SNOW AND CLOUD DISCRIMINATION USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT:

Snow is an important feature on our planet, and measuring its extent has advantages in climate studies. Snow mapping through satellite remote sensing is often affected by cloud cover. This issue can be resolved by using short wave infrared (SWIR) sensors. In order to obtain an effective cloud mask, our study aims to use SWIR data of a ResourceSat-2 satellite. We employ Convolutional Neural Networks (CNN) to discriminate similar pixels of clouds and snow. The technique is expected to give a high accuracy compared to traditional methods such as thresholding. The cloud mask thus produced can also be used for creating the metadata for Indian Remote Sensing products.

1. INTRODUCTION

1.1 Remote Sensing for Cryosphere Applications

The cryosphere refers to the region of the world that exhibits temporarily or permanently frozen water and plays a pivotal role in the Earth system. Sea ice, permafrost, snow, and ice masses (continental ice sheets and mountain glaciers) are key elements of the cryosphere domain. As a result, the scientific study of these components helps to analyse the existing issues of global sea-level, climate and other associated ecological changes(Tedesco, 2015).

Nowadays, optical images are often used to discriminate snow and cloud and subsequently produce snow cover maps. Snow is an important feature of our environment. It helps in balancing the heat flow between the Earth surface and atmosphere. Its presence in a basin also affects surface moisture, thereby contributing to water runoff (Maurer, Rhoads, Dubayah, & Lettenmaier, 2003). Thus, analysing snow cover helps to understand climate change, while studying the snowmelt aids in assessing water requirements for agricultural and other societal needs (National Snow and Ice Data Center, 2017). Apart from hydrological aspects, detailed snow cover maps are also utilised in weather forecasting and military operations (Miller, Lee, & Fennimore, 2005). Thus, understanding the spatial extent of snow has a variety of applications in the cryosphere paradigm(Allen, Rastner, Arora, Huggel, & Stoffel, 2015; Birajdar, Venkataraman, & Samant, 2016; Man, Guo, Liu, & Dong, 2014; Mankin et al., 2015; Tedesco, 2015; Tekeli, Sönmez, & Erdi, 2016; Zhan et al., 2017).

Such spatial understanding has historically been made through snow surveys, which are mainly just point measurements, and thus do not provide good estimates of the areal cover. Furthermore, as snow is present in a mountainous (rough/undulating) terrain, the measurement excursions can easily translate into becoming a hazardous, costly and labour intensive activity (World Meteorological Organization (WMO), 2012). With the advent of newly developed remote sensing techniques, a multitude of research works have been carried out to quantitatively assess and monitor the cryospheric elements. These include snow depth and snow water equivalent estimation, measuring snow cover extent, snow wetness, distinguishing cloud and snow and several other related studies (Birajdar et al., 2016; Crane & Anderson, 1984; Deems, Painter, & Finnegan, 2013; Gao, Han, Tsay, & Larsen, 1998; Kulkarni, Singh, Mathur, & Mishra, 2006; Li, Wang, He, & Man, 2017; Man et al., 2014; Mankin et al., 2015; Mateo-García, Muñoz-Marí, & Gómez-Chova, 2017; Srinivasulu & Kulkarni, 2004; Tekeli et al., 2016; Thakur, Garg, Aggarwal, Garg, & Shi, 2013; Zhan et al., 2017).

In order to carry out such remote sensing measurements, studies like Rango (1993) have summarised the sensor responses to snow properties. In order to capture the areal extent and albedo from snow, working in the Visible/Near-infrared region is quite helpful. However, this brings its own challenges. Clouds, in the visible part of the spectrum, also show high reflectance. Therefore clouds hovering over an expanse of snow, might imitate or sometimes cause a hindrance to the signals coming from the snow beneath (Meier, 1980). For distinguishing between these two similar features, a photo interpreter would have to be extremely experienced, and rely on characteristics like neighbourhood information (terrain surfaces), spatial variation of reflectance values, etc.

Various studies like Crane & Anderson (1984), Dozier (1984, 1989) & Miller et al. (2005), have noted that the shortwave infrared (SWIR) band (near 1.6 and 2.2 μm) can be used to discriminate between clouds and snow. These studies reason that in this spectral range, snow cover gives a lower reflectance compared to clouds, hence it appears darker and easier to

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classify (Figure 1). As some sensors like Linear Imaging Self Scanner- IV(LISS-IV) & Landsat Multispectral Scanner 1-5 do not have a SWIR band, there exists a significant challenge to use their images for the aforementioned discrimination purposes.This study aims to provide a classification technique for snow and clouds on SWIR images, which can be further used for images without a SWIR band.

