**Assessing High-Resolution CubeSat Imagery and Machine Learning for Detailed, High Resolution Snow-Covered Area.** Anthony F. Cannistra, Nicoleta Cristea.

**Section X:** Methods and Data

We focus our efforts in this study on developing and evaluating a statistical modeling-based approach to enable the identification of snow-covered area in high-resolution remote sensing data. We chose machine learning as our methodological domain after preliminary experiments demonstrated high potential for these flexible statistical methods to be well-suited to the challenges presented by these high-resolution satellite data. Furthermore, the domain of snow-cover identification is particularly suited to a machine learning-driven analysis due to the ready availability of high-resolution airborne lidar-derived snow-cover data, explained further in Sections X.X and X.X. We construct our model following a standard machine learning paradigm (described xxx), and choose well-studied focal areas (described below) as benchmark locations to assess both the absolute performance of our model compared to ground truth (Section XXX) and relative model performance across particular variables of interest.

**X.X**: Study Region

The two focal regions for this study are the Upper Tuolumne Basin in the Sierra Nevada mountains of California, USA, and the Gunnison/East River Basin in the Central Rocky Mountains of Colorado, USA. These regions were selected for their robust temporal catalog of high-resolution airborne lidar data from the NASA Airborne Snow Observatory (See Section X.X), and to create an opportunity for model comparison across climatological zones.

**X.X:** Snow Cover Data

To allow our chosen statistical modeling approach to identify snow-covered regions in these high-resolution imagery data, our methods require the use of separate high-resolution snow covered area data to serve as “ground truth” (see Section X.X). For this we use the NASA/JPL Airborne Snow Observatory (ASO) data product (Painter et al., 2016). These data are gridded 3 meter snow depth derived from airborne lidar collected in chosen watersheds across the western United States. Data are collected on a weekly basis from mid-winter through complete snowmelt (February – June) in ASO target basins. We acquired these data from the National Snow and Ice Data Center’s Distributed Data Access Center (<https://nsidc.org/data/ASO_3M_SD>). We generate binary snow masks from these data by applying a threshold of 10cm to the snow depth field.

**X.X:** Satellite Imagery

Planet Labs, Inc. (“Planet”) is a commercial satellite imagery company that operates the “PlanetScope” constellation of approximately 130 small (10x10x30cm) satellites in sun-synchronous orbit. This constellation collects approximately 200 million km2 day-1 of optical (red, green, blue, and NIR) land-surface imagery at 3.7m GSD (at nadir) between ±81.5degrees latitude, with daily nadir revisit times. Two sensor types (“instruments”) are present in the PlanetScope constellation (“PS2” and “PS2.SD”) resulting from ongoing sensor development and satellite launches. These instruments have comparable (but not identical) spectral band centers and bandwidths (Table X).

|  |  |  |
| --- | --- | --- |
|  | PS2 | PS2.SD |
| Blue | 455 - 515 nm | 464 - 517 nm |
| Green | 500 - 590 nm | 547 - 585 nm |
| Red | 590 - 670 nm | 650 - 682 nm |
| NIR | 780 - 860 nm | 846 - 888 nm |

**Table X:** Spectral bandwidth of PS2 and PS2.SD instruments within the PlanetScope constellation, (Planet Labs, Inc., 2019).

For the purposes of this study we consider these instruments to be identical, and acquire data from each interchangeably.

Planet provides several levels of processing of collected imagery data. For this study we used the Level 3B PlanetScope “Analytic Ortho Scene,” an orthorectified multispectral surface reflectance product. Planet’s atmospheric correction procedure converts top of atmosphere radiance (derived via coefficients from sensor darkfield and flat field corrections) to surface reflectance using near-real-time MODIS data inputs and the 6SV2.1 radiative transfer code (Kotchenova et al., 2008; Planet Labs, Inc., 2019). This data type is recommended by Planet for analytic applications.

Scene Selection and Acquisition

To pair relatively cloud-free imagery with Airborne Snow Observatory (ASO) collections (see Sections XXX and XXX), scenes with spatial and temporal overlap with individual ASO collect spatial footprints were selected from the Planet imagery catalog. We applied a 3-6 day temporal buffer to the ASO collection date of interest to ensure a higher probability of cloud-free imagery acquisition. (Temporal image density in the Planet catalog has increased dramatically over time, but regions of ASO collects prior to 2017 often required a larger (5-7 day) buffer to find spatially-overlapping imagery.) Image candidates were manually inspected for relative cloud fraction, and images with fewer clouds were selected for inclusion into our analysis. We used porder version 0.5.7, an open-source tool (Roy, 2019) for the Planet Orders v2 Application Programming Interface (API) (Planet Labs, Inc., 2019), to both query the Planet catalog for imagery data and submit imagery orders. Analytic Ortho Scene assets were queried via the “PSScene4Band” identifier and the “analytic\_sr” bundle identifier. We used the Planet Clips API to acquire only those pixels overlapping our areas of interest (e.g. areas covered by ASO collect footprints) both to conserve our imagery quota and reduce data volume. Image assets were delivered from Planet directly to Amazon Web Services Simple Storage Service (S3) buckets for further processing.

Imagery Processing

**X.X:** Machine Learning Methodology

“Machine learning” is a set of statistical techniques to build predictive models of an outcome variable from data. Models are “trained” or “fit” to data by selecting a “training” subset of examples from the population of data. These examples are used to derive a predictive relationship with the response variable, and each machine learning technique varies on the precise methodology used to derive this relationship. Once fit, models are assessed for their ability to accurately predict response variables given “unseen” samples of data (the “test” subset) which is disjoint from the training set. In this study we employed a “supervised learning” approach, wherein the presence of the response variable in the data (known as a data “label”, in this case lidar-derived snow presence) guides the search for a statistical relationship between the input data (“features”) and the response (“label”). Once a supervised learning model is fit using data that contains the response variable, the resulting statistical relationship can be employed to predict the response variable from unlabeled data.

Identifying the spatial extent and categorical classification of regions within images is known as “image segmentation” or “instance segmentation” (CITE?). Classification of snow in satellite imagery fits well within this task definition, and this allowed us to use machine learning techniques specific to image segmentation. In our version of the task, the four bands of PlanetScope imagery in each pixel (red, green, blue, NIR; see Section XXX) represent the input data to our model (the “features”), and airborne lidar-derived binary snow masks (see Section XXX) represent the response variable (“labels”).

We employ a neural network to accomplish this image segmentation task. Neural networks are specific types of machine learning methods designed to extract statistically meaningful linear combinations of input features from data (PlanetScope bands) and model a dependent variable (snow presence/absence) as a nonlinear function of these derived linear combinations (Hastie et al., 2009, Section 11.1). We chose a method based on a network architecture demonstrated to perform very well in biomedical image segmentation (Known as the "U-Net" architecture; Ronneberger et al., 2015) and modified to perform well with satellite remote sensing imagery. The resulting network, known as TernausNetV2 and developed by Iglovikov et al., provides state-of-the-art satellite image segmentation when applied to the task of building detection in satellite imagery (Iglovikov et al., 2018). To our knowledge this method has not been applied to the segmentation of snow in satellite imagery.

**Section X.X:** Model Training