel high-resolution (20 m), snowcover indices from remotely sensed imagery (Landsat-8 and Sentinel-2) to evaluate snow redistribution models over alpine areas without in-situ or airborne snow observations. A snowcover absence (SA) index, calculated from snow-free areas during the winter, identifies areas of wind erosion or avalanche source areas. A snowcover persistence (SP) index, calculated from snow-covered areas during the summer, identifies snow deposition in drifts and avalanche deposits.

The snowcover indices captured the relative differences in surface observations of snow presence and absence between exposed and sheltered sites on an intensely instrumented ridge in the Canadian Rockies Hydrological Observatory. Within the Tuolumne River Basin in central California (1100 km^2), the SP index captured roughly half of the spatial variability (R^2 = 0.49 to 0.56) in peak SWE as estimated from airborne LiDAR-derived snow depths. At the individual mountain ridge scale (~800 m), variability in both ablation and snow redistribution controlled the SP patterns over 7979 ridges. Differences in shortwave irradiance explained 76% of the SP variance across ridges, but could not explain smaller-scale (~100 m) SP peaks that are associated with snowdrifts and avalanche deposits. The snowcover indices can be used to evaluate snow redistribution models of the finer scale impacts of snow redistribution by wind and gravity as long as the larger scale influences of spatially variable solar irradiance effects are also simulated.

1. Introduction

Mountain snow is a critical natural reservoir of water resources for the world (Li et al., 2017; Meehl et al., 2007) and has significant economic impacts (Sturm et al., 2017). Over the Canadian Rockies, alpine terrain above treeline covers more than half of the total area and has a significant contribution to snowpack storage and the areal albedo. As blowing snow and avalanches dominate alpine snow redistribution, these processes must be represented in land surface models to accurately simulate surface energy and mass fluxes (Pomeroy et al., 1998). However, observations of horizontal snow transport are rare at the basin scale, posing a challenge for model development and evaluation.

Blowing snow observations fall into two categories: 1) direct measurements of snow saltation or suspension (Aksamit and Pomeroy, 2016; Bintanja et al., 2001; Brown and Pomeroy, 1989; Gubler, 1981; Schmidt and Jairell, 1987; Vionnet et al., 2017, 2013); and 2) indirect measurements of snow redistributions before and after blowing snow events (Fang and Pomeroy, 2009; MacDonald et al., 2010; Musselman et al., 2015; Pomeroy and Gray, 1995). Although direct measurements have been critical for understanding and developing the physics of blowing snow models, indirect methods are required to evaluate the impact of snow redistribution on snow hydrology over multiple scales (Palm et al., 2011). Indirect measurements include manual snow depth measurements across ridges (MacDonald et al., 2009), terrestrial LiDAR

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(Grünewald et al., 2010; Prokop, 2008; Schirmer et al., 2011; Schön et al., 2015), and airborne LiDAR (Deems et al., 2006; Hopkinson and Chasmer, 2009). The use of operational airborne LiDAR has become more common and feasible over many basins (Painter et al., 2016), however, it still remains expensive when deployed on airplanes or drones and so is often limited to specialized field campaigns.

As an alternative to terrestrial based approaches, satellite based remote sensing can provide global coverage with varying temporal and spatial resolutions. In alpine terrain, Bernhardt et al. (2010) used 30 m snowcover from two Landsat images to evaluate a distributed blowing snow model, finding the model's spring snowcover was too homogenous compared with observations. Macander et al. (2015) utilized 11,645 Landsat scenes over Alaska to develop climatological snow disappearance maps to characterize caribou habitat, but stopped short of identifying snow redistribution. Déry et al. (2005) used daily fractional snowcover from the Moderate Resolution Imaging Spectroradiometer (MODIS) to inform snowcover depletion curves within a land surface model in order to capture persistent snowdrifts in the Arctic. Blowing snow events have also been identified over the gentle terrain of Antarctica (Scarchilli et al., 2010) using satellite based LiDAR and MODIS. Over complex terrain, the MODIS snowcover products at a nominal 500 m resolution are too coarse to resolve snowdrifts caused by blowing snow. Snow redistribution features such as snowdrifts normally occur at scales from 1 mm to roughly 100 m (Aksamit and Pomeroy, 2016; Clark et al., 2011; Pomeroy and Gray, 1995).

The objectives of this study are to identify mountain regions dominated by snow redistribution, and develop snowcover indices suitable for testing snow redistribution models over large spatial domains ($> 1000\ km^2$). The approach takes advantage of multi-year and multi-platform snowcover records by focusing on Landsat-8 and Sentinel-2A imagery, at 30 m and 20 m resolutions, respectively that can resolve many snowdrift patterns. These platforms are limited by repeat times (16 days and 10 days, respectively) and cloud cover, but, combined, greatly increase the chances of capturing cloud-free temporal variations in snowcover patterns caused by blowing snow and avalanches.

The study domains and data used are described in Section 2. Section 3 details the derivation of snowcover indices and spatial analysis methods applied. Results of the evaluation of the indices and their pattern classification are provided in Section 4. A discussion of the applications and limitations of snowcover indices is given in Section 5 and summary conclusions in Section 6.

