Forest Conservation with AI

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This is a two-week college course module designed to introduce GeoAI (geospatial AI) with machine/deep learning applications in forest conservation studies using satellite remote sensing. In this course module, students are first introduced traditional machine learning including random forest (RF), support vector machine (SVM), and pixel-based deep learning using forest cover mapping in Madagascar as a case study. Then, Convolutional Neural Network (CNN) approach is introduced, which utilizes spectral, texture and spatial information from WorldView-3 VNIR and SWIR data for classification and forest cover mapping in a fully automated learning process. The CNN approach used in this lab is U-Net (similar to Object-Based Image Analysis, OBIA) in remote sensing field. By completion of this lab, students can understand pros and cons of pixel-based (SVM, RF, DNN) and CNN-based OBIA; students also investigate forest change and impacts of human geography and conservation efforts on preserving forest habitats in Madagascar.

Learning Objectives:

1) Familiar with end-to-end automated deep learning for forest cover mapping using WV-3 imagery,
2) Learn how to implement pixel-based and CNN-based classification and segmentation algorithms,
3) Understand (through stepwise practice) pros and cons of pixel-based and CNN-based machine/deep learning methods, and
4) analyze the impact of conservation efforts in the region by international organizations by reviewing land cover change from 2010 to 2019.

Required skills: introductory remote sensing, GIS, python coding skills.

Acknowledgements

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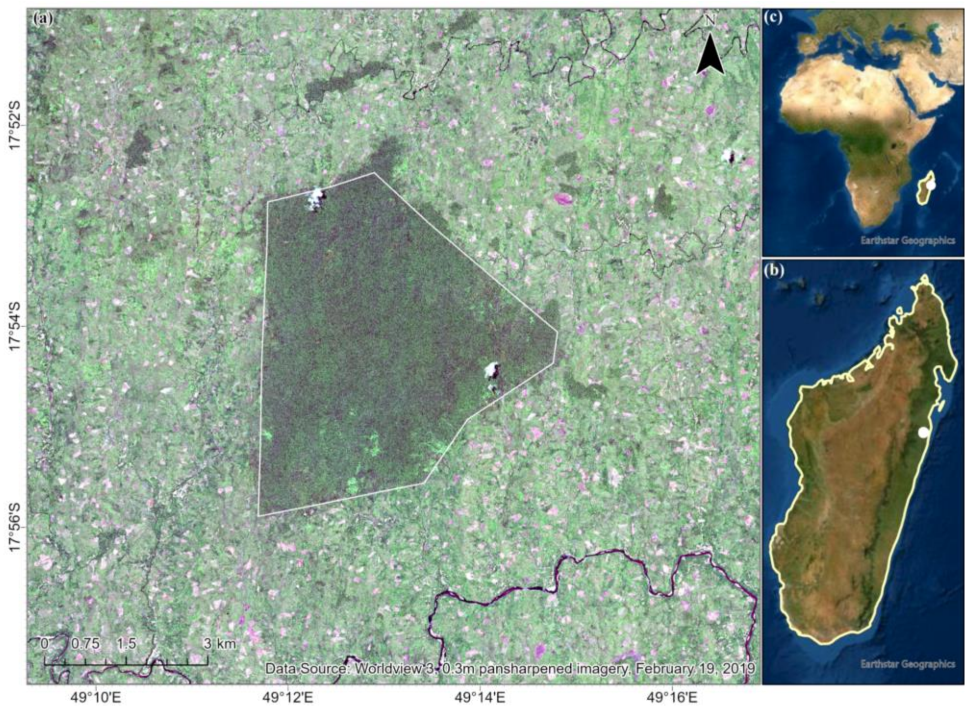
How to cite this course module:

"Sagan, V., Bhadra, S., and Cota, G. Forest Conservation with AI. (2021). In Sagan (ed), *GeoAI for Everyone*, https://github.com/MissouriView/Forest-Conservation-with-AI"

1. Study site - Betampona Nature Reserve (BNR)

The study area located in eastern coast of Madagascar includes the Betampona Nature Reserve in white boundary in Figure 1 (a) and surrounding areas roughly 100 square km. This is a species rich area which provides the researchers with a “living laboratory” for the studies of human-forest interactions.

Madagascar houses a lively and diverse ecosystem, but due to encroachment, deforestation tactics (illegal logging), aggressive agricultural practices and urbanization, the environment has greatly altered. Additionally, with the presence of invasive species such as Molucca Raspberry, Madagascar Cardamom, and Strawberry Guava, biodiversity continues to be threatened.



