AN OBJECT-BASED APPROACH TO STATEWIDE LAND COVER MAPPING

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ABSTRACT

Despite the plethora of data-acquisition programs collecting remotely sensed high-resolution imagery in the United States, few corresponding high-resolution statewide land-cover datasets have been developed. This is understandable given the challenges inherent in extracting information from massive, highly-variable datasets encompassing heterogeneous landscapes. To overcome these challenges during development of a statewide, high-resolution tree-canopy dataset for Maryland, USA, we designed and deployed a rule-based expert system for mapping land-cover features from multispectral imagery and LiDAR. This object-based approach facilitated integration of imagery and LiDAR into a single classification workflow, exploiting the spectral, height, spatial information contained in the datasets. Rule-based expert systems provided an intelligent approach to feature extraction, ensuring consistency in the output despite variability in collection parameters, data quality, and data completeness, among others. Finally, by distributing the processing load to multiple computing cores, we efficiently extracted land cover from remotely-sensed datasets constituting terrabytes of digital data, covering the entirety of Maryland's 25,640 km^2 (9,900 mi^2) land area. We conclude that an object-based approach that incorporates expert systems and enterprise processing is a cost-effective method for statewide land-cover mapping.

KEYWORDS: Object-Based Image Analysis, OBIA, GEOBIA, Land Cover

INTRODUCTION

Federal, state and local governments have long invested heavily in high-resolution remotely sensed datasets. Historically the focus of these data acquisitions has been on imagery, principally orthophotographs. More recently, LiDAR data has come into the picture, with several states embarking on statewide LiDAR initiatives. These high-resolution datasets are invaluable for supporting a broad range of mapping initiatives and decision-making activities, but there are few examples in which these datasets have been turned into comprehensive "wall-to-wall" land cover datasets at the statewide level. This is understandable given the challenges inherent to extracting information from very large datasets in highly heterogeneous landscapes. National land cover products, such as the National Land Cover Database (NLCD) do exist, but the moderate resolution (~30 m) datasets such as NLCD are suffer limitations when attempting to resolve fine-scale features, and are thus not suitable for all applications.

This project sought to develop a high-resolution (1 m) tree canopy dataset for the State of Maryland's 25,640 km^2 (9,900 mi^2) land area. The driving factor behind the mapping was to generate input datasets to estimate local-scale, high-resolution carbon stocks and future carbon sequestration potential. A secondary goal was to insure that such dataset that would be accurate and detailed enough to support forest resource monitoring throughout the state, such as mandates set in place by Maryland's Forest Preservation Act of 2013, and further research on Urban

Tree Canopy (UTC) (e.g. Locke et al., 2013; Troy et al., 2012). Previous work has shown that highly accurate tree canopy mapping can be accomplished when optical imagery and LiDAR are integrated into an object-based image analysis (OBIA) system (MacFaden et al., 2012; O'Neil-Dunne et al., 2012). Our team had extensive experience in developing such OBIA systems, but doing so for the State of Maryland posed a particular challenge, chiefly due to the inconsistency of the data. In the State of Maryland geospatial data collection, maintenance, and distribution largely occurs at the county level. As such, LiDAR datasets were acquired with varied collection parameters, delivered in a variety of formats, and ranged in dates from 2003 to 2012. Building footprints, which are helpful as an ancillary dataset in separating out tree canopy from buildings in LiDAR, were only available for select counties. Fortunately, imagery from a consistent time period did exist in the form of 4-band data collected by the National Agricultural Imagery Program (NAIP) in the summer of 2011. The NAIP data was not without issue as it was often shifted horizontally, by up to 3 m, when compared to the LiDAR. In addition, the NAIP acquisition period for Maryland was spread over several weeks, resulting in noticeable tonal shifts in the imagery.

Our task was to develop a system capable of extracting tree canopy for the entire state based on 2011 ground conditions. The system had to deliver accurate, consistent results despite the diverging data sources. Furthermore, the system had to be capable of handling massive amounts of data (total data holdings exceeded 6 TB) throughput and cost effective in order to meet the project's budgetary requirements.

