CloudSegNet: A Deep Learning Based Segmentation Method for Cloud Detection in Multispectral Satellite Imagery

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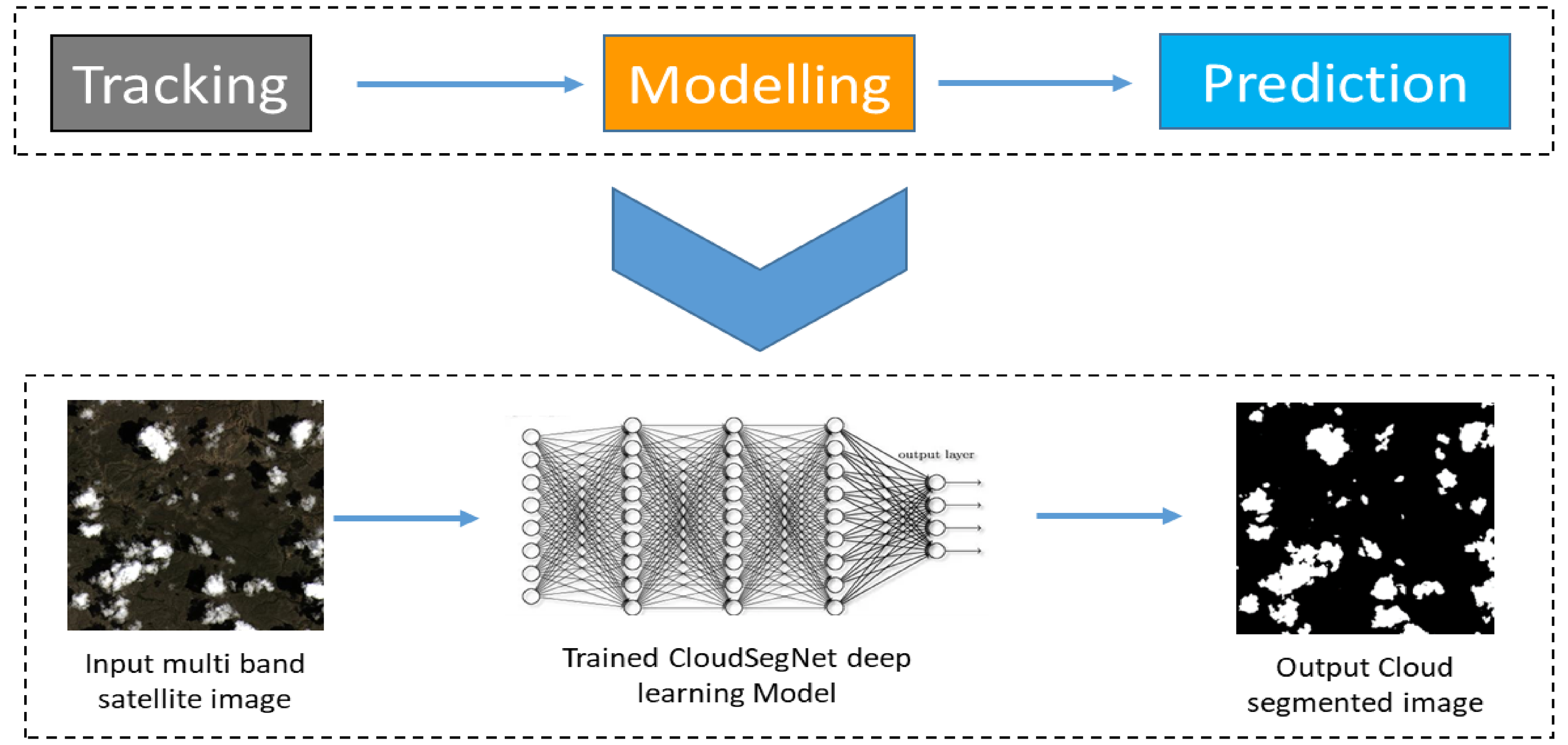
Background

- Occlusion by cloud happens nearly 80% of the time in tropical
- Clouds block a vast area, and impose a major limit
- Cloud detection can help in minimize the dominant areal coverage of cloud in high-resolution satellite imagery

