Final Report:
Spectral Data Analysis and Applications for the Urban Forest of the City and County of Denver for the Field Season of 2018

20 March 2019

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Executive Summary

This study continues project activities conducted in 2017 for early-detection of the Emerald Ash Borer (EAB) threat to the City and County of Denver. The initial report (Final Report Early Detection of Emerald Ash Borer Project for the City and County of Denver, dated: 2 March 2018) determined that spectral imagery collected from an Unmanned Aerial System (UAS) provided sufficient spatial and spectral resolution for the early detection and monitoring of an EAB infestation.

This report focuses on two main objectives of the 2018 phase of the project:

1. Efforts to scale both the collection and analysis to determine the best methods to collect data at the municipal scale to detect Emerald Ash Borer, and
2. To develop additional spectral and spatial analyses for Urban Forestry efforts.

This report details the 2018 outcomes of this project, including

1. A description of the methods used to conduct low-cost data collection in the City and County of Denver and Boulder County to detect EAB
2. Further refining techniques to detect and monitor EAB, including the lack of detection in the City and County of Denver
3. Using machine learning to segment urban forest canopy for future Canopy Cover Analyses
4. Refinement of the Plant Health Analysis tool for large scale health assessments of the urban forest
5. The ability to accurately identify tree species
6. Successful development and application of Artificial Intelligence techniques for large-volume data analysis
7. Determining “leveraged utility” of both the data and analytic processing to benefit other aspects of Urban Forestry applications.

This report includes detailed appendices of the findings that will allow City staff to assess the results and make decisions about additional detection and monitoring efforts going forward. These appendices include results and processes for context.

Introduction

The development of ultra-high-resolution aerial sensors and the deployment of other data collection systems necessary for Urban Forestry applications has the potential to service a wide variety of Urban Forestry concerns, as well as elevate the contributions of Urban Forestry for the overall improvement of city operations and resident health and wellbeing. In addition to developing tools and techniques to address the EAB problem, this report also addresses the inclusion of Urban Forestry into the greater City Operations and Planning enterprise utilizing many of the same data collection and analysis techniques.

The central challenge to understanding these benefits and linkages is the efficient collection, analysis and presentation of the data to decision-makers across the city that showcase the many benefits of a healthy and thriving urban forest. Our efforts to scale both the collection and analysis of Ash tree data to the "municipal-level" created challenges the City will face across the full breadth of imagery-related Urban Forestry programs involving an expansive data collection and analysis effort.

Overview

This 2018 project consisted of three phases, each building on the other to achieve the collection goals:

Phase 1: Demonstrating an efficient and cost-effective means for data collection to manage EAB.
Phase 2: Developing scalable data analysis tools in anticipation of large-scale remote sensing operations
Phase 3: Developing tools for tree species Identification, canopy cover analysis and plant health assessment

Each phase builds upon the others to address the challenges of large-scale urban forest remote sensing to detect pests and disease, assess canopy cover, track overall forest health, perform aerial inventories, and assess disasters and disaster response.

Phase One: *Demonstrating a cost-effective means for data collection to address EAB.*

Data collection on the municipal-level (>80 square miles) presents challenges for employing a cost-effective collection platform that is timely, reliable (factoring weather delays) and delivers sufficient

spatial and spectral resolutions to identify features of interest. While Unmanned Aerial Systems deliver sufficient resolution and are less dependent on weather impacts, they lack efficiencies in flight times

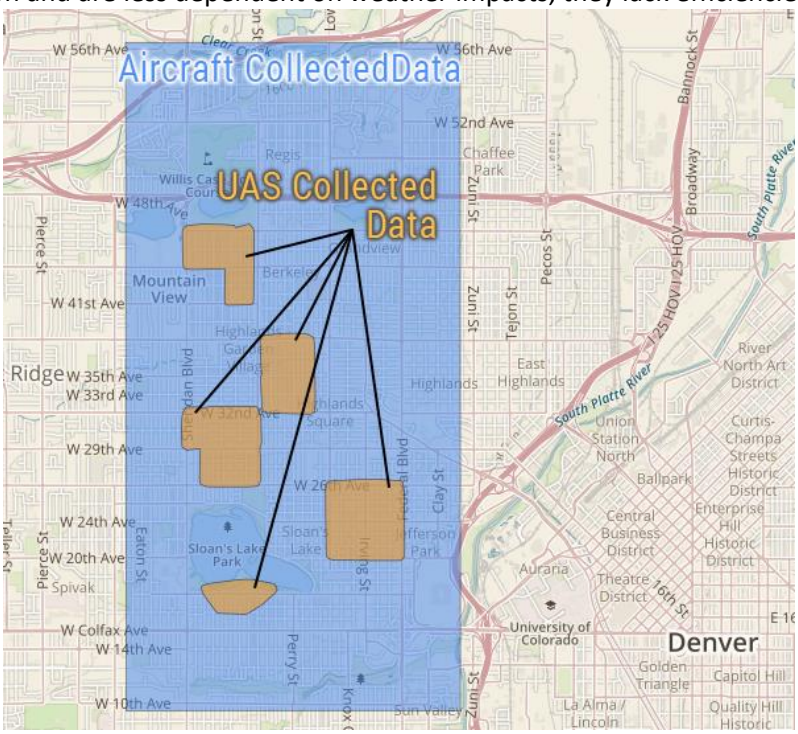


Figure 1. A combination of manned and unmanned aircraft was used to image the northwestern portion of Denver in 2018.

and must remain in sight of the Pilot in Command which limit their effective ranges. Aircraft, while able to remain on station for hours, must fly at a higher altitude (generally above 1000 feet Above Ground Level), which decreases spatial resolution and adds significant operating costs to the project. Also, mobilization of manned aircraft with appropriate sensors for urban forest remote sensing is heavily schedule-dependent and it is currently difficult to schedule flexible flight options. For the Denver collection, the flight was scheduled many days in advance, and the day of the flight smoke from western wildfires partially obscured the data collection area.

