ORIGINAL RESEARCH ARTICLE

Snow Coverage Prediction using Machine Learning Techniques

Ziming He[a] and Greg Turk[a]

[a]College of Computing, Georgia Institute of Technology, Atlanta, Georgia, USA;

ARTICLE HISTORY
Compiled February 17, 2020

ABSTRACT
Snow coverage is often predicted through analysis of satellite images. Two of the most common satellites used for predictions are MODIS and Landsat. Unfortunately, snow coverage predictions are limited either by MODIS images sets' low resolution quality or Landsat dataset's low temporal frequency. In this study, we employed a set of various machine learning techniques, including multilayer perceptrons (MLP), random forest regressor (RF), and convolutional neural networks (CNN) to model the relationship between high temporal frequency of MODIS data and high spatial resolution of Landsat data. Through various experiments, we propose an improved Fractional Snow Coverage (FSC) based on relationship between RGB, lower frequency infrared channels and regional locality.

KEYWORDS
machine learning; snow coverage; random forest; convolutional neural network; Landsat; MODIS; multilayer perceptron; NDSI; fractional snow cover; optimization

1. Introduction

Snow coverage predictions have largely relied on data collected through satellite images. The two major resource of remote sensing comes from Landsat and MODIS satellites. Landsat provides high resolution (around 30 meters) data, but the data is recorded in low frequency (roughly around 16 days). MODIS provides daily low resolution images (around 300 meters). A key measure of the amount of snow in a region is Fractional Snow Cover, which is the fraction of the region that is covered in snow (ranges from 0 to 1). The Normalized Difference Snow Index (NDSI) was used as the major indication of snow cover presence in comparision with Fractional Snow Cover (FSC). In order to join the advantages from both data provider and produce high quality data samples, we propose a new method in modeling snow coverage through machine learning techniques such as multilayer perceptron, random forest, and convolutional neural network. Our research focused on using machine learning models to produce a more accurate version of Fractional Snow Cover calculated based on Normalized Difference Snow Index and spatial locality inherent in remote sensing imagery.

CONTACT Ziming He. Email: zhe66@gatech.edu

2. Related work

Throughout the years, machine learning techniques, especially those of deep learning, have been used in remote sensing projects that includes cloud segmentation (Drönner et al. 2018), image classification (Wang et al. 2018), and facade labeling (Lotte et al. 2018). Research has also shown potential in detecting snow coverage presensce and boundaries (Bonev 2017). However, snow quantification still largely relies on expert opinions (Pimentel, Herrero, and Polo 2017). Snow coverage quantification has relied on human made features from the beginning (Hall, Riggs, and Salomonson 1995). Novel snow quantification methods seeks to derive new formulas based on reflectivity and differential phases (Bukovčić et al. 2018).

Machine learning research has been largely focusing on identifying snow, rather than quantifying snow (Bonev 2015, 2017). However, in recent years, researchers started to recognize the potential in forecasting and estimating snow water equivalent (SWE) in real time through machine learning techniques such as regression trees and feedforward neural networks (Bair et al. 2018). Researchers also worked on explaining and drawing inferences from those machine learning models (Jiang 2018).

3. Data collection and processing

3.1. *Study areas*

The main area of interest is the Tuolumne River Basin (Figure 1), located in California's Sierra Nevada. The region is located in the central location of California, inside Yosemite National Park. The O'Shaughnessy Dam constructed in 1923 and the new Don Pedro Dam, completed in 1971, have been providing water for farmers and San Francisco residents. The area covers the two major origins of stream flow, Mount Dana and Mount Lyell. Elevation within the area ranges from 3762m to 485m as the two streams flows down the mountains on the east side of the region to the valleys on the west side. A large part of the region is covered in snow and ice from mid-November to late April, with the heaviest snow coverage centered around months of February and March. The region covers a few distinct zones of forest, including trees adapted to hot, dry climate, like blue oak, California lilac, and gray pine, and other higher regions dominated by mountain hemlock and lodgepole pine (Epke et al. 2010).

