CLASSIFICATION OF SNOW ANISOTROPIC SURFACES FOR MOUNTAINOUS TERRAIN WITH MIXED VEGETATIVE COVER USING OPTICAL AND THERMAL SPECTRA FROM LANDSAT-8

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ABSTRACT: New remote sensing platforms under development will improve availability of optical and thermal spectral data for mountainous regions on a more regular basis, possibly on a daily basis at targeted areas. Newly available spectral remote sensing data will allow to characterize the evolution of the snow surfaces, particularly during the winter months when little is known with respect to large spatial scale development of snow surfaces. Understanding of snow surface development during winter has been hampered due to limited remote sensing data due to a combination of inclement weather, bi-monthly satellite passes, and the difficulty of producing training and validation data for the snow surfaces. Landsat-8 optical and thermal spectral data from January 16-2017 for Central Idaho was used to demonstrate that snow surface with significant anisotropic development can be classified. During ski touring label data was generated to identifying snow surfaces. This GPS referenced data was used to generate the training and validation data sets for the same Landsat pass period. Spectra Optical and thermal spectra were processed using machine learning classification techniques. This study suggest that winter snowpack surfaces can be tracked with optical and thermal spectral sensors. Tracking of the snow surface temporal development is not only important for the forecasting of avalanches but it also valuable in complementing snowpack development models, as well as identifying snow layered structures that will impact snow melt dynamics.

KEYWORDS: snow anisotropy, neural networks classification, support vector machines classification.

1. INTRODUCTION

Globally one sixth of Earth's Population depends on snow or glacier melt for water resources (T. Painter, et al., 2009). Closer to our research area; a significant proportion (as much as 75%) of the annual fresh water in Western North America comes from mountain snow. Water resources management practices are being challenged by climate change, whereas we cannot only rely in long term statistics statistics, and we need to accelerate the development of physical based model of processes for the ablation, development, and melt of the mountain snowpack. For snowpack modeling to be successful, it is essential to develop adequate spatial and temporal descriptions of mountainous snow covered areas.

Remote Sensing from a diverse constellation of satellites provides image domain data of snow covered areas that is rich in snow spectral data at the optical and thermal bands. Landsat 8 offers an unequal opportunity to advance cryosphere research due to its coverage of reflective and thermal wavelength observations with increased spectral and spatial fidelity (D.P. Roy et al, 2014). This study is evidence of Landsat 8 capability to continue advancing science and offering new opportunities, by demonstrating how thermal and optical indexes can be fused into new snow indexes to classify anisotropic snow surfaces. Thus providing new opportunities to temporally track the development of the mountainous snowpack.

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"Characterization of snow is critical for understanding Earth Systems" - This is how K. Rittger, et al, 2013) introduce readers to their paper about "Assessment of methods for mapping snow cover from MODIS. T. Painter et al, 1998, also stated that on earlier work dating almost 20 year ago; snow crystal sizes field data as well as adequate samples of crystal end-members with anisotropic and/or isotropic surface are required. Mixing of snow pixels due to vegetation and various snow surfaces must be also considered (T. Painter, et al, 1998). In this study we are are taking first steps in researching areas suggested by T. Painter, et al, 1998, simply because we need to understand snow in order to understand Earth's systems!

T. Painter, et al., 1998 asserted that remote sensing would benefit from "further work" in areas such as; the impact of shaded snow, effect of mixing of snow and vegetation pixels, scattering of snow crystals due to faceting, and selection of end members representing the crystal in the field. In this study we attempted to address some of these factors, primarily through the inclusion of the thermal bands, and a field training set (end-members) with an advanced anisotropic surface.

This study also integrates optical and thermal bands with different spatial resolutions, 30 versus 100 meters respectively, while it characterizes snow surfaces spectral response resulting from ice crystals sizes ranging from 0.25 mm to 1-4 mm that have changed in time from isotropic to anisotropic surfaces. In fact, It is quite amazing that remote sensing spectral analysis techniques can successfully be employed to not only to classify snow crystal sizes but also detect the presence of anisotropic faceted snow surfaces.