The team determined that a combination of platforms *(Figure 1)* that exploits the high-resolution abilities of UAS flights and the coverage from economies of scale from aircraft to be a cost-effective strategy that compensates for the limitations for each platform. One of the tasks for this project was to identify cross-over technologies developed to accommodate data from UAS for data collected by manned-aircraft. In some cases, detailed study of tree conditions required the spatial and spectral advantages of the UAS over manned aircraft imagery.

Each of the UAS-collected areas represents roughly four hours of collection time and one day of image processing time to assemble the data for follow-on analysis (using one UAS data collection platform), and samples approximately 15% of the manned aircraft data. The aircraft data collection area was completed in roughly two hours of flight time over Denver flying a “lawnmower” pattern and collected 14 square miles (36 square kilometers) of multi-band spectral data. Given adequate weather the entire City and County of Denver can be imaged in three to five days of manned aircraft flight time.

All the data collected from UAS and manned aircraft was processed and analyzed on Spectrabotics proprietary software for mosaic construction using commercial cloud enterprise systems.

Phase Two: *Development of scalable data analytic tools to accommodate the 100x increase in the volume of data collected from the previous EAB study effort for the City of Denver.*

Cutting edge data science tools that combine high-performance cloud computing services with emerging Machine Learning routines can effectively manage the increase in data volume, velocity, and formats. Data science tools built to analyze small-scale collections and satellite imagery data are not well-suited to efficiently manage even the limited data collected for this project. The team's new tools are based on the advances in Artificial Intelligence (AI) applications for computer-vision analysis of objects. The nature of AI requires a significant effort to "train" the computer models to separate and identify objects contained within the imagery. We trained the computer to "recognize" objects within the data (e.g. cars, trees, lawns, streets, sidewalks, rooftops) as a means to separate lawns, shrubs, and groundcover from trees for more accurate analysis.

While training the models requires time and resources to improve results, the actual image processing time is significantly shorter; by current processes, a one-square kilometer section of Denver can be analyzed within 15 minutes to separate and label all of the search objects. This represents a roughly 70% decrease in processing times for a typical multi-band imagery dataset. Because the underlying object-identification routines can be adapted to recognize any input object through training, data

Figure 2. Early results of a Canopy Cover Analysis performed with proprietary Machine Learning algorithms. This image was taken over the Berkeley neighborhood.

collected for Urban Forest Studies can be repurposed for other areas of study (roadway maintenance, utility management, etc).

Phase Three: *Development of Tools for Tree Species Identification.*

Appendix A further discusses the results of this development effort.

Modern spectral imagery tools used for material identification from satellite and low-resolution aircraft imagery are ill-suited for high-resolution analysis of tree species because of the increase in "false-positive" results from pixel-by-pixel analysis. Modern AI tools using high-resolution UAS data are able to recognize "trees" as a distinct object and thereby analyze the feature as an "object" and not pixels. This allows for the inclusion of qualities like "texture", "shading", and "relative size" in species determination. Treating trees as "objects" also allows for the inclusion of other qualities such as height and Diameter at Breast Height (DBH).

The efforts in Denver and elsewhere to date show excellent promise for developing additional tools for the City and County to better manage it's urban forest detailed results of these efforts can be found in the appendices at the end of this document.

Phase Four: *Integration of the analytic results into a larger Urban Forestry application for increased exposure and utility of the program's goals.*

Urban Forest studies include a large portion of the geographic coverage of Denver. Understanding how the urban forest both interacts and affects other aspects of city life and operations requires a holistic view that integrates both analytic results and coverage information. As learned in Phase Two, adding new data to the data models for tree-species increases the accuracy of the Machine Learning routines and as learned in Phase One, data collection can often be cost-prohibitive. An effective way to both increase citizen-engagement and Urban Forest studies is to disseminate results on a web-based platform that enables citizens to upload specific information about city trees that improves the accuracy of tree data-models and at little cost, increases the volume of data related to city trees maintained by the city.