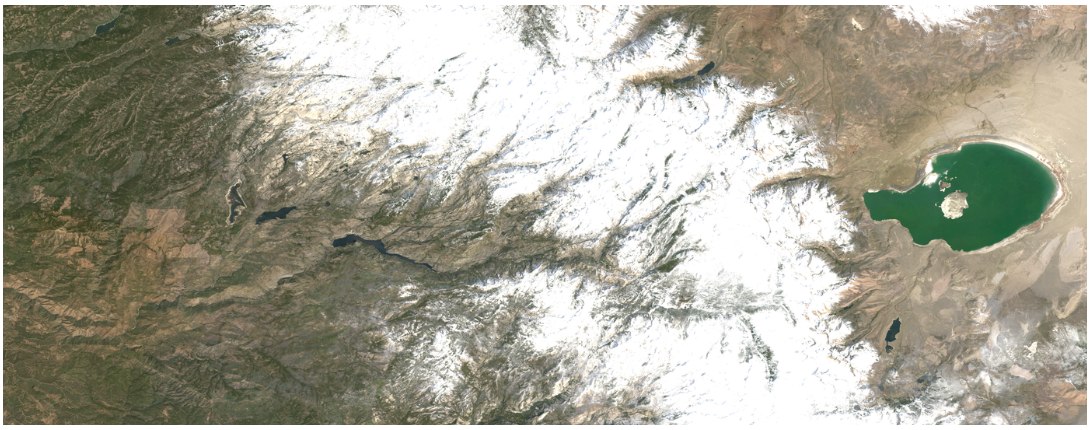
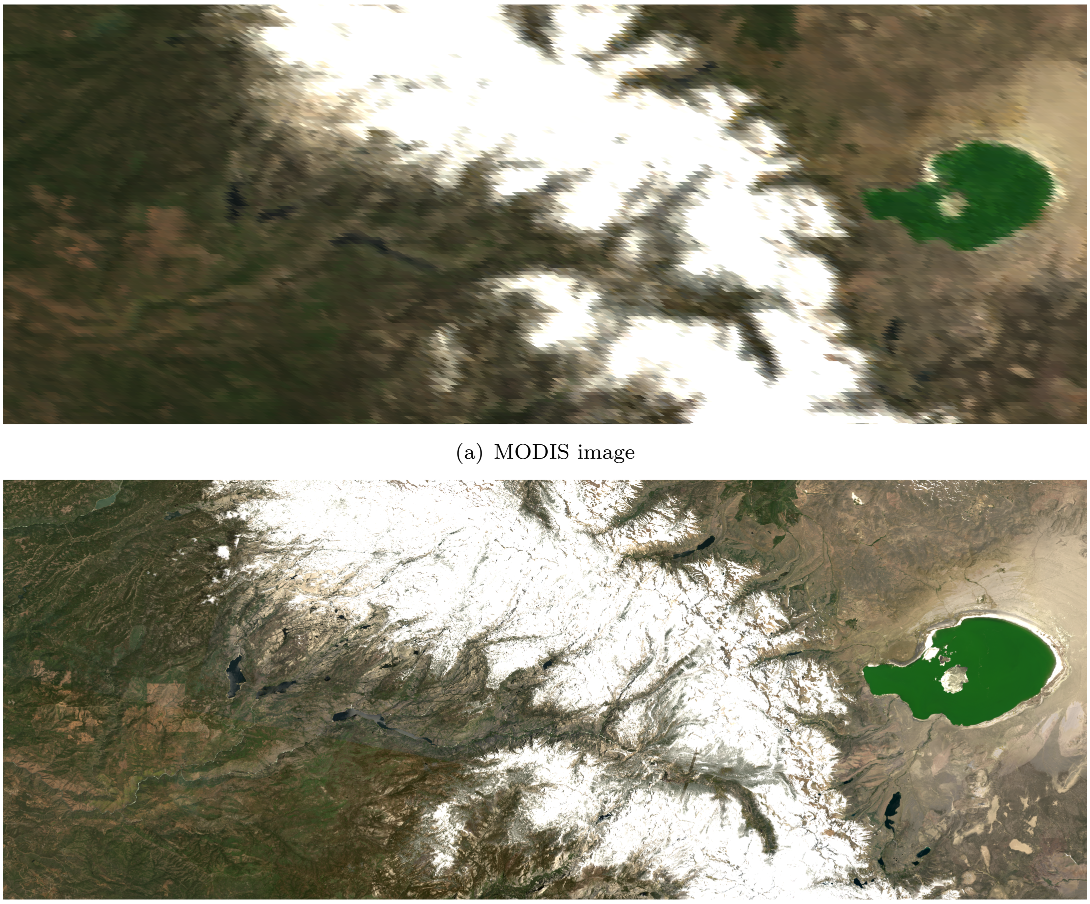