The integration of optical and thermal bands is expected to improve mapping of snow in forests. This is a fundamental if we are to study the temporal nature of facet development. It is well known that NSF and SH are more common at forest areas than open alpine areas.

2. BACKGROUND

The snow surface temporal development is impacted by temporal cumulative effect of solar radiation and topography, particularly during the winter at mid-latitudes corresponding to this study (latitude ~ 43°).

During certain climate conditions present during the snow accumulation season snow surfaces characterized by anisotropic structures develop over large mountainous areas. These anisotropic snow surfaces have different emissivity and albedo from isotropic snow surfaces. The emissivity and albedo differences between isotropic and anisotropic are intrinsically different and allow to employ optical and thermal snow indices to classify snow surfaces.

Snow isotropic structures are common for precipitation snow, snow that have undergone melting (crusts), or aging of precipitation snow under conditions lacking temperature gradients, such as cloudy skies or areas where radiation cooling is inhibited.

The presence of anisotropic structures is the result of one of two processes; snow faceting metamorphosis or deposition of surface hoar crystals (SH). Snow metamorphosis driven by strong temperature gradients, permeable snow, and low thermal conductivity and results in the development of "Near Surface Facet" (NSF) crystals. The temperature gradient direction is normal to the snow surface and is fueled by long wave infrared cooling. The temperature gradients favor the sublimation and deposition of new hexagonal crystals and structures oriented normal to the snow surface. **Figure 1** shows the anisotropic snow surfaces observed during the survey day.

Figure 1

Deposition of surface hoar crystals is favored by climatic conditions with ample availability of water vapor in the atmosphere, clear skies promoting long-wave IR cooling in the snowpack surface, and tranquil weather that drives the deposition of "surface hoar" (SH). Similar to NSF, radiative cooling will drive the deposition of large hexagonal "platelike" crystals. Deposition of SH crystals is directional and normal to the snow surface.

In summary, NSF and SH snow surface are highly anisotropic unlike most typical snow surfaces during the accumulation snow season, where the snow is characterized as precipitation snow and/or combination of round and sintered (R-S) snow. It is unlikely that that NSF and SH can be differentiated through satellite spectral separation due to their similar anisotropic structure. Future research will attempt to differentiate between NSF and SH assuming differences in average crystal sizes and the ability to develop adequate training and validation field data sets.

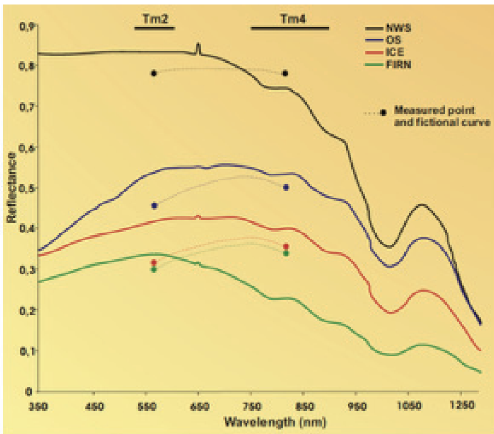

Figure 2

Using remote sensing to estimate anisotropy is not new (Hendriks, et al) and it has been used to characterize snow surfaces at glaciers as it can be seen on **Figure 2** where Landsat 7 image data was studied. In our study we intend to advance this body of work by characterizing an advanced faceting event in central Idaho during mid January 2017.

For this study, the Red, Green, Near-infrared, short-wave infrared, and Thermal spectral bands are used in the classification. The next paragraphs provide the foundation for the selection of these spectral bands.

Recent studies employing Landsat 8 data, have advanced the understanding of optical and thermal spectra in complex mountainous terrain (R. Kour et al., 2016). Mountainous terrain have areas of sunlit and shades that demand to carefully select spectral bands, such as the thermal band, that is insensitive to shadowing effect. Inclusion of the thermal spectra is important in order appropriately classify snow surfaces.