Results

This study demonstrated three key technical advancements for data collection, analysis, and dissemination needed to institute a city-wide effort to improve urban forest health, to augment current ground-based inventory, and to better determine threat assessments:

Finding 1: Emerald Ash Borer. *The team **did not find EAB** in the UAS collection area (the manned aircraft sensors were not capable of collecting the bands needed for the specialized tool developed for early-onset EAB detection). See Appendix C for more detailed information on EAB.*

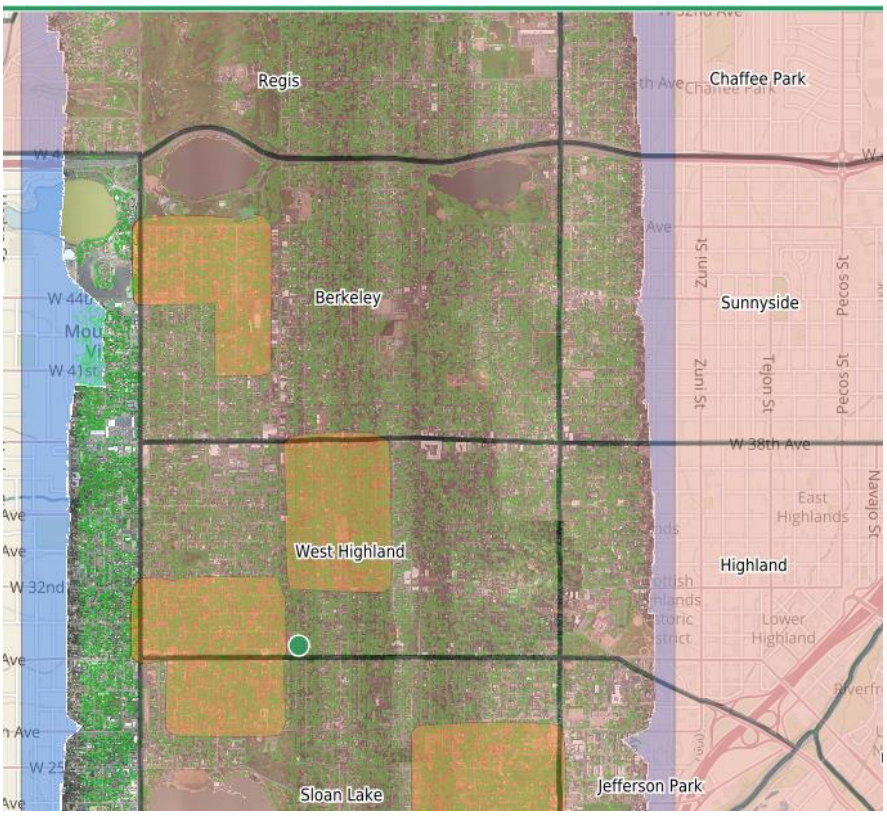


Figure 3. Overview of data collection areas with UAS collection areas in yellow and aircraft collection area in blue, tree canopies outlined in green.

Fine-tuning of the tool the team developed in 2017 to detect early onset EAB has allowed for more refined analysis in areas where EAB is present. For example, the team can **now detect trees treated for EAB** (Appendix C). Detection of distinct Phases of Early Onset EAB is possible in other areas as well, including Gunbarrel, Longmont and Superior in Boulder County.

Finding 2: Canopy Cover Analysis (CCA). *The team performed CCAs with both manned aircraft and UAS data, using Machine Learning algorithms for the entire process. The results are mixed, with the manned aircraft analysis achieving **~80% accuracy** and the UAS analyses achieving **~90% accuracy**. See Appendix B for more detailed information.*

Figure 4. Depiction of the development of machine learning algorithms for Canopy Cover Analyses. Find more detail and applications in Appendices.

Due to lower image resolution from **aircraft imagery**, the ability of the algorithms to accurately detect tree canopy and segment trees from buildings, lawn, hardscape and groundcover is approximately 80% accuracy after the first phase of algorithm development and testing, with some areas better than average and a few areas with slightly less accurate coverage (Figure 4, see Appendix B for more information). Given that this is likely one of the first attempts at using Machine Learning for urban forest CCA, this is seen as a good result and the team will continue to refine the algorithms to achieve greater accuracy.

The **UAS imagery** provided the Machine Learning algorithms much higher resolution and noticeably clearer data. The result of this increased resolution is that the initial CCAs in Denver achieved ~90% accuracy after the first phase of algorithm development and testing (Figure Z and Appendix B). The team is confident these results can be improved, and has set a work goal of accuracy improvement for the 2019 flight season, including using CCA output for the development of aerial inventories (more on this topic below).

Finding 3: Plant Health Analysis (PHA). *The team slightly refined its PHA tool developed last year. In the 2018 data we are better able to separate areas in the canopy with different conditions, making it* ***easier to analyze overall health*** *and better representing the process of health assessment from the ground by human inventory collection.*