METHODS

Data

LiDAR data for each county in Maryland came in one of two formats. The first, for the older collects (2005 and prior), consisted of bare earth and first return points in separate ASCII XYZ files. The second, fore more recent collects (post-2005), consisted of LiDAR point clouds in LAS format. The LAS point clouds included a classification that identified ground points, information on the number of returns for each point, and intensity values, among others. For all the LiDAR data the point density ranged from 0.6 to 3.3 points per square meter, depending on the county and collection parameters. The imagery consisted of 4-band (blue, green, red, near-infrared) data acquired during leaf-on conditions in the summer of 2011 through the National Agricultural Imagery Program (NAIP) at a resolution of 1 m. Building polygon data were available for seven of the twenty-three counties in the state. The combination of LiDAR, imagery, and building polygons lead to four data scenarios:

1) ASCII LiDAR and NAIP imagery without building polygons
2) ASCII LiDAR and NAIP imagery with building polygons
3) LAS LiDAR and NAIP imagery with building polygons
4) LAS LiDAR and NAIP imagery with building polygons

Each county LiDAR collection was processed to create various raster surface models. The raster cell size was set based on the average point spacing. The ASCII LiDAR data were processed to yield a raster Digital Surface Model (DSM) consisting of the first return ASCII files, and a raster Digital Elevation Model (DEM) from the ground point ASCII files. The DEM was then subtracted from the DSM to create a Normalized Digital Surface Model (nDSM), in which each pixel represented the height above ground. A similar process was carried out for the LiDAR data in LAS format but using the respective return and classification information contained in the LAS attributes. In addition to the nDSM the LAS LiDAR data were processed to yield a Digital Terrain Model (DTM) from the last returns. A Normalized Digital Terrain Model (nDTM) was then created by subtracting the DEM from the DTM. The final outputs from this phase were an nDSM for all counties and an nDTM for counties that had LiDAR in LAS format. The NAIP imagery was simply assembled into county mosaics. Building polygons were retained in their original vector format (Shapefile).

System Design, Development and Deployment

The system for extracting tree canopy had to meet several criteria: 1) flexibility to account for differences in the source data, 2) yield a product with a 95% or better user's accuracy, 3) integrate raster and vector data into a single processing environment, and 4) efficiently process large amounts of data. Based on these criteria we developed a system centered on the eCognition® software platform (Trimble, Sunnyvale, CA). eCognition's object-based technology met the criteria outlined above by enabling raster and vector datasets to be combined in single operating environment in which rule-based expert systems could be employed to classify features based on their spectral, height, and spatial properties. eCognition's GRID processing environment provided the means by which to distribute the processing load to multiple cores and make use of 64-bit architecture, therby providing an effective framework for large dataset processing. To account for the fact that no automated system can be perfect we budgeted 25 person-hours per county to review the data at a scale of 1:5,000.

Data were processed on a county-by-county basis. For each county the raster datasets (LiDAR and imagery) and vector datasets were loaded into an eCognition project. Building on systems developed for prior tree canopy mapping projects (MacFaden et al., 2012; O'Neil-Dunne et al., 2012) we built four rule-based expert systems to handle each one of the four data scenarios listed above. Each rule set contained a series of tiling, segmentation, classification, and morphology algorithms designed to extract tree canopy. The purpose of the tiling operations was to break the data into smaller chunks to distribute the processing load. Following the tiling operation, the rule sets followed the steps presented in Figure 1. In the first step a single height threshold was used to separate out tall features, defined as those objects 2 m or higher, the minimum height definition for tree canopy for this project. Included in this step was a gap filling routine designed to ameliorate the gaps in deciduous canopy stemming from the leaf-off nature of the LiDAR. In the second step tree canopy was differentiated from buildings based on a combination the imagery, LiDAR, and, if present, building polygons. This step is where the main differences in the four rule sets arose. The rule set for counties without LiDAR in LAS was modified to emphasize the spectral differences between tree canopy and buildings in this stage. In those counties where LiDAR in LAS format were present, the imagery was used in combination with the difference between the nDSM and nDTM layers. The nDSM/nDTEM difference emphasized tall features with a complex return structure (typically trees) from those without (typically buildings). For counties that had building polygons, additional rules were incorporated to account for the fact that tall features within building polygons were most likely buildings, with the exception of the overhanging tree canopy. The rules in the second step consisted of simple thresholds that could be modified to account for the unique characteristics of the datasets in each county. In the third step context-based rules were used to refine the tree and building classes based on spatial relationships. The context-based rules served to address issues of class confusion, primarily along tree/building borders (Figure 2). However, the rules also addressed other issues such as objects in the middle of a forest, that while sharing all the properties in the imagery and LiDAR of buildings, were unlikely to be so due to the absence of other buildings in the vicinity. Once this iterative process was completed morphology routines were employed to restructure the canopy, removing slivers and spurious objects. In the finally step the tree canopy features were exported to a vector dataset.