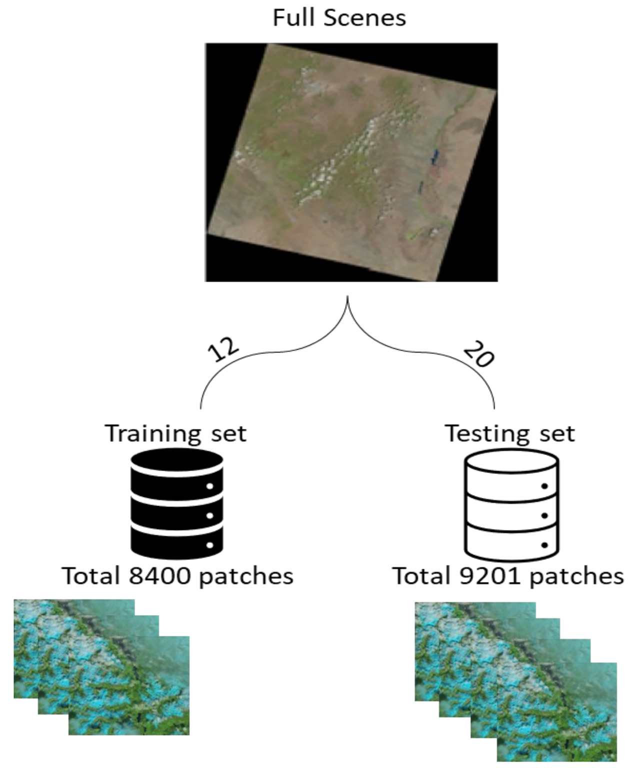
Research Goals

- To develop a robust deep learning based cloud detection method for optical imagery
- Development of the system for time series cloud detection using multi-sensor satellite Imagery



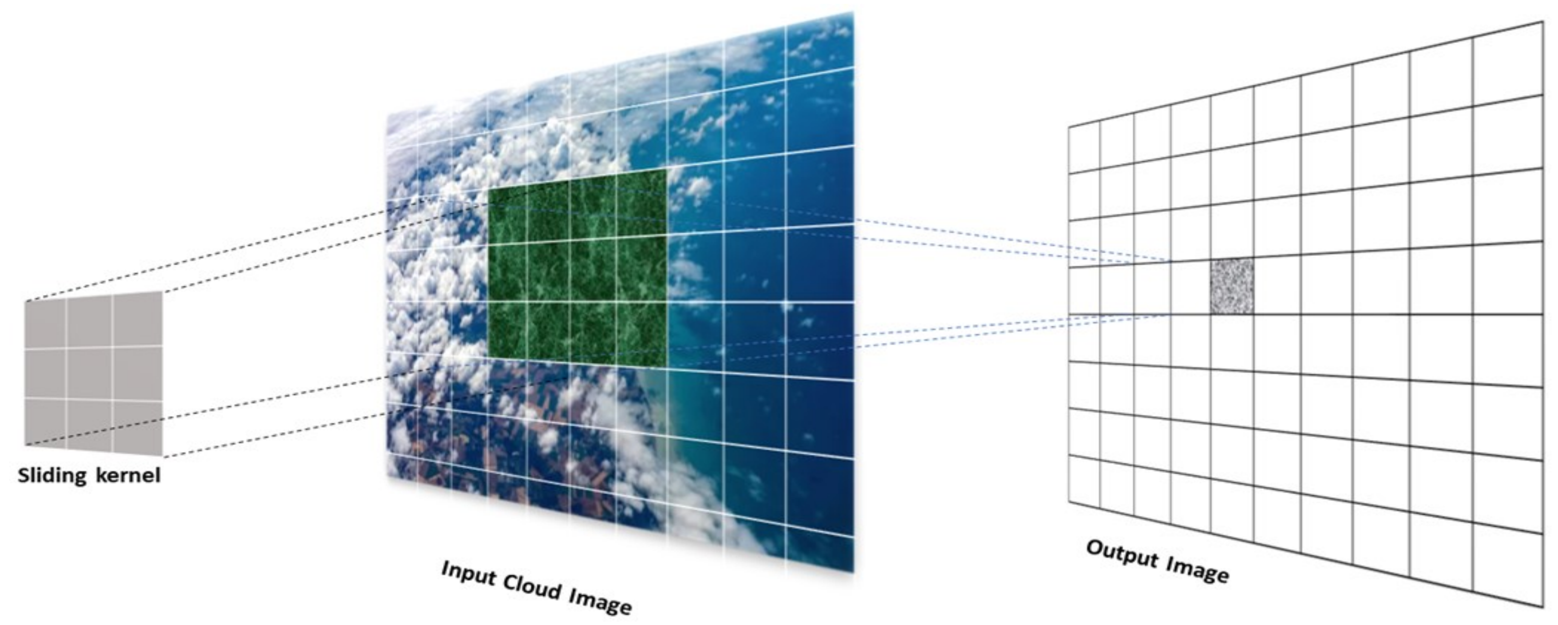
Dataset

- Landsat-8 satellite images
- Scenes are divided into small patches each of size 384 x 384
- Red, Green, Blue, and NIR in training set
- All ground truths (GTs) are manually annotated
- The input size of each patch is reduced to 192x192 instead of 384x384



Methodology

- The proposed method, CloudSegNet, is an adaptive method with cloud detection as objects in imagery based on U-Net architecture
- The proposed method, uses hybrid integration and modification of spatial segmentation
- Model is invariant to different spectral bands
- Convolution operation is used for cloud feature extraction
- Input is four bands of landsat-8 from band 2 to 5