The optical reflectance (albedo) of the snow surface is determined by the wavelength-dependent refraction index of ice crystals and the size/shape of the ice crystal scattering the optical radiation (J. Dozier et al., 2007). NIR wavelengths are employed in remote sensing analysis to estimate snow crystal size.

Of interest to this study is the evolution of newly fallen snow into NSF, where snow crystal size sharply increases due to the climatic induced strong gradients described earlier in the text. It should be noted that research work is needed to characterize the albedo of highly anisotropic and non-spherical crystals typical of NSF, since it is usually assumed that non-spherical crystal snow structures can “mimic” sphere radiative flux models (J. Dozier et al., 2007). This assumption is possibly violated due to the divergence of surface area to volume ratio present in advanced facets such as NSF and SH. J. Dozier et al., 2007 recognized issues requiring further research such as the impact of grain size due to diurnal snow facet metamorphism as well as the formation of SH.

The inclusion of the green and SWIR spectral bands in our analysis is leveraged from commonly used ‘Normalized Difference Snow Index’ or NDSI:

$$NDSI = \frac{\rho_{Green} - \rho_{SWIR}}{\rho_{Green} + \rho_{SWIR}} \qquad (1)$$

Red and NIR bands reduces chances of errors associated with mixed snow and vegetation (R. Kour et al., 2015), which is important considering our study are results in a large fraction of mixed pixels of snow and forest vegetation. Recall that Red and NIR spectral bands are used by the widely used Normalized Difference Vegetative Index (NDVI) so important in vegetative cover characterization:

$$NDVI = \frac{(\rho_{NIR} - \rho_{Red})}{(\rho_{NIR} + \rho_{Red})} \qquad (2)$$

It appears that this study is unique on its approach to use Thermal Snow Indexes to classify snow anisotropic surfaces. The author could not identify previous remote sensing work related to the detection snow anisotropic surfaces such as NSF and SH with the exception of with the successful detection of SH in Greenland using RADARSAT (T. Manninen, et al, 2016), although the detection is limited to flat and homogenous terrain (non-mountainous and devoid of vegetative cover). In another work the idea of SH detection with MODIS was discussed but no results have been yet provided (R. Solberg, et al, 2009).

This study employs Landsat 8 optical and thermal data with contrasting spatial resolutions, thus it is relevant to comment on its impact to image processing. During this study data processing it was observed image quality improvements. These image quality improvements have been documented by remote science researchers when fusing 100-meter resolution TIRS data with the 30-m OLI resolution results in image data “sharpening” effect (D.P. Ray, et al, 2014). This sharpening effect has also been demonstrated before when combining surface temperature with vegetative indexes. In addition, the fusion of spectral data with different spatial resolution, has been shown to improve classification performance (Panpan Xu, et al., 2017), and it is reasonable to expect similar results when fusing spectral data with different spatial resolutions in our study.

3. STUDY AREA

The area of study is in the Boise Mountains, in Central Idaho, USA. The survey area is located to the southwest of Mores Creek summit, along Idaho-21 state road. The area surveyed is known as the southeastern ridge of Freeman Peak and contains the 12-mile creek watershed.

Vegetation cover ranges from sagebrush and other brush with coniferous forest at southerly aspects to a mixed forest of mostly conifers with some decorous trees with vary gin canopy cover from 100% to sparse and mostly open forest. Terrain elevation ranges from 6000 feet to 8000 feet above sea level.

The study has snow in the ground generally from December through April. The mostly forested area enjoys moderate winter temperatures that favors the development of NSF and SH surfaces.

Figure 3 corresponds to the snow depth and air temperature at a Mores Creek Summit snow monitoring (SNOTEL) station for the Natural Resources Conservation Service.