Figure 1. Tuolumne Basin Landsat

3.2. *Data collection*

We collected 15 pairs of MODIS (Figure 2(a)) vs. Landsat (Figure 2(b)) corresponding pairs from Jan 1st, 2017 to May 1st, 2017. We use the 8-day composite for MODIS Terra Surface Reflectance and Landsat Top of Atmosphere (TOA). We focus on bands 1, 4, 3, which correspond to Red, Green, and Blue channels for MODIS Terra Surface Reflectance, and band 3, 6 for Landsat TOA, which correspond to Green and Shortwave Infrared channels.



(a) MODIS image

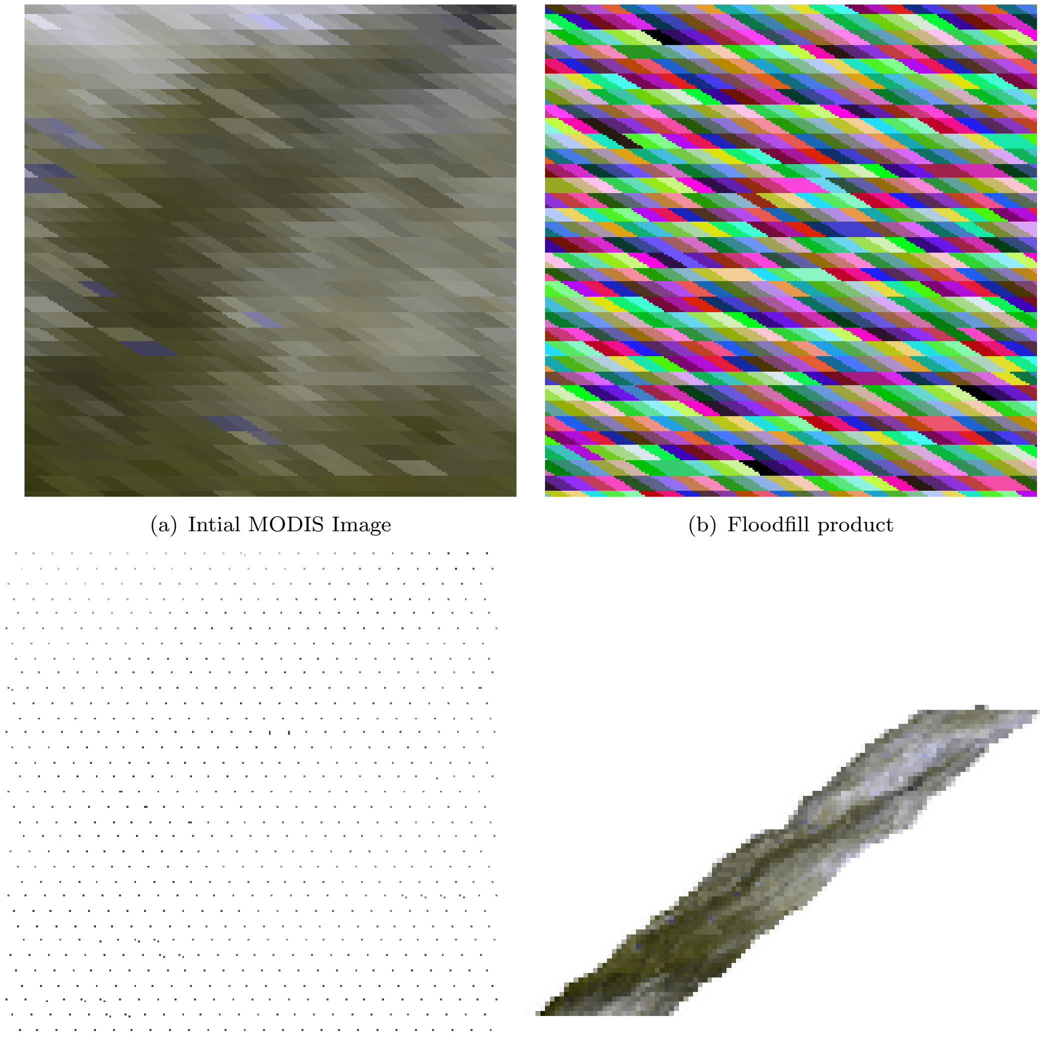
(b) Landsat image

Figure 2. MODIS vs Landsat correspondence

3.3. *Data processing*

Because of the sinusoidal mapping of MODIS imagery, the images appeared to be composed of tilted parallelograms in comparison with Landsat images.

For each MODIS image, we utilized a Flood fill algorithm to collect information about colors of the same region. Since the amount of pixels in the region can be fairly large, in order to avoid stack overflow problems caused by very deep recursion, we used a iterative implementation of Flood fill algorithm based on queue (also known as Forest Fire algorithm). The general steps of the algorithm can be seen in the appendix. Using the flood fill algorithm (Appendix A), we can collect the information about the MODIS grid as well as the corresponding Landsat region. We can compute a new



(a) Intial MODIS Image (b) Floodfill product

(c) Centroid extraction (d) Corrected grid

Figure 3. Floodfill and data extraction process

corrected matrix for the condensed information.

Although most of the regions can be extracted by the above algorithm, some regions can have same color as its neighbors, which makes it more difficult to extract the exact regional information. We devised another algorithm (Appendix B) to approximate the regional correspondence for grids that have same color as its neighbors.

After finding the information for the MODIS grid and corresponding Landsat regions, we fed the data into the machine learning models.

Figure 4 illustrate the products of each image processing step.

4. Methods

4.1. *Fractional snow cover*

