Land Cover Change Detection using Neural Network for Satellite Images

Data Science Institute
COLUMBIA UNIVERSITY

Ashkan Bozorgzad, Hari Prasad Renganathan,
Karveandhan Palanisamy, Masataka Koga, Yewen Zhou, Yuki Ikeda,
Saba Rahimi (Mentor), Adam Kelleher (Instructor), Cathy Li (CA)

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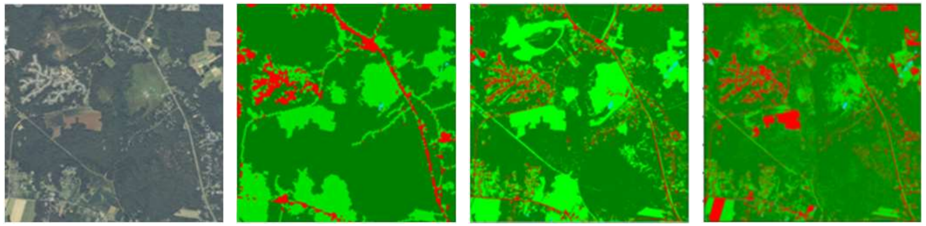
Abstract

The goal of the project is to create high-resolution (1m / pixel) land cover change maps of a study area, the state of Maryland, USA, given multi-resolution imagery and label data. This project aims to provide an example of situations commonly found worldwide. In the field of earth observation, new images produce faster than high-quality, high-resolution labels. However, old and low-resolution labels are available, for example, 30m National Land Cover Database (NLCD) in the United States or 500 m MODIS land cover available worldwide. Therefore, it is significant to investigate how machine learning can be used to build a model that predicts high-resolution change without having a lot of higher-resolution change data.

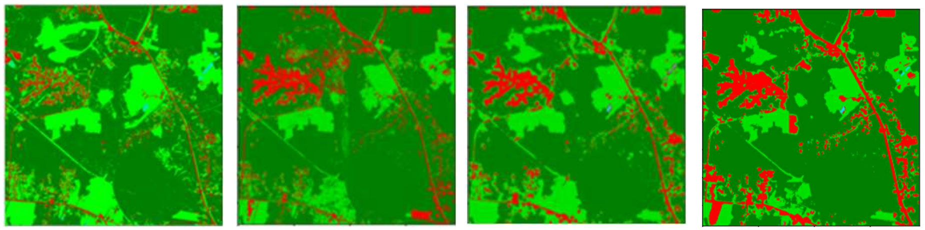


NAIP image | NLCD label | Ground truth | 1-layer FCN

Figure 1. Sample NAIP image, NLCD and ground truth label, and base model prediction

Methodology

To establish a baseline the model was trained using a 1-layer FCN model above. Further to improve the accuracy, we trained a 5 layer FCN. The architecture of the model is the number of input channels = 4 for (Red, Green, Blue, and Near-IR), #output classes = 5 (Water, Tree Canopy, Low Vegetation, Impervious, and None), filter size = 3, stride = 1, and padding = 1. Later, to compare the accuracy with another model we utilize the U-Net architecture with the encoder of ResNet-18 (U-Net 18), encoder depth = 3, and decoder channels = (128, 64, 64), and one with ResNet-50 to train. Shown in Figure 2, It was observed that the U-Net 18 model performed the best.



Ground Truth | 5-layer FCN | U-Net 18 | U-Net 50

Figure 2. Output of 3 different models learned on NAIP input images in 2013

Results

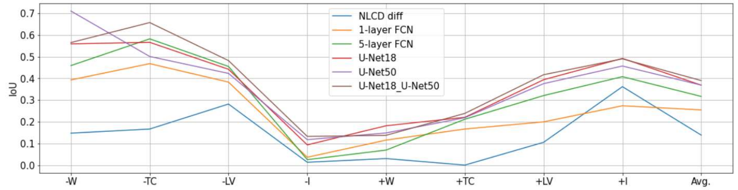
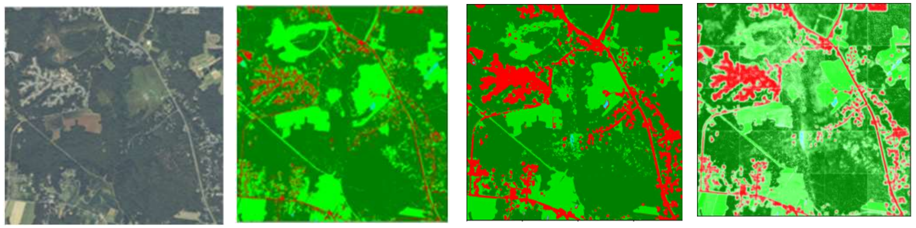


Figure 3: IoU scores for the 1-layer FCN, 5 layers FCN, U-Net 18, U-net 50, and chained model (U-Net 18 and U-net 50).
−C and +C denote the loss and gain of class C, respectively. Avg. is the average of 8 IoU scores.



NAIP image | Ground truth | Chained Model | Ensemble Model (M = 10)

Figure 4. Outputs of Refined Models

As you can infer from the results Figure 3, the average IoU improved and became stable for the chained model of U-Net 50 using U-Net 18 prediction label as input label. When compared to the baseline model or other single model, the chained model is capable of predicting of almost all classes better.
Also, we adopted the deep ensemble methods to show uncertainty of predictions. Shown in Figure 4, this methods can be used to comprehend which predicted labels are more uncertain. In Figure 4, more uncertain pixels are shown in more blight.

Recommendations:

Using other input resources such as dynamic works labeling to improve the accuracy of the results. Considering soft labeling and uncertainty instead of hard labeling and comparing the performance of the models

Acknowledgments

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References

1. N. Malkin, C. Robinson, and N. Jojic, "High-resolution land cover change from low-resolution labels: Simple baselines for the 2021 IEEE GRSS Data Fusion Contest," Jan. 2021.
2. Z. Li et al., "The Outcome of the 2021 IEEE GRSS Data Fusion Contest—Track MSD:Multitemporal Semantic Change Detection," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 15, pp. 1643–1655, 2022.