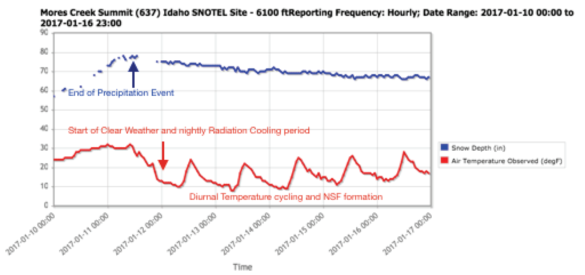

Figure 3

Notice in **Figure 3** the resulting snow depth after the end of a precipitation event just six days prior to Landsat8 pass over the area of interest. The diurnal temperature fluctuation below water freezing temperate explains the significant abundance of near-surface facets found at the study area.

The study area and GPS track follows during the labeling of the snow surface is shown in **Figure 4**. The survey data was used to generate the training and validation data used for the snow classification.

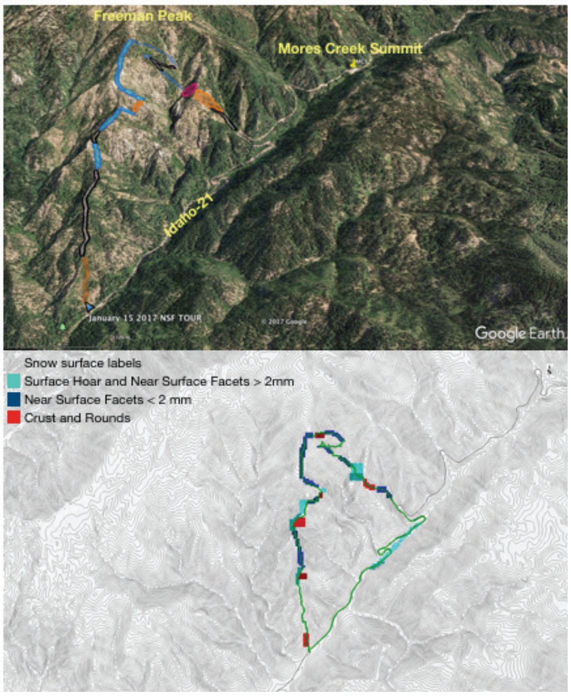

Figure 4

4. RESULTS AND DISCUSSION

Neural Networks and SVM classification methods employed for the snow surface classification produced results above benchmark values, exceeding 75% overall accuracies with kappa coefficients above 0.5, as well as producer and user accuracies above 50%.

The confusion matrixes results from **Figure 5** summarizes overall accuracies, kappa coefficients, and producer/user accuracies for various combinations of optical and thermal bands;

- Red, Green, NIR, SWIR1, SWIR2, Thermal 1, Thermal 2 - seven bands
- Red, Green, NIR, SWIR1, SWIR2 bands - five bands
- Thermal 1, Thermal 2 - two bands
- PCA - Top three “Eigen" layers - three bands

			Producer / User Accuracy %		
Classification Method	Overall Accuracy	Kappa Coefficient	NSF/SH > 2 mm	Crust/Rounds	NSF < 2mm
Support Vector Machine (RG-NIR-SWIR1/2-TH1/2 bands)	78%	0.65	81 / 100	74 / 51	78 / 77
Support Vector Machine - No Thermal (RG-NIR-SWIR1/2 bands)	74%	0.58	72 / 98	79 / 49	73 /72
Support Vector Machine - Only Thermal (TH1/2 bands)	79%	0.62	89 / 94	0 / 0	96 / 70
Support Vector Machine (Principal Components - 3 Eigenvalues)	76%	0.61	76 /100	74 / 50	77 / 74
Neural Networks (RG-NIR-SWIR1/2-TH1/2 bands)	76%	0.60	65 / 100	79 / 59	82 / 71
Neural Networks - No Thermal (RG-NIR-SWIR1/2 bands)	76%	0.62	86 / 99	82 / 44	66 / 80
Neural - Only Thermal (TH1/2 bands)	58%	0.30	60 / 100	18 / 13	69 / 57
Neural Networks (Principal Components - 3 Eigenvalues)	80%	0.68	81 / 100	76 / 55	81 / 78

Figure 5

The success of the classifications can be attributed to the spectral separability of the labeled data. **Figure 6** shows the marked “separability” or differentiation between the 3 labels; NSF/SH > 2 mm crystals, NSF < 2 mm crystals, and surface crust/rounds. It should not be overlooked that this separability is direct result of the very distinctive crystal structure of the snow surfaces studied.