The goal of the research is to predict an optimized version of fractional snow cover percentage of the MODIS regions. A typical MODIS tile region has roughly 96 Landsat pixels within it. Because of the high spatial resolution of Landsat images, we can use the Landsat pixels to give an accurate fractional snow cover for the MODIS pixels. Essentially, the Landsat data give us ground truth for the Landsat/MODIS image pairs.

The ground truth fractional snow percentage for a MODIS region is computed based on Normalized-Difference Snow Index of the Landsat pixels. This is calculated based on the normalized difference between green and mid-IR bands (Riggs, Hall, and Salomonson 1994). The Normalized-Difference Snow Index (NDSI) value is calculated based on the following formula (Hall, Riggs, and Salomonson 1995).

$$NDSI = \frac{B_3 - B_6}{B_3 + B_6} \tag{1}$$

B_3 is the green color band and B_6 is the Shortwave infrared band 1. And we proposed an adjusted NDSI to model the correspondance between MODIS and Landsat NDSI. We then thresholded the NDSI value to estimate the presence of snow. If the NDSI value is within the bound of 0.0 and 1.0 and over the threshold of 0.5, then there is a great probability of snow presence, and vice versa. By thresholding each Landsat pixel and summing over all pixels in a MODIS region, we calculated the fractional snow cover percentage for the MODIS region as follows:

$$SnowCoverPercentage = \frac{1}{N}\sum_{1}^{N} Snow_{binary} \tag{2}$$

where

$$Snow_{binary} = \begin{cases} 1, & \text{if } NDSI_{pixel} < threshold \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

N is the total number of Landsat pixels inside the MODIS region. The error between the model outputs and the actual pixel values is calculated based on the mean squared error between observation and predicted values.

4.2. *Machine learning models*

We experimented on three machine learning methods, multilayer perceptron, random forest regression trees, and fully convolutional neural networks. We used Mean Squared Loss (MSL) for all three models to assess the performance of each model.