Hardware Specification and Training Time

- The CloudSegNet model is trained on the device:
  - Having 40 Intel(R) Xeon(R) Silver 4114 CPU @ 2.20GHz processor
  - 125 GB RAM
  - GPU of NVIDIA Tesla V100 PCIe with 32 GB
- The total training time for the model is 11:48 hours for 53 epochs early stopping

Results

- The obtained validation accuracy is 93.46%
- The obtained validation loss is 0.0567
- The proposed model does not require a time-consuming preprocessing step like noise reduction or atmospheric correction.
- Provides an end-to-end solution
- Our experimental findings demonstrate that the suggested model preformed better than many developed methods
- Even without thermal band this method is useful

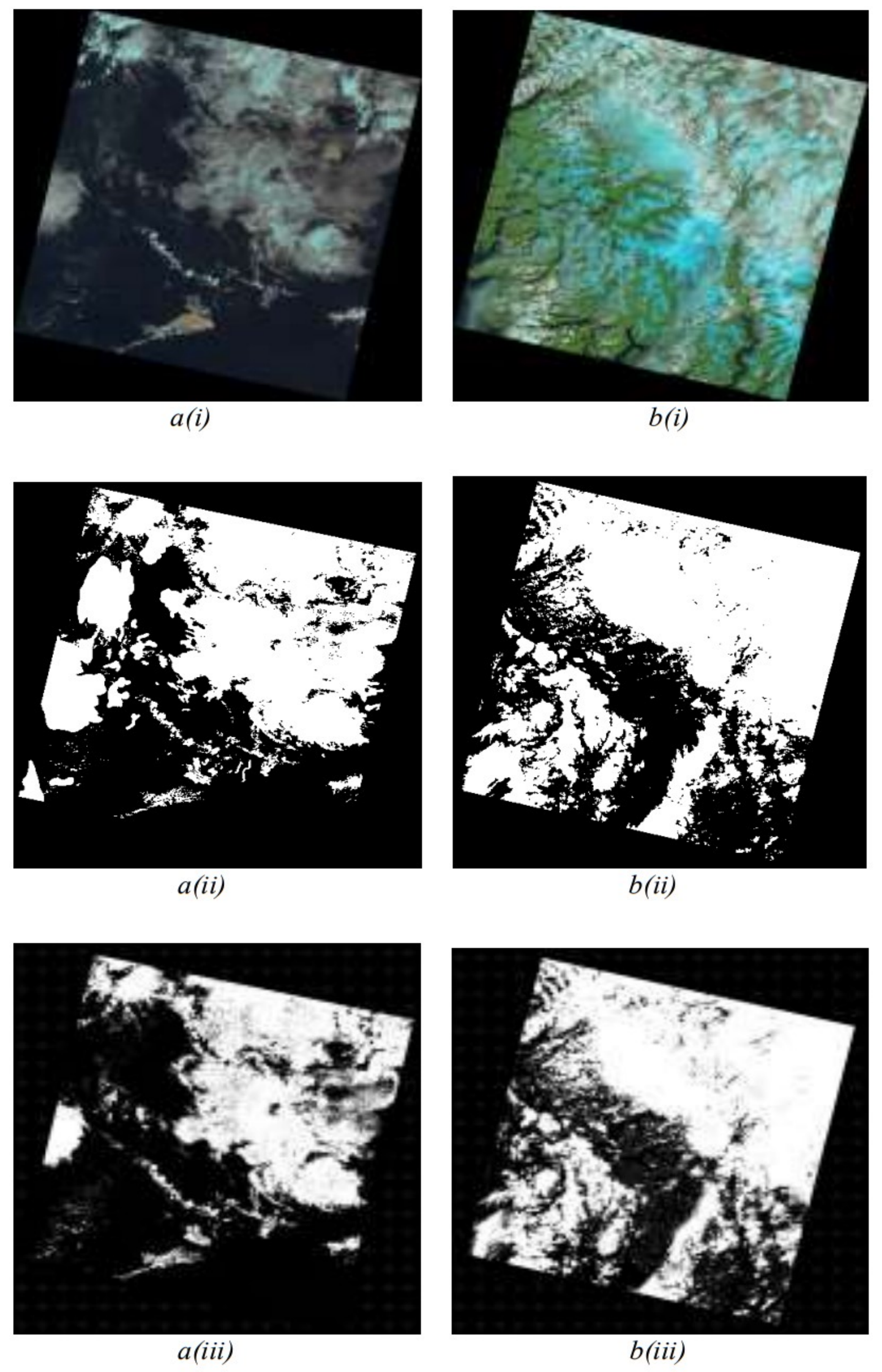


Fig. 3: Entire two (a and b) different scenes. (i) is for false color composite, (ii) ground truths, and (iii) predicted cloud masks

Conclusion

- The deep learning capabilities of detection and semantic segmentation of cloud pixels in Landsat satellite imagery explored
- The CloudSegNet architecture is robust in cloud pixels segmentation
- Even some of the segmented cloud pixels are better than ground truths
- In the future, our aim is to develop end to end multi-sensor cloud segmentation system

Acknowledgement

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