2. Study domains and data

2.1. Study domains and site measurements

Three study domains (Fig. 1a, e) are used for the analysis and evaluation of derived snowcover indices. The Fortress Mountain Snow Laboratory (hereafter Fortress) is located in the Canadian Rockies at 50.82°N, −115.21°W and ranges in elevation from 2100 m to 2890 m (red area in Fig. 1e, expanded in Fig. 1b). Fortress is part of the Canadian Rockies Hydrological Observatory and includes in-situ meteorological and snow measurements of an alpine environment representative of much of the eastern slopes of the Canadian Rockies. Data was collected between 2014 and 2018 (and continuing), thus overlapping temporally with remote observations (see Section 2.2). Two meteorological stations used for this study are shown in Fig. 1c. The exposed Fortress Ridgetop station (hereafter Exposed) is in a wind-exposed environment with frequent blowing snow erosion. In contrast, the sheltered Fortress Southface station (hereafter Sheltered) is located 70 m southeast of the ridge within a cluster small trees on a south facing slope. Sub-nival krummholz vegetation (Jones et al., 2001) results in the frequent deposition of windblown snow and locally deep snow accumulations. At both sites, snow depths were measured with ultrasonic sensors (SR-50) at 15-min intervals, and bi-weekly snow surveys near both sites measured snow depth and snow water equivalent (SWE) using an ESC-30 or Mount Rose sampler and scale following Pomeroy and Gray (1995). Incoming shortwave was measured at a 15-min sampling interval at the Exposed site with a Kipp & Zonen CNR4 net radiometer.

Areal evaluation of snowcover indices was conducted in the Tuolumne River Basin (black square in Fig. 1a, expanded in Fig. 1d) located in the central Sierra Nevada at 37.93°N, −119.57°W, because of the availability of multiple years of Airborne Snow Observatory (ASO) flight data (Painter et al., 2016). Painter et al. (2016) estimated SWE derived from LiDAR snow depth and Snobal density modeling, aggregated to a 50 m resolution. Data for the flights nearest to the timing of peak SWE were obtained. Quality controlled and gap-filled shortwave irradiance observations from the Tuolumne Meadows station (Lundquist et al., 2016) were used to drive calculations of spatially distributed shortwave irradiance across the domain following Dozier and Frew (1990).

The third study domain (white area in Fig. 1a, e) encompasses a west-east transect (hereafter Transect) across the Canadian Rockies (51.27 to 50.74°N and −119.13 to −113.91°W) to identify regional patterns in snow redistribution from the maritime to alpine to prairie snow climates (Sturm et al., 1995).

2.2. Satellite data

Landsat-8 and Sentinel-2A imagery were obtained and analyzed using the Google Earth Engine (GEE; Gorelick et al., 2017). The GEE workflow employed consisted of data import, cloud masking, shadow masking, forest cover masking, and normalized difference snow index (NDSI) (Hall et al., 1995) calculation and classification. The GEE code can be scaled globally.

For each study domain, Landsat-8 tiles and 16 Sentinel-2A tiles (Table 1) were obtained that contained < 30% cloud cover during each satellite's operational period (March 2013 to May 2017, and June 2015 to May 2017, respectively). The availability of pixels of varied seasonally (Fig. 2), due to higher cloud cover and shadowing during winter months. Landsat-8 clouds were masked using the GEE *simpleCloudScore* algorithm with a confidence value of 80%. This value was selected to provide the best classification of clouds over our study domains, but may not be optimal over other regions. Sentinel-2A clouds were masked using an algorithm similar to *simpleCloudScore* (*sentinelCloudScore*), after the quality control flags provided by the European Space Agency were found to perform unsatisfactorily over our study domains. The tile-average solar azimuth and solar zenith angles were used in conjunction with the Temporal Dark Outlier Method (Housman et al., 2015) to calculate cloud shadows for both satellites. Terrain shadow masking was especially important during winter months when large shadow areas occurred during overpasses. Terrain shadows were calculated using the GEE *hillshadow* algorithm and the 30 m resolution Shuttle Radar Topography Mission (SRTM) Version 3 void-filled DEM (Farr et al., 2007). Because SRTM only covers 56°S to 60°N, the ASTER GDEM product at 100 m spatial resolution can be used as an alternative but with less accurate shadow estimation (not used here). Forested areas were masked using the Hansen et al. (2013) tree cover dataset based on Landsat data; all 30-m pixels with tree cover > 30% were excluded from our analysis. Lakes were masked using the Pekel et al. (2016) dataset, where pixels with 70% annual water occurrence are discarded. Finally, the NDSI was used to classify snow pixels with NDSI values > 0.4 and non-snow pixels with NDSI values less than or equal to 0.4. Datasets were combined by resampling the Landsat-8 (30 m) to match the Sentinel-2A (20 m) grid, using the nearest neighbor approach.

2.3. Global environmental multiscale model shortwave irradiance

Observations of incoming shortwave irradiance are sparse over the