4.2.1. Multilayer perceptrons

Multilayer perceptron has been largely employed in regression problems as it is rather easy to implement, and performs well for most of the regression problems (Collobert and Bengio 2004). There has also been researches done using neural networks (a collection of perceptrons) to forecast snowfall (Roebber et al. 2007). In addition, neural networks has also been used to predict snow cover in high altitude (Mishra, Tripathi, and Babel 2014). We use multilayer perceptron as a baseline of comparison for our models. We employed a three layer fully connected neural network with hidden layers size (16, 8, 16) and tanh activition to model the relationship between color channels and fractional snow cover.

4.2.2. *Random forest regressors*

Random forest regressor is an ensemble-learning algorithm that takes advantage of combination of weak learners (Ho 1995). Random forest regressors has been used to quantify errors in snow cover datasets (Tinkham et al. 2014). This machine learning technique also performs well for classification problems on MODIS timeseries data (Nitze, Barrett, and Cawkwell 2015). As the dimension of our input data is fairly small, we expect that weak learners like random forest to be able model the relationship fairly well. We employed a random forest regressors composed of 10 estimators.

4.2.3. *Convolutional neural networks*

Convolutional neural network has gained its popularity from computer vision tasks, such as identifying objects from pictures, recognizing scenes, and segmenting objects (Radford, Metz, and Chintala 2015). In order to take advantage of the neighboring information inherent in satellite imagery. We employed a fully convolutional neural network to model the relationship between neighboring regions (Springenberg et al. 2014). We employed the neural network architecture shown in [Figure 4] with ReLu activations layers and Mean Squared Loss. The kernel size are (5, 5), (3, 3), strides 1, with same padding on the boundary pixels.

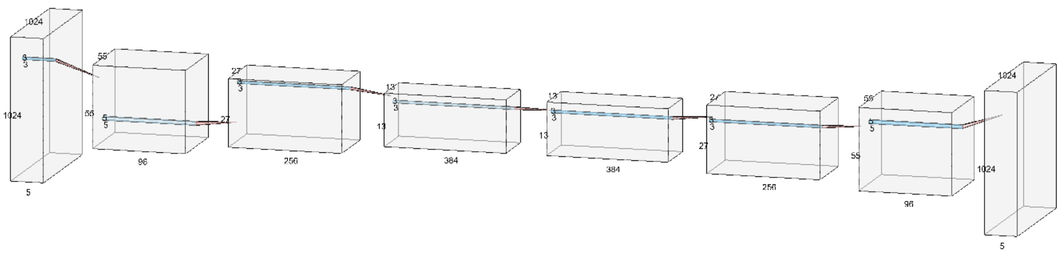


Figure 4. Fully Convolutional Neural Network Diagram

5. Results and discussion

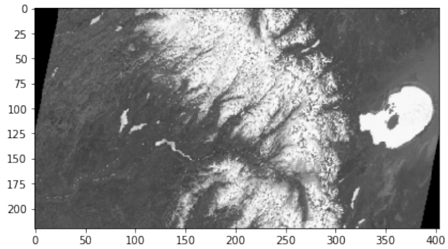
We divide the dataset into 72% training set, 20% testing set, and 8% validation set. Out of the three machine learning models, fully convolutional neural network produced the best result with relative low mean squared error (See Table 1). The fully convolutional neural network is able to be trained in relatively short amount of time with the help of GPU parallelism (Krizhevsky, Sutskever, and Hinton 2012). A visual comparison between the models is shown in Figure 5.

6. Conclusions and Future Works

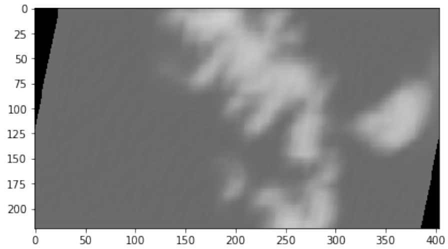
We propose an improved infrastructure for predicting snow cover using machine learning techniques such as Multilayer Perceptrons (MLP), Random Forest Regressors