2. Datasets

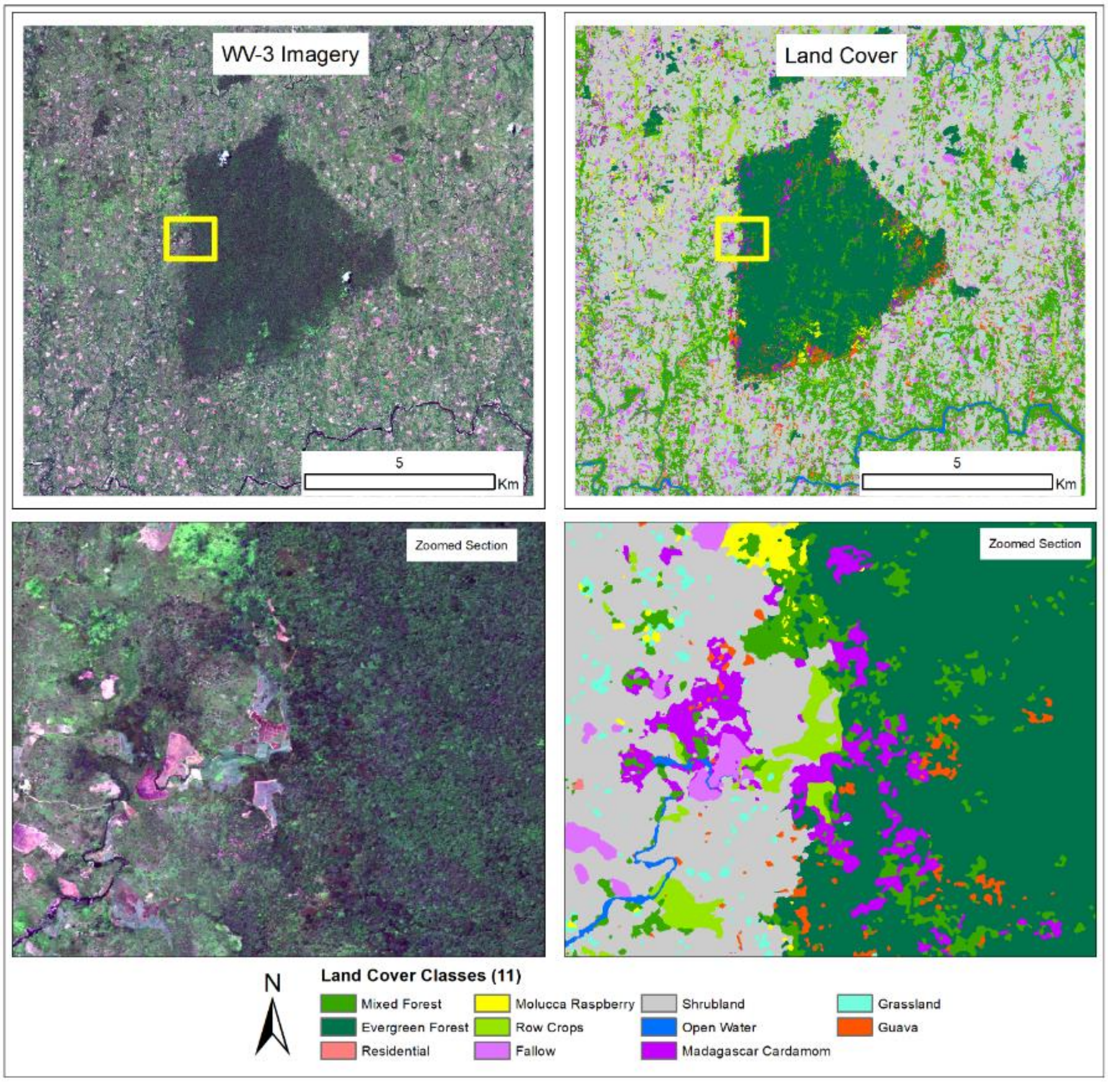
File Name	Description
Bet_LandCover_2019.tif	This is the “gold-standard" land cover/use map of the study area produced by object-based classification/segmentation of WV-3 imagery and significant post-processing and manual investigation using field surveys and ancillary data.
Bet_LandCover_2010.tif	• Classification map of the BNR and surrounding areas in 2010, created using IKONOS-2 and Hyperion image analysis. • Ghulam, A., Porton, I., Freeman, K. (2014). Detecting subcanopy invasive plant species in tropical rainforest by integrating optical and microwave (InSAR/PolInSAR) remote sensing data, and a decision tree algorithm. *ISPRS Journal of Photogrammetry and Remote Sensing,* 88: 174-192.

