Training New Automated Feature Extraction Models for Canopy Classification Using the 2019 60cm NAIP Imagery

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Abstract

In this phase of the canopy study, it is our objective to analyze 2019 canopy in the state of Georgia. We proposed to use the existing 2015 Automated Feature Extraction (AFE) models to create a 2019 canopy product. However, based on our preliminary test, these models produced canopy outputs that are not acceptable for this study. We have found a few potential factors that might have affected the performance of the original models. This methodology report discusses those issues found from using the 2015 AFE models to analyze 2019 canopy using the new higher-resolution 2019 60cm NAIP imagery. It also presents how we designed new AFE models for all the physiographic districts in a consistent manner.

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1. Introduction

The objective of Phase 1.5 of this canopy assessment study is to assess tree canopy in 2019 across the state of Georgia. We initially proposed to use the existing 2015 Automated Feature Extraction (AFE) models from the 2016 canopy study to analyze 2019 data. Unfortunately, these models produced poor results in our preliminary test using four 2019 60cm NAIP imagery tiles. One of the most notable changes in the NAIP product is its resolution. The new 2019 NAIP imagery is provided in a 60cm resolution as compared to the older 1m resolution. The 2015 models were developed using 1m NAIP imagery and internally resampled 60cm cells into 1m even though the newer 60cm NAIP imagery was directly fed to the models. We have tried resampling the 60cm NAIP data outside Feature Analyst, but it did not help improve results. For this reason, we decided to train new AFE models using the 2019 60cm NAIP imagery from the ground up.

2. CanoPy Python Module for Canopy Classification Using Feature Analyst

CanoPy is our AFE-based canopy classification framework that we developed for the Phase 1 of this project. A main goal in the creation of the CanoPy Python framework is to help facilitate the research of future groups conducting updated research through the GFC. With batch processing being the main goal of the CanoPy software, it is constructed around a central configuration file that holds all file and data paths needed to seamlessly conduct the work needed for a statewide study. Initially, the configuration file was an external Python file (*.py) with variables that needed to be manually declared appropriately before the CanoPy module was imported. While simple, the manual set up of the configuration file is seen as a main source of user errors and particularly so if the user is not familiar with the Python language.

To address potential user errors caused by the configuration process, we developed a new system. The new system uses the generic text-based configuration file (*.cfg) to read and write configuration data directly from. To facilitate the use of the new configuration file, an additional Python object is created titled "Config." This new object enables the user to directly read configuration parameters in a Pythonic system and more importantly it allows for the direct writing of configuration parameters into the configuration file without the need to open the file directly in a text editor. The integration of write capabilities for the configuration file additionally allows for important configuration parameters such as the key output file structure to be hidden from the end user and maintain consistency. When the "Config" object is first initialized, if a config file is not detected, then a new file is generated at the desired location.

All processing scripts are set up as independent functions and classes. The new “Config” object is in turn used as the input for each one. The usage of this new config system allows for the user to set up multiple configurations for multiple sets of data seamlessly.

3. Issues with the 2015 Models for 2019 Analysis

3.1. Aggregation Issues

We conducted a pilot test using four 2019 60cm NAIP tiles across three different physiographic districts. The current AFE models from the 2016 study produced 1m outputs even though we fed 60cm input tiles to them. We communicated this finding with Textron Systems and, according to them, their AFE models produce the same resolution as that of the original training data. First, higher-resolution data is aggregated into the lower trained resolution, the trained algorithm is run, and then, the lower-resolution output is generated. They provided a how-to document showing how to incorporate resampling into their models, but they mentioned that this resampling technique is not much different from the standard ArcGIS resampling tool. The only advantage, they said, would be to be able to pick our own grids. However, using the Snap Raster environment from ArcGIS would produce equivalent results without us having to modify the 24 AFE models manually.

3.2. Snapping Issues

With the GFC’s confirmation that the 1m output from 60cm input would be fine for our purposes, we tried to address potential snapping issues between the existing 2009 1m output and new 2019 1m output from 60cm input. To address the differences between grids, the 2009 1m output grid is used as the snap raster grid for future geospatial processes within CanoPy. The first approach tested was the use of resampling of the new 2019 1m output into the 2009 1m grid for snapping purposes. This approach accurately aligned the grids as can be seen in Figure 1.