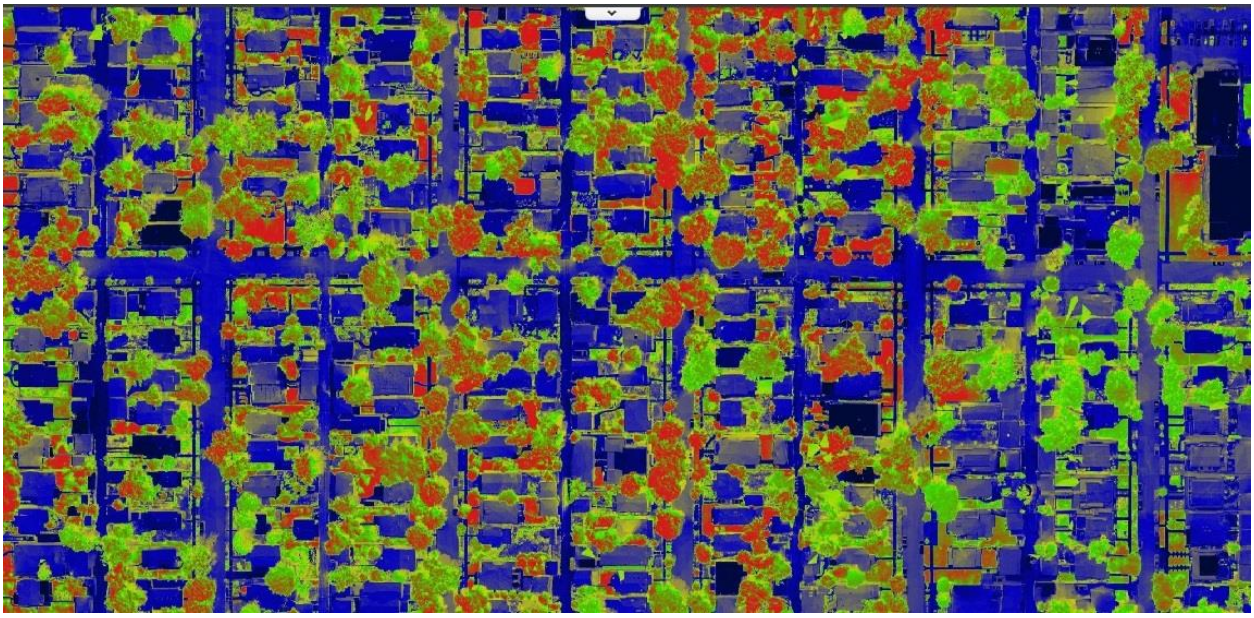


Figure 5. Development of a tool for aerial classification of plant health. This tool will be used in the development of an aerial inventory process.

Due to the time passed since the last ground inventory and very dry weather in 2018 - as well as widely varying watering and exposures across private parcels - calculating a realistic inventory comparison accuracy percentage is problematic at this time. However, the team has a number of training trees across the collection area and the PHA tool does generally accurately represent their current health at this time (see Appendix A for more detail).

The ability to accurately assess overall canopy condition using aerial remote sensing affords urban forest managers the ability to do spot checks on forest health during times of drought or extreme heat; after infrastructure work such as street improvements or sidewalk maintenance; or after a harsh winter or unseasonable freezes.

The ability to analyze plant health from above means that aerial inventories are possible. The team has set a work goal of finding appropriate work flows to **develop initial aerial inventories** for the 2019 flight season.

Finding 4: Tree Species Identification. *The team greatly refined its ability to identify species from the air. Current accuracy is a **solid ~80%,** but more algorithm training is needed.*

The team now has machine learning algorithms attacking the species identification problem. With a 5-band multispectral sensor, at this time and with the amount of work expended thus far, it appears multispectral sensors have an accuracy limit somewhere less than 90%. Compared with citizen-volunteer inventory accuracy this might be an acceptable result. As the team collects more data and devotes resource time to machine learning training, it is expected that results will begin to approach 90% with 2019 data.

Figure 6 - Initial test effort final results to improve Machine Learning routines to address Urban Forest Aerial Inventory studies.

Finding 5: Data Collection Platform Performance. *The combined-approach to data collection using both the UAS and manned aircraft outfitted with similar imaging technologies overcomes issues related to scaling data collection with sufficient spectral and spatial resolution to conduct meaningful analysis of the data.*

UAS data collection of urban forests on a municipal-level presents numerous challenges for a coordinated effort.

For example, a 200 square kilometer area of interest (roughly city-size) and a time frame for one-month of collection requires roughly 30 drone operators and a combined cost over $100,000 (estimated at $500/day per operator.) Cost can be significantly higher based on equipment and sensors used and do not include data processing and analysis. By comparison, a small manned aircraft (eg. Cessna 180) can collect the entire area in roughly five days at roughly half the operating cost of UAS collection. For this effort we contracted Tailwind Imaging (http://www.tailwindimaging.com/) to configure their sensor pod to collect data in roughly the same spectral bands as the UAS sensor *(Figure 2)* to conduct a side-by-side comparison of the data for use in follow-on analysis and to investigate cost-effective large-area data collection options.

