SNOW-COVERED AREA USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

In this study, we used an artificial neural network method to estimate the *fractional snow cover area (*fSCA), which is fast and accurate, and that can be easily adapted to different remote sensing instruments. We tested our approach using SnowEx data from NASA's Cloud Absorption Radiometer (CAR) over Grand Mesa; one of the largest flat-topped mountains in the world, which features sufficient forested stands with a range of density and height (and a variety of other forest conditions); a spread of snow depth/snow water equivalent conditions over sufficiently flat snow-covered terrain. The retrieved fractional snow-covered area from CAR compares reasonably with a Sentinel-2 image over the same location and demonstrates CAR's unique capability to improve the retrieval of snow properties using machine learning. The retrieved snow fraction parameter from our method is expected to minimize the error associated with the traditional binary snow detection scheme, and improve the retrieval quality of key parameters such as surface albedo.

***Index Terms*—** fractional snow cover area, snow grain size, Cloud Absorption Radiometer, CAR, Multilayer Neural Network.

1. INTRODUCTION

Snow can be reliably distinguished from other surface features (e.g., soil, rock, vegetation, and water bodies) by utilizing differences in the visible and near-infrared parts of the electromagnetic spectrum among the different surfaces. As such snow cover is generally mapped as binary, where each pixel is classified as either "snow" or "not snow" in many widely used snow cover products such as MODIS snow cover product (Hall et al., 2002). However, this binary snow mapping does not allow for mixed pixels including portions of the ground surface that are only partially snow-covered due to a number of factors including elevation, topography and vegetation (Elder et al., 1998). The fractional snow cover area (fSCA) approach was developed to better represent this sub-pixel heterogeneity of snow cover, but the accuracy is especially limited in forested regions (Painter et al., 2009). In this study, we used the artificial neural network method to estimate the fSCA, which is fast and accurate, and can be easily adapted to different remote sensing instruments (Fan et al., 2017). We tested our approach using SnowEx data from NASA's Cloud Absorption Radiometer (CAR), which flew aboard the Naval Research Lab (NRL) Orion P-3 aircraft (Gatebe and King 2016). Measurements were taken on February 16, 2017 over Grand Mesa; one of the largest flat-topped mountains in the world, which features sufficient forested stands with a range of density and height (and a variety of other forest conditions); a spread of snow depth/snow water equivalent (SWE) conditions over sufficiently flat snow-covered terrain.

SnowEx was conceived in order to advance our understanding of how to measure snow in forested regions and as such help improve streamflow forecasting, numerical weather forecasting, and overall understanding of the role of snow in the Water and Energy Cycle. SnowEx will span five to six years, beginning in the 2016-17 Northern Hemisphere winter to help improve measurements of how much snow is on the ground at any given time, and how much liquid water is contained in that snow (SWE). The field campaigns will consist of airborne and in-situ ground-based measurements.

2. METHODS

We used a coupled atmosphere-surface radiative transfer model (RTM) to simulate the radiances from NASA's CAR instrument (Lin et al., 2015; Stamnes et al., 2017). The RTM is based on the well-tested discrete-ordinate radiative transfer (DISORT3), which includes a complete bidirectional reflectance-distribution function (BRDF) of snow and mixed vegetation/soil surfaces, using a 2-layer non-spherical particle snow model and a well known Soil-Leaf-Canopy BRDF model to help define a realistic lower boundary conditions for Grand Mesa (Ishimoto et al., 2012; Verhoef et al., 2007). We computed the reflectance for vegetation/soil and snow surfaces separately for a 128K dataset and then used a snow fraction (f = 0.0 – 1.0) to mix the simulated vegetation and snow reflectance (where f = 0.0 is snow-free and 100% vegetation/soil mixture; f = 1.0 is pure snow and 0% vegetation/soil fraction). We used a mixture of snow-vegetation/soil to train a multilayer neural network (MLNN), which was used to derive the snow fraction (and can also be used to derive snow grain size, and impurity concentration). The neural network training dataset is based on synthetic data that include all possible snow situations with snow grain size between 10 microns and 3000 microns, and impurity concentration between 0.001 and 1 ppmw. We used the neural network in the inverse processing mode to generate snow parameters retrieval (going from reflectance to snow parameters). We trained two MLNN retrieval algorithms; one for snow fraction retrieval, which was applied to every CAR pixel to estimate the snow fraction, and another one for snow physical parameter retrieval, which was applied only to pixels with snow fraction larger than 80%.