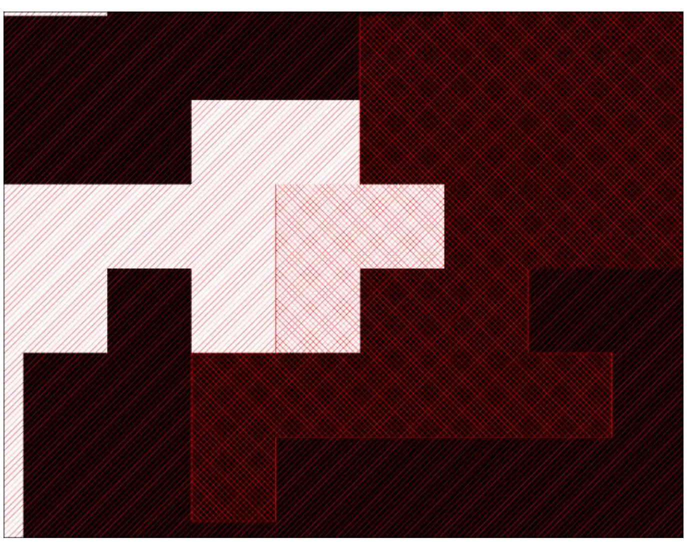

Figure 1. Alignment of cells resampled from 1m to 1m.

As another test, the grids were aligned without incorporating resampling to determine which solution would be more exact. It was done by setting the snap raster at the beginning of the CanoPy process to ensure that all raster outputs will be aligned to the new grid without resampling. The comparison between the two approaches yielded exactly the same results in value counts, meaning that resampling adds an additional unnecessary step to align the two grids.

Following visual inspection on several physiographic districts, we found that the models from the 2016 study lead to high drop-offs in the % accuracy. To test the causes outside of the models, the original NAIP imagery was reprojected, resampled, and snapped to a 1m grid before being classified within Feature Analyst. The hope was that the resampling algorithm provided by Esri would be better than that used by Feature Analyst. The resampling technique used was cubic convolution as the NAIP data is continuous data. This method did not solve our issues either.

3.3. Shadow Issues

When we used the 2015 models for the 2019 data, major issues arose. The largest issue was the models only classifying shadow as tree canopy and everything else as non-canopy as shown in Figure 2. The presence of shadows within NAIP imagery is a tricky element of the data to work around particularly when it comes to the classification of canopy as there are shadows present within tree stands, which are canopy, and shadows outside and along the edges of tree stands, which are not canopy. Within tree canopy studies, ancillary texture information is typically used with models to better differentiate shadow. In our case, the near infrared (NIR) band is used with a sliding window algorithm to determine the texture of the imagery. When the 2015 models are used with the 2019 data, they fail to separate canopy from shadow and only classifies shadow as canopy. This misclassification is a major issue and, because of the black box nature of the created models, it cannot effectively be explored as to why shadows are being classified exclusively as canopy. This unknown factor in the existing models in turn was a major reason for the creation of new models for the 2019 data.

Figure 2. Misclassification issues between canopy and non-canopy.

4. New Model Creation

4.1. Inputs and Workflow

The models created utilize six raster bands as inputs for classification in addition to vector input training polygons. The six input raster bands are red reflectance (R), green reflectance (G), blue reflectance (B), NIR reflectance, Normalized Difference Vegetation Index (NDVI) reflectance, and texture derived from the NIR band. Per Textron Systems, the texture band is computed on the fly with variance for each cell created from a 3-by-3 moving window. Further aggregation is set to 100 pixels or 60m for each classified pixel. Figure 3 shows the workflow diagram of the new AFE models.