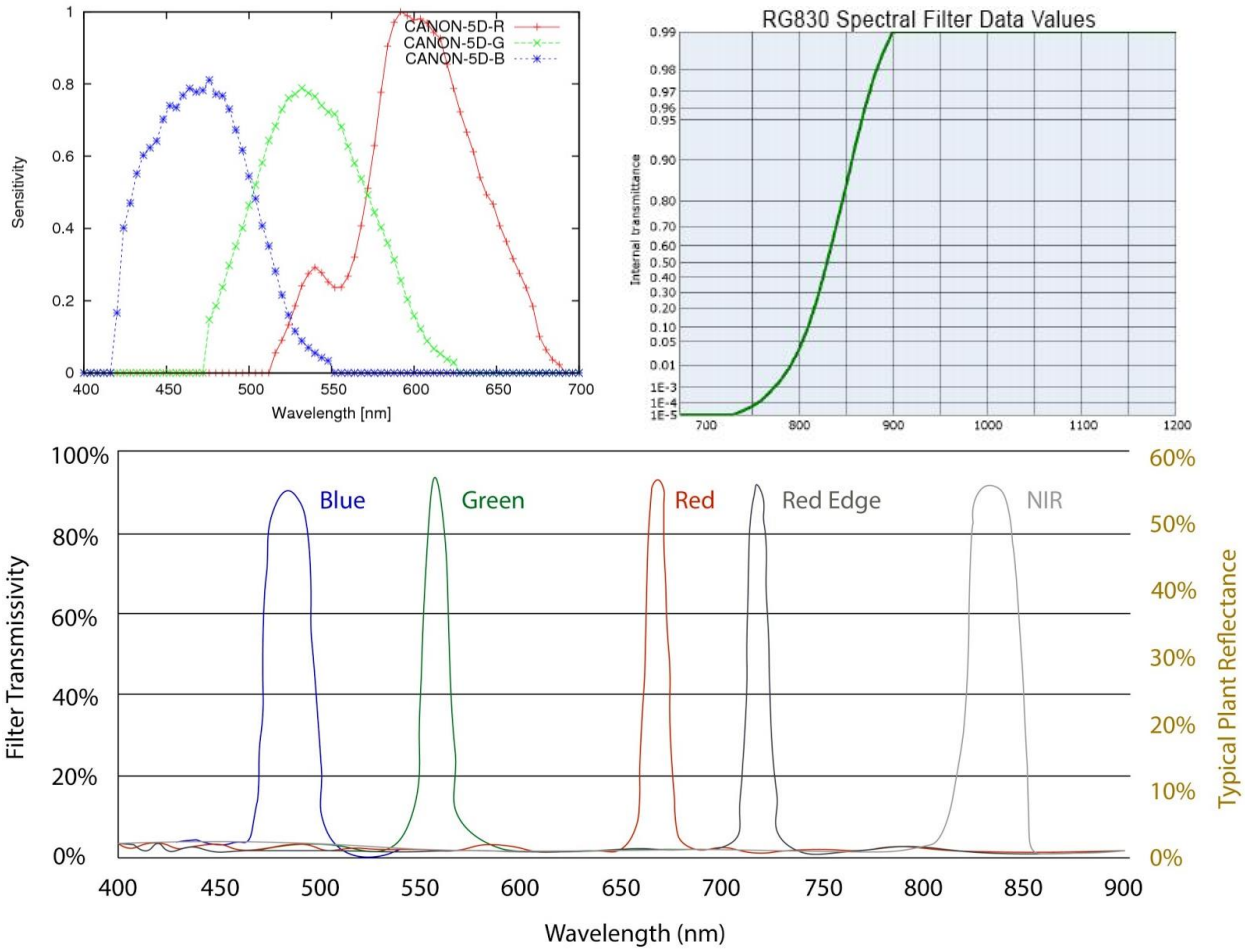


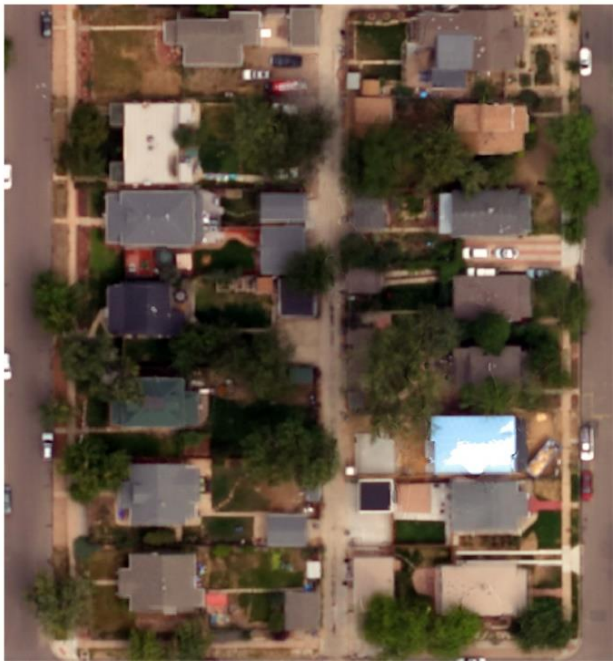
Figure 7. Comparison of wavelengths collected by the sensor array on the personed aircraft (top) and sensor mounted on the team's UAS (bottom).

The UAS carried a five-band multispectral sensor specifically designed for UAS operations at an operating altitude of 120 meters. At this altitude the average spatial resolution of the collections was 6-centimeters per pixel.

There were trade-offs in the datasets between the two platforms. UAS-collected data has a higher spatial resolution (< 6 centimeters per pixel) while the aircraft can collect at roughly 9 centimeters/pixel. The UAS sensor was designed specifically for multispectral agricultural analysis

UAS Imagery: 6cm Pixel Resolution

Manned Aircraft: 9cm Pixel Resolution



whereas the Tailwind sensors were professional-grade cameras used for photography and configured with lenses able to provide sufficient spatial resolutions for aerial remote sensing.
It is our assessment that a combination of sensors is the most effective collection option due to the limitations of both sensors (e.g. coverage, bands collected, resolutions) and the need for continued analytics testing to develop new products from the datasets and refine machine-learning data models. Key to an effective co-collection plan is the flexibility of the manned-aircraft sensor suite. Since the UAS sensors are largely fixed in design and operation, augmenting the UAS with manned flights benefits greatly from a flexible and more robust sensor suite that can be tailored to augment and enhance the UAS systems.