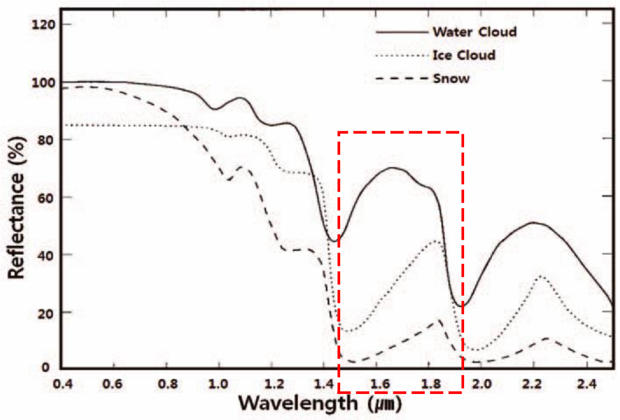


Figure 1. Spectral reflectance of Water Cloud, Ice Cloud and Snow surface (Gao, Han, Tsay, & Larsen, 1998). The red box depicts the SWIR spectrum.

1.2 Current Trends in Satellite Image Classification

Classification of remotely sensed images involves grouping of homogeneous pixels based on predefined semantics. Essentially, classified maps are extensively used as end products for conducting various environmental surveys. In recent years, several techniques have emerged to improve the classification accuracy such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF) and many more(Bergado, Persello, & Stein, 2018; Ghasemian & Akhoondzadeh, 2018; Gómez-Chova, Mateo-García, Muñoz-Marí, & Camps-Valls, 2017; Hazirbas, Ma, Domokos, & Cremers, 2017; Lu & Weng, 2007; Mateo-Garcia, Gomez-Chova, & Camps-Valls, 2017; Persello & Stein, 2017). However, preparing thematic maps still remains a challenge owing to a number of constraints, such as landscape complexity, selected remotely sensed imagery, and the optimisation of tunable parameters that are involved in the image classification approaches. In this study, convolutional neural network (CNN) has been applied to classify clouds and snow.

1.3 Convolutional Neural Networks for Cloud Filtering

CNN is a variant of ANN connected in a sequential feed forward manner and involves both convolution and aggregation (pooling) operations. The convolution step significantly reduces the number of learnable parameters. The rationale behind such a task is to allow the network to use the same filter for detecting similar spatial patterns exhibited by different parts of an image. Also, pooling with downsampling introduces a degree of translational invariance in the network (Bergado et al., 2018).

Cloud detection or cloud masking algorithms are generally developed by assuming that clouds tend to display certain useful characteristics for its identification. The simplest approach is a binary classification scheme wherein specific thresholds can be applied (e.g., over reflectance or temperature measurements) on individual pixels of the selected image pixels. However, such simplistic techniques provide poor results in case of thin clouds which are semi-transparent to solar radiation. Moreover, bright pixels attributing to the high albedo of ice and snow on the surface can be misclassified as clouds. Also, land covers displaying high brightness values tend to have similar reflectance behaviour as that of clouds and hence, thresholding on reflectance is practically an ineffective solution (Gómez-Chova et al., 2017).

2. DATA AND STUDY AREA

2.1 Data

The dataset used is of the LISS-III sensor from the Indian ResourceSat-2 satellite. LISS-III has a spatial resolution of 23.5m and carries 4 spectral bands, out of which only three will be used for our study. The image used for our study was captured on 6th February, 2015, and the scene has a central latitude of 30.983 and central longitude at 79.0466. Figure 2 shows the captured scene.

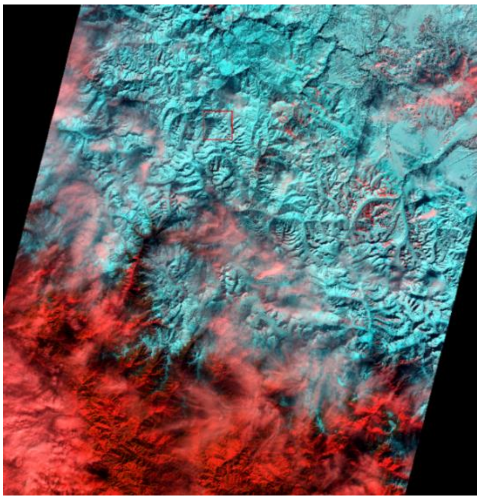


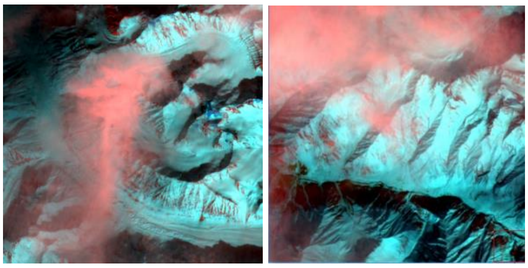
Figure 2. LISS-III image of ResourceSat-2. RGB distribution: 1.55-1.7μm, 0.77-0.86μm, 0.62-0.68μm

2.2 Study Area

The study area belongs to the northern part of Uttarakhand, India. The area has some of the highest mountain peaks in the world. Since the Kedarnath flash floods of 2013, there have been extensive studies in this area to understand the role of snow and glaciers in causing the flash floods.