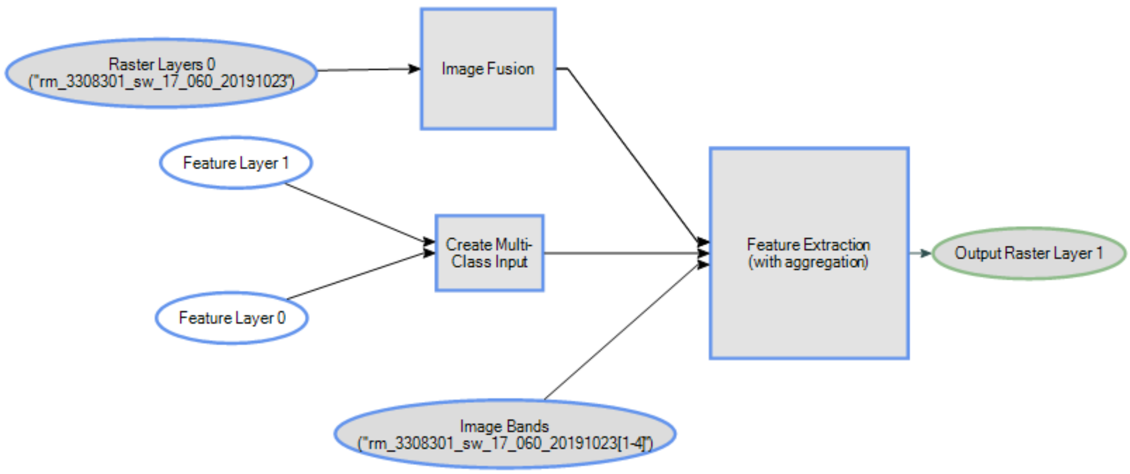

Figure 3. Workflow diagram of the new AFE models.

The input pattern recognition used is titled "Bull's Eye 3" with Feature Analyst and is coupled with a pattern width of 13 pixels. Figure 4 shows the grid pattern of Bull's Eye 3. For each pixel in the image, a total of 102 pixels are computed across all six bands in order to provide the necessary ancillary data to Feature Analyst. Unlike the 2015 AFE models, we used the same model for all the 24 physiographic districts for consistency.

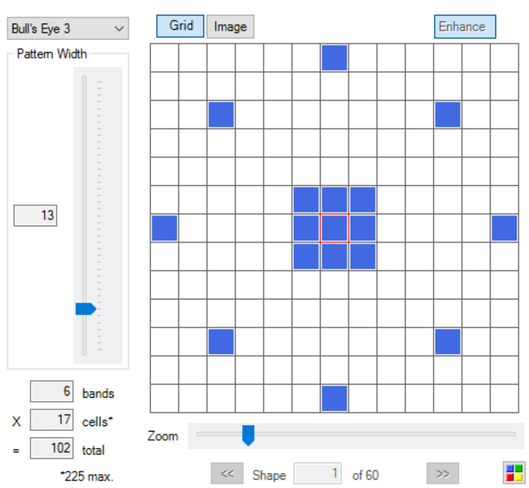

Figure 4. Input pattern for training the new AFE models.

4.2. Selection of Training Tiles

The previous studies' training data could only be seen with the use of proprietary tools for analyzing AFE files that only Textron Systems possesses. For this reason, we were not able to inspect how the previous team selected training tiles. To choose NAIP tiles for training without human bias, we formulated the following objective function that utilizes the National Land Cover Database (NLCD):

$$F = \sum_{j=1}^{n} \left(G_j - L_{ij}\right)^2 + w \times (G/20 - L_i/20)^2 \tag{1}$$

where G_j is the district-wide global percentage of land cover j, L_{ij} is the local percentage of land cover j in tile i, L_i is the number of classes in tile i, and w is the weight for the number of classes in the tile. This function is incorporated into CanoPy.

5. Conclusions

We examined the feasibility of using the existing 2015 AFE models for 2019 canopy analysis. However, the performance of these models was not acceptable. To achieve our target accuracy of 85%, we trained new AFE models using the 2019 60cm NAIP imagery. For training, an objective function was defined to select training tiles without human bias. For consistency across the 24 physiographic districts, we used the same workflow and inputs when developing the new models.