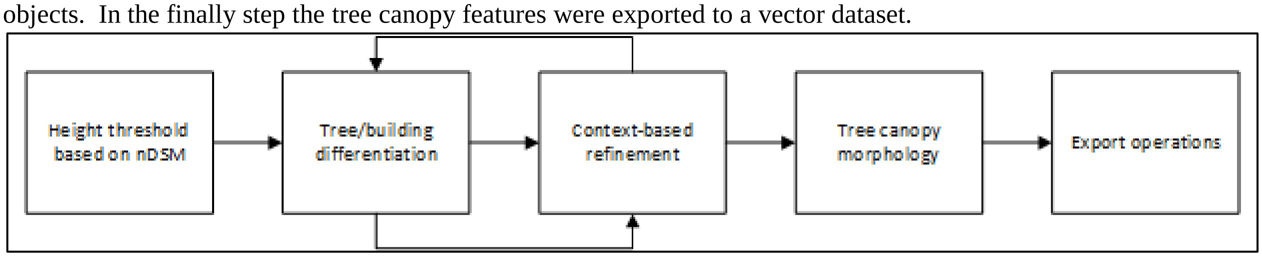

Figure 1. Rule-based expert system steps.

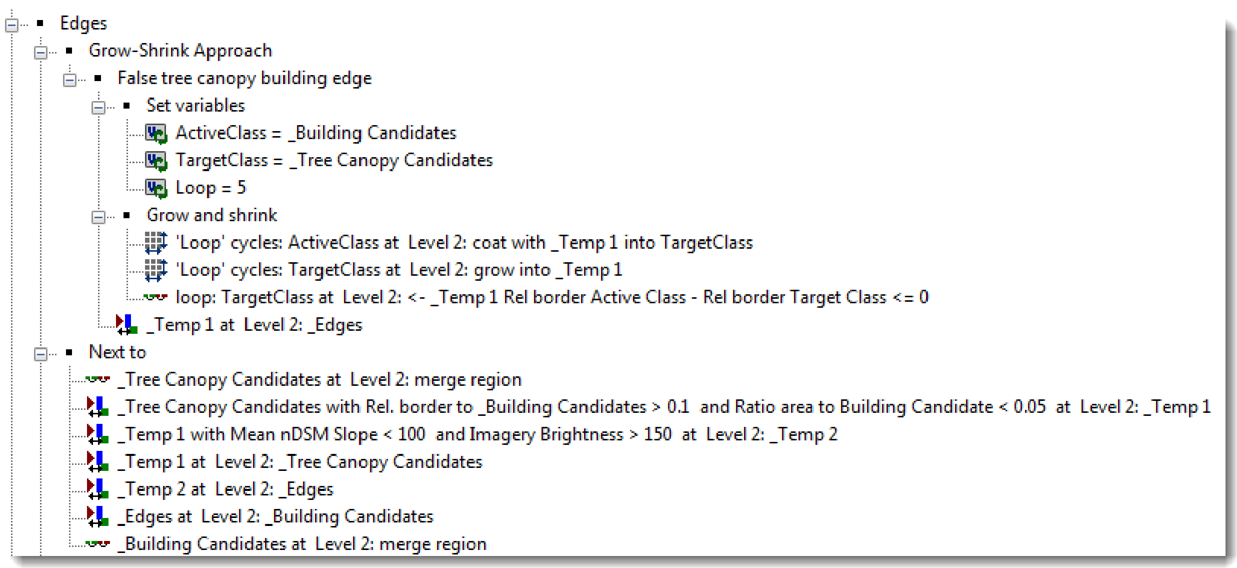

Figure 2. Portion of the rule-based expert system devoted to context-based refinement routine for resolving issues along tree canopy and building border areas.