3. METHODOLOGY

Two subset tiles were selected from the captured image for training and testing. The tile for training had dimensions of 395x393and the tile for testing had dimensions of 409x413. With the help of ENVI software, different regions were selected visually on the training and test image to classify as clouds and snow. The adopted image tiles are shown in Figure 3



(a) (b)

Figure 3. Tiles selected from the main image for (a) training and (b) testing

The image tiles were processed using the MatConvNet library of MATLAB, to produce class maps. Figure 4 shows the basic work flow.

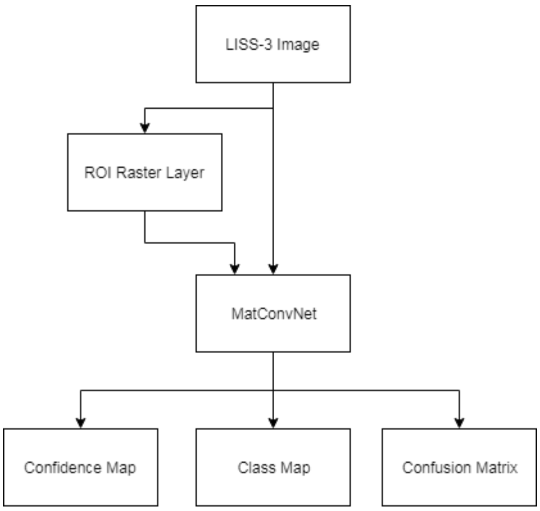


Figure 4. Work flow to implement MatConvNet

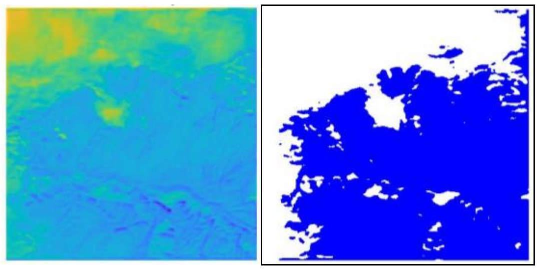
3.1 Network Structure

For the neural net, an input patch size of 13 was selected and the network had alternating layers of Convolution, Rectified Linear Units and Max Pooling. The network structure is shown in Table 1. The Filter Bank has dimensions of H×W×D×K; where H×W corresponds to the height and width of a single two dimensional filter kernel, D corresponds to the number of image channels, and K corresponds to the number of Kernels in the bank. The last convolutional layer is followed by a dropout layer of rate 0.5, and then a softmax layer. The training was performed for 100 epochs.

Layer	**Filter Bank**	**Stride**	**Padding**
conv1	9×9×3×16	1	5
relu1	-	-	-
maxpool1	2×2	2	1
conv2	9×9×16×16	1	4
relu2	-	-	-
maxpool2	2×2	2	1
conv3	4×4×16×2	1	0

Table 1. Adopted CNN structure

4. RESULTS AND DISCUSSION



(a) (b)

Figure 5. (a) Confidence Map of test tile: yellow pixels have been classified with highest probability (1), and shades of blue have the lowest probability (0); (b) class map of test tile: blue represents snow and white represents clouds

↓ Actual | Predicted →	**Cloud**	**Snow**
Cloud	11475	6810
Snow	24308	13228

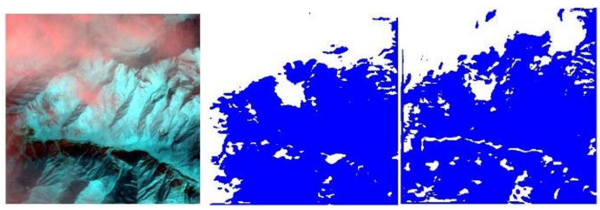
Table 2. Confusion matrix of the test tile

	Training	Test
Overall Accuracy	73.99	44.25

Table 3. Accuracy of the CNN

The accuracy of the CNN on test tile was found to be 44.25% (Table 3). Simultaneously, an SVM was performed on the same training & test image, which produced an overall accuracy of 87.45%. Thus, there lies a scope to test the CNN classifier further with varying amounts of patch size, and convolutional layers, so as to achieve a higher overall accuracy.

The confusion matrix of Table2 portrays that clouds show lower commission error as compared to snow, and snow has been highly misclassified.



(a) (b) (c)

Figure 6. (a) Original test tile, (b) Class map during initial stages of testing and (c) Class map during later stages of testing; blue represents snow while white represents clouds

Figure 6 shows the advantage of Machine learning. As we can see, classification becomes more accurate and realistic as we move from Figure 6 (b) to (c). The mountain ridges and cloud distribution is better depicted in Figure 6 (c).

5. CONCLUSION

While this paper has focused on distinguishing just two classes – snow and clouds, more realistic results can be found if we incorporate background vegetation as a class, or different types of clouds as separate classes. Our study shows the advantages of training via machine learning. With repetitive iterations, the class maps become more accurate, but at the cost of higher processing time.

The study also showcases the scope of training/tuning the hyper-parameters further in order to obtain more accurate classification results. Moreover, techniques can be explored in which the results from this work can be used to classify VNIR images, where snow and clouds show similar reflectance values.

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