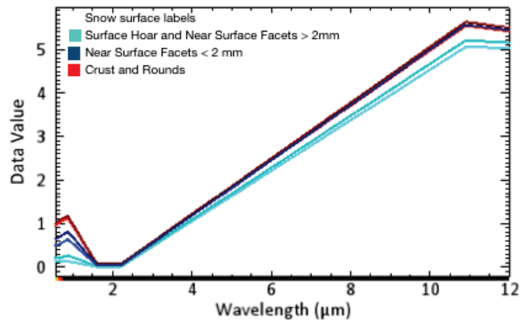

Figure 6

In **Figure 5**, notice that the classifications relying exclusively in thermal bands were not satisfactory due to the miss-classification of crust and round crystals surfaces. This is not unexpected, since there is poor separability between crust/round surfaces and NSF surfaces with smaller than 2 mm crystals in the thermal bands as it can be seen in **Figure 6**.

It is notable to point to the classification where the thermal bands were not employed. Overall accuracies and kappa values were not impacted with the exception of an increase for rate of misclassification of NSF surfaces with smaller than 2 mm crystals. Once more, inspection Figure 8 suggest that without the thermal bands there will fewer data to separate SH/NSF surfaces from NSF surfaces with less than 2 mm crystals.

Neural network analysis of data processed using the main three Eigen layer product of Principal Component Analysis (PCA) produced the best results. When selecting the top Eigen layers, in effect the noisy data and redundant spectral data is removed from the classification analysis that results in augmenting classification accuracies.

Statistical analysis of the reflectance data for the spectral bands utilized in the analysis confirmed why PCA is effective with only three Eigen layers. These analyses showed redundancy of spectral information with certain band combinations, such as the Green and Red, SWIR2 and SWIR2 and Thermal 1 and Thermal 2 pairs. For the data classified most of the observed variance is carried by the NIR, a single SWIR, and single Thermal bands. NIR colinearity with Green and Red bands, allows us to reduce the classification dimension into three orthogonal hyperplanes.

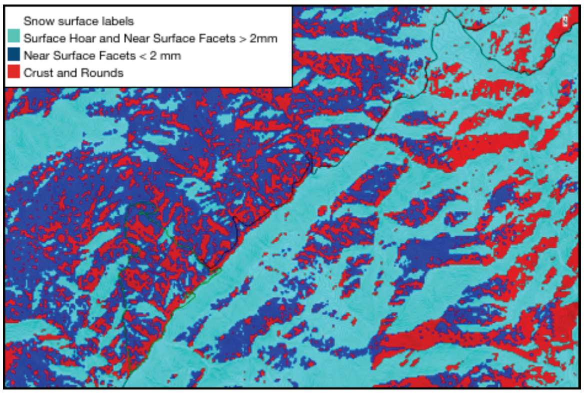

Figure 7

Figure 7 shows the classification results for the Neural network technique with PCA. Classifications maps were produced for each of the classification combinations listed in Figure 5, but are not included for the sake brevity, besides they were hardly indistinguishable between each other.

5. CONCLUSIONS

We learnt that Neural Networks and SVM techniques work well classifying winter snow surfaces from Landsat 8 optical and thermal bands. Best results were resulted from the application PCA for dimensional reduction due to the colinearity of spectral bands used; green, red, NIR, SWIR1, SWIR2, TIR1 and TIR2.

The fusion of 30 and 90-meter spatial resolution from Optical and Thermal bands complemented each other, whereas the machine learning classification benefited from the separability in the thermals band, that was crucial in the discrimination between small and large anisotropic surfaces (SH/NSF versus small NSF).

A final word - this study demonstrates that it is feasible to identify anisotropy with Landsat 8 data in complex mountainous terrain and with very variable canopy cover! The authors hope this work inspires more initiatives dedicated to the characterization of snow during the winter months.

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