The result from our efforts was approximately 14 square miles (36 square kilometers) of manned aircraft collected multispectral data in four bands (Green, Blue, Red, Near Infrared) and three square kilometers of UAS collected multispectral data in five bands (Green, Blue, Red, Red-Edge, Near Infrared). All data was collected over the same area *(Figure 1)* to use both datasets to augment and enhance the analytic development. It is our recommendation that municipal-level data collection efforts utilize both platforms in ways that optimize costs for broad-area collections, and encourage enhanced collections from low-flying UAS for precision *collections.*

Finding 6. Artificial Intelligence and Machine Learning Performance. *The development and migration to an Artificial Intelligence-based analytic approach for tree health assessment and species identification overcomes many of the limitations of conventional analysis built for satellite data and adapted for UAS data.*

UAS and manned aircraft collected data are a roughly 100x increase in the amount of data covering the city. Traditional spectral imagery built for satellite data analyzes objects on a per-pixel basis for vegetation health assessments and object classifications. The high spatial resolution of the UAS and aircraft data create a large number of classification errors. Artificial intelligence (AI) overcomes this

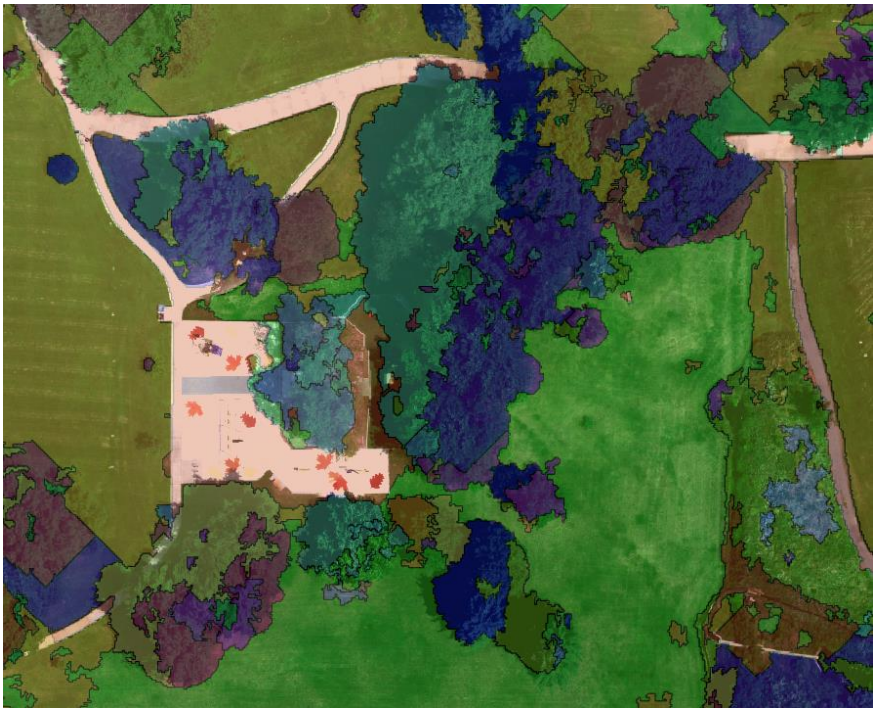
error by “recognizing” objects based on a data-model that represents typical in-scene objects (rooftops, trees, grass fields, streets, sidewalks, etc.) In effect, the computer “recognizes” objects the same way humans recognize objects based on shape, texture, angles, color, and placement. Just as a human can rapidly identify a tree in an image based on being taught to recognize trees (and not looking at each leaf individually!) so can the AI algorithms making large areas classifications efficient and computationally economical.

Key to improving the accuracy of the AI predictions on in-scene object detection is the addition of more data about the objects. Thus, the purpose of the UAS data was to augment and enhance the manned aircraft collections to make that dataset more accurate in its classifications. Appendix B highlights the improvements of the overall analytic products based on inputs from analyzing the manned aircraft collections with and without the UAS data.

Artificial Intelligence processing consists primarily of utilizing Machine Learning algorithms on data collected for this project. The algorithms are first taught how to recognize an object and the resultant is a “data model” that mathematically represents in-scene objects (tree, roof, road). Once the models are built, large swaths of collected data can be rapidly classified (2-10 minutes per square kilometer of imagery on average).

Vegetation species identification using Machine Learning Data Models requires more development of the data models to improve the accuracy of the analytics over simple object classification (rooftop vs. tree). This is ideally suited for UAS flight missions able to collect with varying sensors and at relatively low-cost. Each sample collect adds to the growing library of data that “represents” a tree species under differing lighting conditions, different health and water conditions, and different periods of [leaf-out] through the summer months.

For this period of performance we concentrated analytic development of a species identification routine on sample UAS imagery. As with all computer vision and Machine Learning efforts, there is a period of



training where early efforts often yield incorrect results and improve over time as new imagery and modifications to the routines improve accuracy. To date we have successfully trained the analytics to recognize and separate trees from other background materials and objects. Tree species identification shows promising results and will improve over time with expanded efforts to combine ground truth data with UAS-collected imagery for analysis.