The appropriate rule-based expert system was applied to the county based on which one of the four data scenarios it belonged to. As the data in each county proved to be unique, the rule-based expert system was tested, and modified accordingly on subsets of the data prior to execution. The output vector tiles were then subjected to manual edits by a team a trained image analyst operating at a scale of 1:5,000. The focus of the manual editing process was to address issues that could not effectively be automated. Following the completion of the manual edits the data were compiled into a countywide tree canopy mosaic.

Accuracy Assessment

To assess the accuracy we employed a stratified sampling approach. 1000 points were randomly generated for locations as identified as tree canopy. Another 1000 points were randomly generated for locations not identified as tree canopy. Large water features (e.g. Chesapeake Bay) were excluded from the latter so as not to bias the sampling. A trained imagery analyst using the imagery and LiDAR source data, supplemented by reference imagery from Google Maps and Bing Maps, independently classified each point as “tree” or “not tree”. For the 1000 tree points, 64 had to be replaced as they fell on the edges of tree canopy where the analyst felt that he/she could not accurately determine the land cover class. 22 of the points for the non-tree class had to be replaced due to similar issues. Following Congalton and Green (2009) we computed the user’s and producer’s accuracies.

RESULTS, DISCUSSION, AND CONCLUSIONS

The project succeeded in meeting its objectives of developing an automated workflow for extracting tree canopy over the State of Maryland from massive amounts of disparate imagery and LiDAR with a user’s accuracy of 99% and a producer’s accuracy of 98%. Even in heterogeneous areas with high vertical and horizontal landscape complexity the tree canopy mapping proved to not only be accurate, but also cartographically pleasing (Figure 3). Furthermore, the project was able to remain within budget and deliver the final products on schedule to meet the carbon modeling requirements.