Polygon.shp	This polygon represents the boundary of image patches, which will be later used to train the UNet architecture and evaluate the results. There are a total 100 features in the polygon shapefile.
WV3_19Feb2019_BNR.tif	• 16 band WorldView-3 imagery in reflectance including VNIR and SWIR bands, which are atmospherically and radiometrically corrected and orthorectified. • WV-3 VNIR and SWIR ground sampling distance (GSD) is 1.2 m and 3.7 m, respectively. • VNIR-SWIR bands are layer-stacked and resampled to VNIR resolution using nearest-neighbor resampling. • The SWIR bands can detect non-pigment biochemical phenomenon within plants including water, cellulose, and lignin. SWIR-4 (1729.5 nm), SWIR-5 (2163.7 nm), and SWIR-8 (2329.2 nm) can identify absorption phenomenon of nitrogen, cellulose, and lignin, respectively. • The data were obtained from MAXAR through priority satellite tasking during the experiment.
WV3_19Feb2019_BNR_subset.tif	• A subset of the WV3_19Feb2019_BNR.tif image that can be used for testing and debugging codes.

3. How was the lab data prepared?

The original ground truth data were collected in the field using GPS surveys. A total of nearly 400 polygons in different sizes and shapes and point samples were collected. These ground surveys were used to produce the “gold-standard" reference imagery (Bet_LandCover_2019.tif) as described in the published paper. For this course module, however, we generated a new set of training samples from the gold-standard reference imagery to simply the implementation.

First, observe the following map.



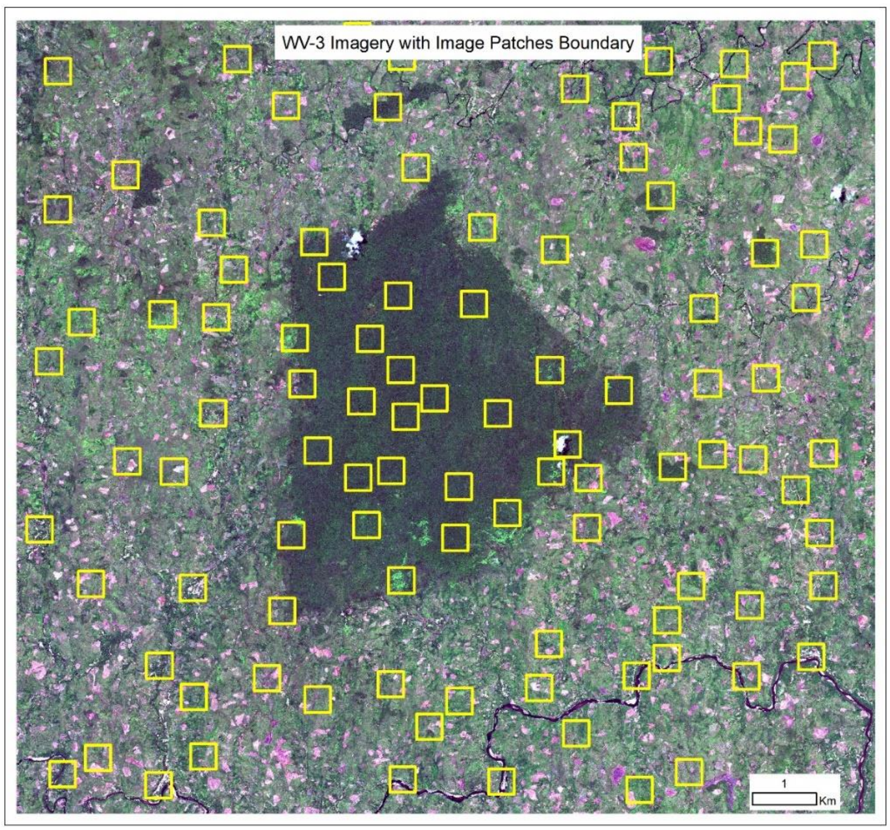
As stated above, the WV-3 image contains 16 bands. Further details about the 16 bands can be found in the Cota et al. (2021). There are a total of 11 land cover classes that were created by CNN-based image segmentation. That means all pixels in the study area are already classified as some land cover/use type. The codes for each land cover class are given below:

Land cover classes

Int Code	Class
1	Mixed Forest
2	Evergreen Forest
3	Residential
4	Molucca Raspberry
5	Row Crops
6	Fallow
7	Shrubland
8	Open Water
9	Madagascar Cardamom
10	Grassland
11	Guava

U-Net requires image patches or image chips as input data. In order to create this data for this tutorial, we generated a polygon shapefile, named ‘polygon.shp”, based on the gold-standard land cover/use map,. This polygon represents the boundary of image patches, which will be later used to train the U-Net architecture and evaluate the results. There are a total of 100 features in the polygon shapefile. The steps to generate these training samples are below.

1. Create a set of randomly generated points using ArcGIS Pro. To do this, open ArcToolbox and open the Data Management Tools > Feature Class > Create random points tool.
2. Create a circular buffer around those points, set the buffer size to 192 meters.
3. Convert the circle to a square-shaped polygon by using “Minimum Bounding Geometry” tool and use “Envelope” as the geometry type.



4. Students, THIS IS your task!!!

Please go through all the provided DEMO notebooks:

- U-Net_part1A_preprocessing_DEMO.ipynb
    - Demonstrate the preprocessing steps.
    - After preprocessing, save the train and test set in npy format.
- U-Net_part1B_training_DEMO.ipynb
    - Perform the training of UNET.
    - Save the best model.
- U-Net_part1C_applying_model_to_map_DEMO.ipynb

- Apply the model to the whole image.
- Divide the image into similar size image patches.
- Then apply model to each patch.

5. Deliverable/Submission

Write a report (no more than 4 pages) about the methods and results from this lab. You can rely on the Cota et al. (2021) publication for reference, but note that the goal for this report is how the U-Net worked and how you implemented it. Focus on how each segments of codes worked and what are the 5 key skills you learned about CNN and U-Net. You can include figures but do not fill up the whole report with just figures. Here is a template you can follow:

1. Introduction: Talk about the background behind the task. Why you are doing this? What are you expecting from the model? The objectives.
2. Methods: (Try to create a short figure showing the overall workflow)
    a. Preprocessing: How did you preprocess the data. Try to briefly describe the tasks of the codes provided in the notebook
    b. U-Net Training: How many parameters were there? What hyperparameter values you used? What loss function and optimizer you used and why?
    c. Applying to Image: How did you apply the model to the whole image?
3. Results: What is the overall accuracy? Show the confusion matrix, kappa scores and other metrics you want to show.
4. Discussion: is this a segmentation or classification approach? What are the advantages and disadvantages between the two? Did U- Net utilize spectral information? What about texture and spatial patterns?
5. Conclusion: What did you achieve? What are the possible next steps that can improve the results?

Use Time New Roman / Arial / Calibri with 11 pt font size. Use default line spacing (Multiple, 1.08). Letter page.

6. Grading Rubric

***Extra credit:**
For extra points, perform at least one traditional machine learning algorithm (SVM, Random Forest) or pixel-based DNN approach. You earn 2 points (1-100 scale) for each algorithm implementation, meaning you can earn maximum 6 points if you complete all three algorithms.

Please note that you need to reshape the npy data you created (consider that each pixel is now a sample). It requires **A LOT of time** to train. However, feel free to randomly select 50% of the training dataset and train either SVM or RFC. Calculate the final accuracy and make a comparison with U-NET results.

Github README file

Codes

This repository contains scripts for three different parts - part 1 for data preprocessing, training a CNN model, and application of the model to WV-3 imagery; part 2 includes scripts for pixel-based machine/deep learning algorithms (SVM, RF, and DNN) available only to instructors who would like to use this material for their machine learning course; and part 3 includes tutorial for forest change analysis using grid-cell approach.

The goal of this repository is to create a tropical forest map (with other land cover/use type) using U-NET as the segmentation algorithm. The imagery used is WorldView-3 (WV-3), which contains 16 bands (8 bands in the visible region and 8 bands in the shortwave infrared (SWIR) region).

Cota et al. (2021) used a Fully Convolutional Neural Network (FCNN) as an end-to-end pixel-based (SVM, RF, and DNN) and patch-based (CNN) image classifier of high-resolution satellite imagery, which was one of the very first implementation of GeoAI to forest conservation and human geography.