Table 1. Model Comparison

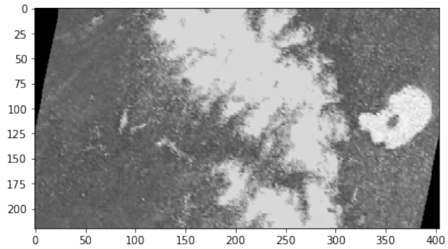
Model	Mean Squared Error	Training Time(mins)
Multilayer Perceptron	0.0371	**44.35**
Random Forest Regressor	0.0190	79.34
Fully Convolutional Neural Network	**0.0165**	69.51



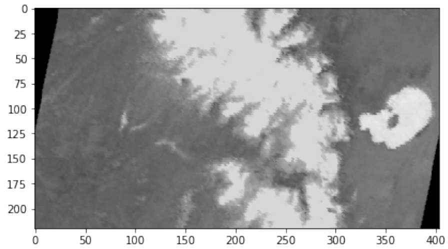
(a) Fractional Snow Cover (from Landsat)



(b) Multilayer Perceptron



(c) Random Forest Regressor



(d) Convolutional Neural Network

Figure 5. Results Comparison: (a) Ground truth from Landsat data, (b) - (d) Results from MODIS data using different learning algorithms.

(RF), and Convolutional Neural Network (CNN). Instead of relying on periodic low resolution MODIS NDSI for snow cover prediction, our solution uses machine learning techniques to model the relationship between various channels (RGBs and infrared channels) and Fractional Snow Cover, which is computed over a region of Landsat high resolution composite. The fully convolutional neural network that we propose produces the most accurate model when compared to traditional machine learning techniques used. This model also produces more accurate snow predictions when compared to traditional snow coverage measurement.

However, there is still more to be done. Cloud masks have been a problem for remote sensing imagery analysis, and especially in the context of snow cover prediction. This is largely due to the similarity in cloud and snow's RGB channels. Our future work will incorporate removing cloud masks from satellite imagery using image segmentation techniques as well as collecting more data from various years and regions to compose a larger training set. This larger and more accurate training set will provide new possibility for deeper machine learning architectures as well as more accurate predictions.

Appendix

Algorithm 1: Flood fill algorithm

```
input  : node, target-color, replacement-color
if target − color = replacement − color then
    return
end
if node.color = target − color then
    return
end
node.color ⟵ replacement − color;
Q ⟵ empty − queue;
Add node to Q;
while Q.isEmpty = False do
    n ⟵ Q.deque;
    w, e ⟵ n;
    Move w towards west until color of node to the west of w is no longer the
      same color as n;
    Move e towards east until color of node to the east of e is no longer the same
      color as n;
    for node between w and e do
        node.color ⟵ replacement − color;
        north ⟵ node.north;
        if north.color = target − color then
            Add n to Q;
        end
        south ⟵ node.south;
        if south.color = target − color then
            Add s to Q;
        end
    end
end
```

Algorithm 2: Centroid approximation algorithm

```
input  : imageMatrix
if minPixels < imageMatrix[i][j].size < maxPixels then
    return
end
if imageMatrix[i][j] > maxPixels then
    left = right = j
    while imageMatrix[i][left] > maxPixels do
        left -= 1
    end
    while imageMatrix[i][right] > maxPixels do
        right += 1
    end
    newCentroids = LinearInterprelation(left, right)
end
```

References

Bair, Edward H, Andre Abreu Calfa, Karl Rittger, and Jeff Dozier. 2018. "Using machine learning for real-time estimates of snow water equivalent in the watersheds of Afghanistan." *The Cryosphere* 12 (5): 1579–1594.

Bonev, George. 2015. "A survey of algorithms developed for satellite snow and sea ice detection." .

Bonev, George. 2017. "Machine Learning Algorithms for Automated Satellite Snow and Sea Ice Detection." .

Bukovčić, Petar, Alexander Ryzhkov, Dusan Zrnić, and Guifu Zhang. 2018. "Polarimetric radar relations for quantification of snow based on disdrometer data." *Journal of Applied Meteorology and Climatology* 57 (1): 103–120.

Collobert, Ronan, and Samy Bengio. 2004. "Links between perceptrons, MLPs and SVMs." In *Proceedings of the twenty-first international conference on Machine learning*, 23. ACM.