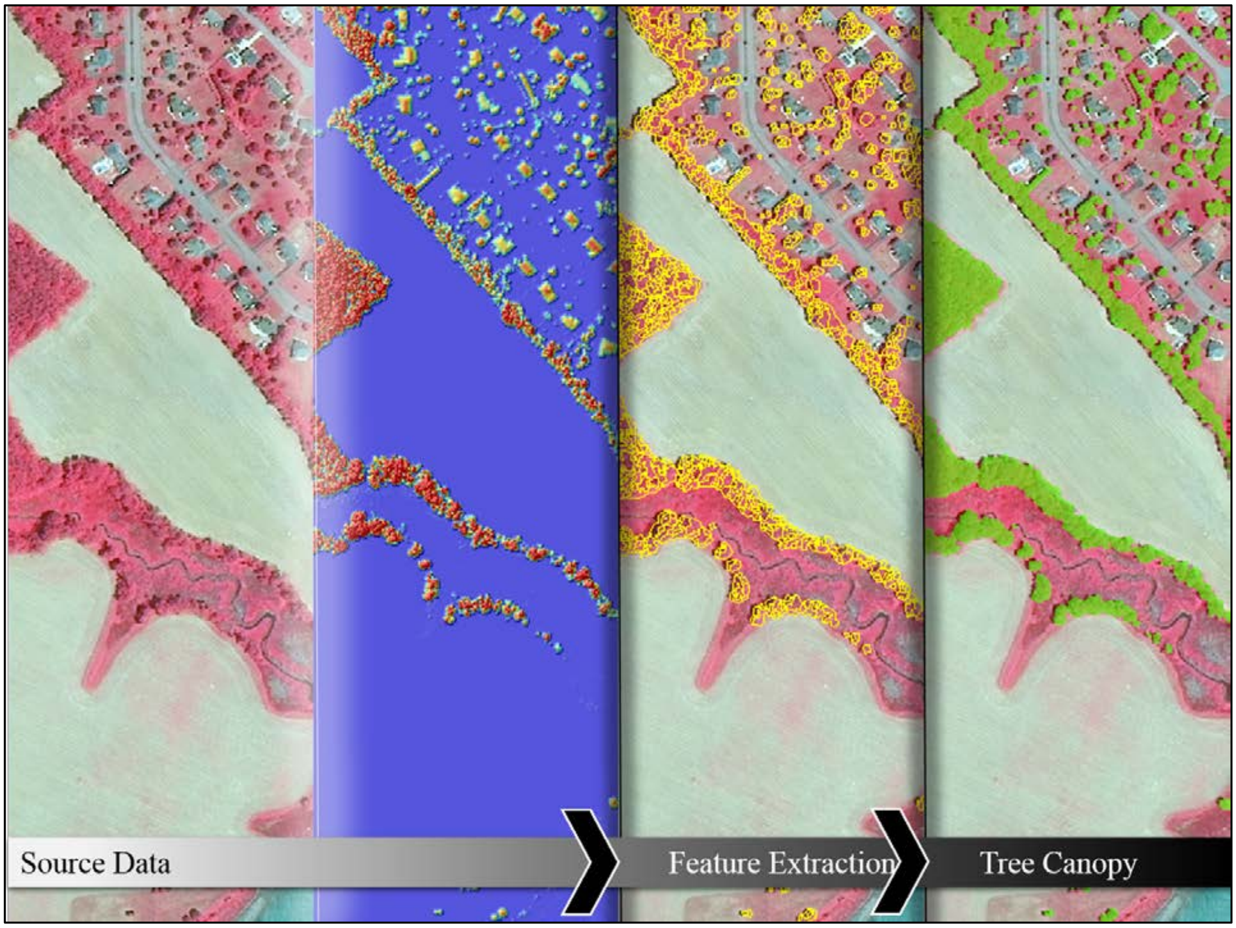

Figure 3. Depiction of the source data (imagery and LiDAR), objects generated for feature extraction, and final tree canopy product for a portion of the project area.

We conclude that object-based systems have substantially matured from the niche technology first introduced at the beginning of the century, to full-fledged production systems capable of processing large datasets. The ability to integrate a rule-based expert system offered us the flexibility to adjust to the varied data inputs, thereby leveraging superior data where it existed, yet retaining the overall structure of the workflow when it did not. The advantage of integrating the imagery, LiDAR, and vector building data into a single feature extraction workflow cannot be understated. These three datasets rarely agreed with respect to positional alignment, necessitating the application of topological rules to resolve boundary issues. Despite the success of the automated workflow we found that manual corrections were an important part of yielding a high-quality dataset. This was particularly true in this study as no automated system could completely resolve the temporal differences that existed between the LiDAR and the imagery that existed in certain counties. In addition we were unable to entirely automate the recognition utility lines. The pulse spacing in the LiDAR data resulted in a situation in which utility lines did not appearing as lines at all, but scattered elliptical objects with heights similar to that of trees. When the utility lines occurred over vegetated areas, their imagery properties, such as Normalized Difference Vegetation Index (NDVI), were indistinguishable from those of actual trees. Human analysts could effectively map these features by following the general location of the utility lines, recognizing that they followed roads and branched off to corners of buildings. While such errors had a minor impact on the overall accuracy, they would have brought into question the overall integrity of the dataset.

Surprisingly the design, development, and deployment of the automated system comprised a relatively small percentage of the overall time spent on the project (~20%). The majority of the time was spent on data preparation (~45%) and manual corrections (~35%). The time spent on data preparation stemmed from not only the variety of the data used, but from the fact that many of the older LiDAR collections were found to have data gaps that had to be resolved by contacting the originating agency. Whether the time and resources devoted to manual corrections was warranted is debatable. In no case did the total tree canopy change by more than 2% for an individual county following manual correction. Nevertheless, our experience from prior projects has shown that datasets are judged not only by the reported accuracy, but also by their cartographic representation. We conclude that the resources were wisely allocated to manual corrections as they remove questions or doubts that would arise from having errors present that are statistically insignificant but visually noticeable.

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