CAR provides comprehensive spectral coverage from the UV through shortwave infrared spectral region (0.34–1.27 μm), and has an angular resolution of 1 degree in zenith and azimuth angles.

3. RESULTS

The CAR BRDF sampling is very unique and can used to improve the retrieval of snow properties. Our results demonstrate this capability by comparing retrieved fractional snow-covered area from CAR with a Sentinel-2 image over the same study location (Figure 1&2). In Fig 1, the red color represents pure snow, while the blue color represents mixed snow-vegetation pixels. Missing data are represented as white. Clearly, the areas covered with snow (red) correspond to the snow covered areas (white) shown in Fig 2. Mixed snow-vegetation pixels (blue) correspond to the dark green forested areas in Fig 2. In future, we will demonstrate the retrieval of snow grain size and impurity information retrievals and compare the retrieved snow grain size with the snow pit measurements at several snow-pit measurement sites collected during the SnowEx'17 field campaign.

4. CONCLUSION

The multilayer neural network approach provides snow fraction that represents a reasonable percentage of snow cover in this snow/vegetation mixed area and the fixed threshold NDSI (normalized-difference snow index) tests that are used in binary snow detection cannot provide a reliable snow/vegetation mixing ratio under complex surface mixing conditions found in complex places such as Grand Mesa. The retrieved snow fraction parameter from our method is expected to minimize the error associated with the traditional binary snow detection scheme, and improve the retrieval quality of key parameters such as surface albedo. Improved estimates of the time evolution of fractional snow cover in different forest types/vegetation zones will enable us to improve the parameterizations of snow processes in climate models. This will in turn improve our capacity to simulate the radiative impact and climate feedback associated with evolving snow in a warming world.

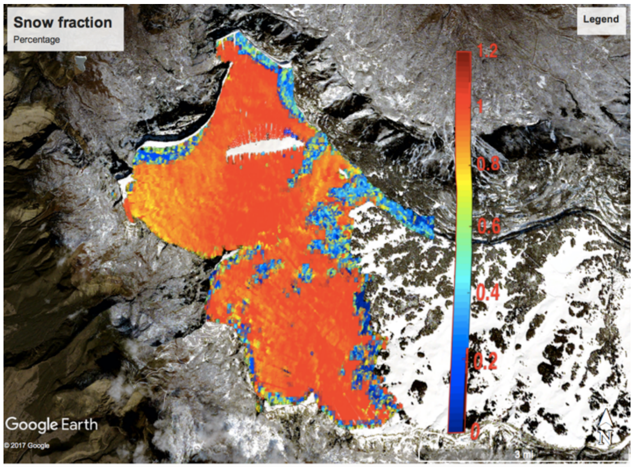

Fig. 1. The retrieved snow fraction retrieved from CAR measurements over Grand Mesa on February 16, 2017 during SnowEx campaign. Red color represents pure snow, while the blue color represents mixed snow-vegetation.

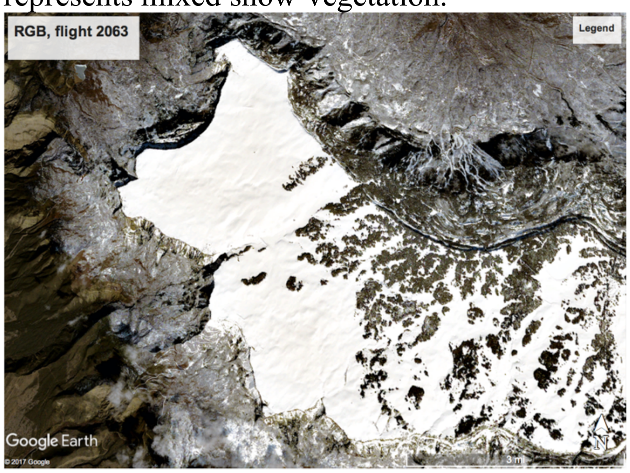

Fig. 2. Sentinel-2 image for comparison (from Copernicus Sentinel data (2017), which is processed by ESA).

5. REFERENCES

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