Drönner, Johannes, Nikolaus Korfhage, Sebastian Egli, Markus Mühling, Boris Thies, Jörg Bendix, Bernd Freisleben, and Bernhard Seeger. 2018. "Fast cloud segmentation using convolutional neural networks." *Remote Sensing* 10 (11): 1782.

Epke, G, M Finger, R Lusardi, N Marks, A Nichols, Sarah E Null, T O'Rear, A Senter, and J Viers. 2010. "Confluence: A Natural and Human History of the Tuolumne River Watershed." *Department of Geology and Center for Watershed Sciences. UC Davis* .

Hall, Dorothy K., George A. Riggs, and Vincent V. Salomonson. 1995. "Development of methods for mapping global snow cover using moderate resolution imaging spectroradiometer data." *Remote Sensing of Environment* 54 (2): 127 – 140. http://www.sciencedirect.com/science/article/pii/003442579500137P.

Ho, Tin Kam. 1995. "Random decision forests." In *Proceedings of 3rd international conference on document analysis and recognition*, Vol. 1, 278–282. IEEE.

Jiang, Lingmei. 2018. "Snow Depth Estimation and Historical Data Reconstruction Based on Machine Learning Technique." In *AGU Fall Meeting Abstracts*, .

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E Hinton. 2012. "Imagenet classification with deep convolutional neural networks." In *Advances in neural information processing systems*, 1097–1105.

Lotte, Rodolfo, Norbert Haala, Mateusz Karpina, Luiz Aragão, Yosio Shimabukuro, et al. 2018. "3D Façade Labeling over Complex Scenarios: A Case Study Using Convolutional Neural Network and Structure-From-Motion." *Remote Sensing* 10 (9): 1435.

Mishra, Bhogendra, Nitin K Tripathi, and Mukand S Babel. 2014. "An artificial neural network-based snow cover predictive modeling in the higher Himalayas." *Journal of mountain science* 11 (4): 825–837.

Nitze, Ingmar, Brian Barrett, and Fiona Cawkwell. 2015. "Temporal optimisation of image acquisition for land cover classification with Random Forest and MODIS time-series." *International Journal of Applied Earth Observation and Geoinformation* 34: 136–146.

Pimentel, Rafael, Javier Herrero, and María Polo. 2017. "Quantifying Snow Cover Distribution in Semiarid Regions Combining Satellite and Terrestrial Imagery." *Remote Sensing* 9 (10): 995.

Radford, Alec, Luke Metz, and Soumith Chintala. 2015. "Unsupervised representation learning with deep convolutional generative adversarial networks." *arXiv preprint arXiv:1511.06434* .

Riggs, G. A., D. K. Hall, and V. V. Salomonson. 1994. "A snow index for the Landsat Thematic Mapper and Moderate Resolution Imaging Spectroradiometer." In *Proceedings of IGARSS '94 - 1994 IEEE International Geoscience and Remote Sensing Symposium*, Vol. 4, Aug, 1942–1944 vol.4.

Roebber, Paul J., Melissa R. Butt, Sarah J. Reinke, and Thomas J. Grafenauer. 2007. "Real-Time Forecasting of Snowfall Using a Neural Network." *Weather and Forecasting* 22 (3): 676–684. https://doi.org/10.1175/WAF1000.1.

Springenberg, Jost Tobias, Alexey Dosovitskiy, Thomas Brox, and Martin Riedmiller. 2014.

"Striving for simplicity: The all convolutional net." *arXiv preprint arXiv:1412.6806* .

Tinkham, Wade T, Alistair MS Smith, Hans-Peter Marshall, Timothy E Link, Michael J Falkowski, and Adam H Winstral. 2014. "Quantifying spatial distribution of snow depth errors from LiDAR using Random Forest." *Remote sensing of environment* 141: 105–115.

Wang, Wenju, Shuguang Dou, Zhongmin Jiang, and Liujie Sun. 2018. "A Fast Dense Spectral–Spatial Convolution Network Framework for Hyperspectral Images Classification." *Remote Sensing* 10 (7): 1068.