Finding 7. Integration into Additional Platforms. *The integration of Urban Forest analytic results on a larger platform provides the foundation for a more complete analytic solution as well as opportunities through leveraging data utility from other sources to become more inclusive across city management departments and citizen engagements.*

Analytic results from Urban Forest studies is highly contextual and a comprehensive understanding of the health and welfare of an Urban Forest requires the inclusion of multiple datasets to provide a comprehensive understanding of the forests' health. For this study we segmented the tree canopy coverage for area studies and health assessments of the trees. Both measurements fall within the scope of the study as well as the data processing capabilities of the emerging AI platform. The resultant data products can be displayed as a common geospatial data-layer for rapid context and interpretation.

Migrating results for study and dissemination to a Geospatial Information Systems (GIS) platform expands the impact of the study and creates the foundation for an interactive Urban Forestry Urban Forestry initiative. Central to this platform is an integrated analysis platform for the collection of the widest assortment of tree-related data which can be ingested by the AI routines and used to enhance tree data-models for more accurate analysis. A Cloud-based GIS platform for information sharing could also be used to solicit and incentivize citizen-collected information specific to tree health and species data that can be added to the AI data models.

As many arborists and Urban Forestry experts agree, the impact of city tree health, placement, and diversity can be measured across numerous Urban Forestry areas of interest (eg. air quality, safety, transportation, utility management). The common elements across all these areas of interest is location and conditional data of the environment. These data values form the foundation of a Urban Forestry application to understand complex interactions between the environment, city operations, and citizen Quality of Life. While there are several data challenges to a comprehensive environmental monitoring program, AI holds potential to solve many of these challenges by connecting subject matter expertise about an issue with available data regardless of data source.

Finding 8. Integration into Other Departments. *There are opportunities to integrate Urban Forestry applications into other city departments.* As many arborists and Urban Forestry experts agree, the impact of city tree health, placement, and diversity can be measured across numerous Urban Forestry areas of interest (e.g.: air quality, safety, transportation, utility vegetation management). The common elements across all these areas of interest is location and conditional data of the environment. These data values form the foundation of an Urban Forestry application to understand complex interactions between the environment, city operations, and citizen Quality of Life. While there are several data challenges to a comprehensive environmental monitoring program, AI holds potential to solve many of these challenges by connecting subject matter expertise about an issue with available data regardless of data source.

Next Steps

For Emerald Ash Borer

Artificial Intelligence approaches to early detection of EAB is the future of urban forestry studies for pest and health-related threats to urban forests. As the cost of data collection decreases and the amount of available data increases, new tools must be built to accommodate both the rapid and automated analytic approach to environmental concerns as well as the ability to integrate with expanding efforts to emplace related Urban Forestry programs. AI analysis for EAB requires more input data to improve the accuracy of the Machine Learning data models. For this effort we used the EAB data from last year's collections over Boulder, Colorado, affected trees. While these models will work with Denver data, more work needs to be done to ensure the models work reliably with unknown data sets.

For Inventory

AI data analysis development for this effort can successfully segment trees from all other background materials within UAS and aircraft data. More input data (and time) is needed to improve accuracies for species identification which, for this effort, is roughly 40% accurate on Denver aerial imagery. Future efforts to improve accuracy will focus on selecting and improving Machine Learning routines and collecting additional tree data to add to the current library of species data models.

For Urban Forestry Programs

Collected data and analytic results for this project are currently hosted on the Spectralink platform for visualization, sharing, and follow-on analysis by Denver Parks and Recreation staff. Since future Urban Forestry efforts will likely be hosted and or integrated on a Software as a Service (SaaS) platform, staff can use this opportunity to gather lessons-learned on utilizing this dissemination medium to interact with the analytic results for future urban forestry studies. Key to utilizing an AI approach to health and species identification is the assembly of various kinds of data to enhance data models. A SaaS platform has the potential to allow the public to help contribute to this effort (data collection) to improve the overall accuracy and content of the Open Data Catalog Denver Tree Inventory from the convenience of a Smartphone application.

Acknowledgements

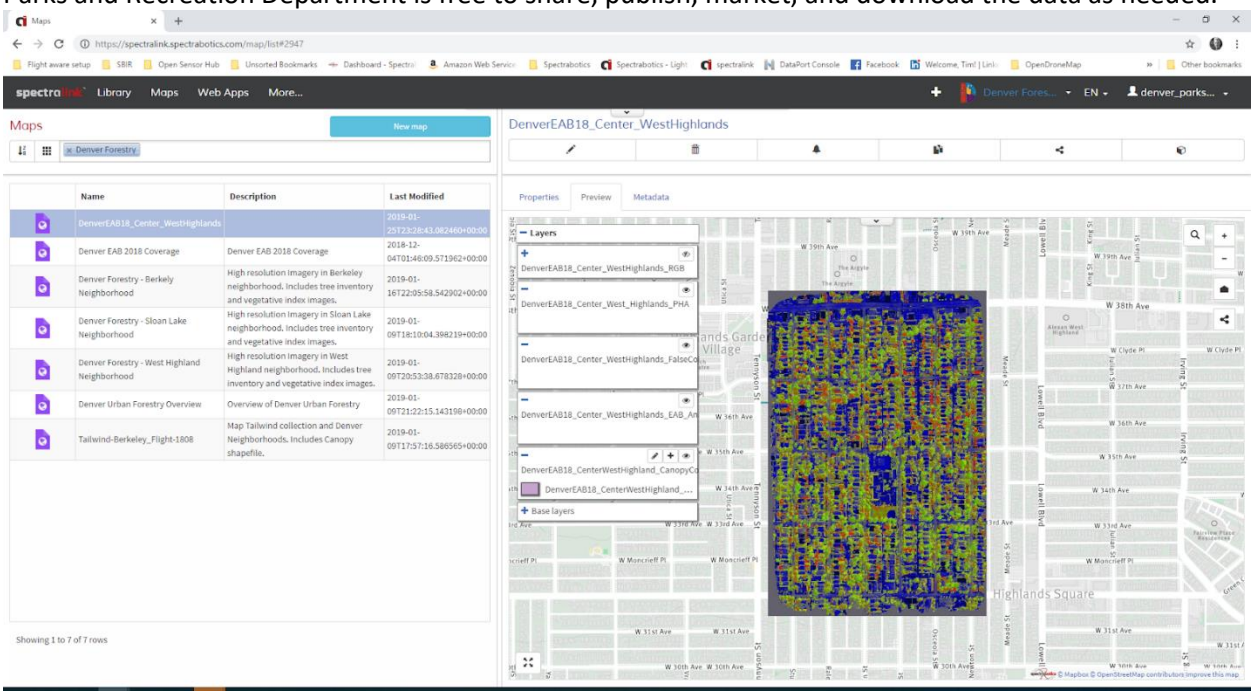
The following have been instrumental in aiding the development of the team's processes:

Colorado College; City and County of Denver; Colorado State University: Horst Caspari, Greg Litus, Frank Stonaker; Vince Urbina; Rich Alward, Aridlands LLC; Bruce Talbott, Talbott Orchards; Mike Fuller, Fuller Orchards; Ken Wicklund, City of Longmont; Payne Jungblut, - Arbor Drone ground crew

Access to Project Data

Online Data

All processed imagery and tabular data is stored within the Spectralink™ platform. Access to the data is controlled by Denver Parks and Recreation personnel and accessible to anyone with login credentials. Spectrabotics will maintain the data for a period of one year for the City of Denver and the Parks and Recreation Department is free to share, publish, market, and download the data as needed.



Site location: https://spectralink.spectrabotics.com/auth/login
Login Name:
Password:

Instructions on map creation and data management are available upon request to Spectrabotics.

Appendix A
Tree Species Identification and Aerial Inventory with Machine Learning Algorithms

Background. This study demonstrates the successful application of emerging Artificial Intelligence data science routines to address the potential of aerial inventory of Urban Forests. Our processing utilizes three feature-based Machine Learning routines that identifies objects based on "teaching" the algorithm

Figure 1 – Original image for Artificial Intelligence processing development for aerial inventory of the Urban Forest

to recognize an object (tree, grass, parking lot, roof top, etc.). This is a departure from standard spectral imagery analysis/classification that analyzes every pixel for a match to a known input signature. The spatial resolution of UAS imagery creates significant challenges for existing Artificial Intelligence (AI) routines to identify trees. Rather than 10 pixels per tree from satellite imagery or 250 pixels per tree from aircraft, UAS imagery may contain 1000-10,000 pixels

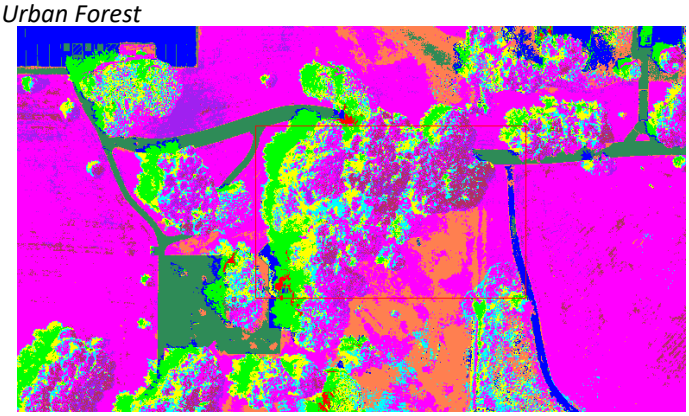


Figure 2 - Pixel-level image classification identifying spectrally different objects within UAS spectral imagery.

per tree – a significant difference for algorithm programming. Mastering this challenge will allow aerial inventories of the urban forest.

Computer Vision (a sub- discipline of Artificial Intelligence) seeks to "recognize" common object based on size, shape, texture, and placement much like how ~~we~~ (humans) recognize objects within imagery. Essential to this object-recognition is the ability to "teach" the routines what constitutes an object and for this, spectral imagery plays a key role in providing detailed information. In this particular case, data within the infrared spectrum speeds the development of learning routines because there is more descriptive information about objects with which to train the classifiers.

The following samples illustrate the progression of our routines to support aerial inventory of urban forest landscapes that work to identify tree species.

Initial Trials. We applied a "Crawl-Walk-Run" approach to aerial inventories by first teach the routines to separate large, recognizable objects with a park. For this project we continued working with our UAS imagery of Keewayden Park, Boulder, Colorado, for which we have extensive ground truth for Emerald Ash Borer detection. The analysis result in Figure 3 was derived from a single image-set and identifies clear delineations between large and discrete objects within the scene. After using in-scene pixels (tree, artificial, grass, dirt) to teach the Machine Learning routines the various objects within the scene, the routines apply that knowledge to the entire scene to find all objects that are similar to the object of interest.

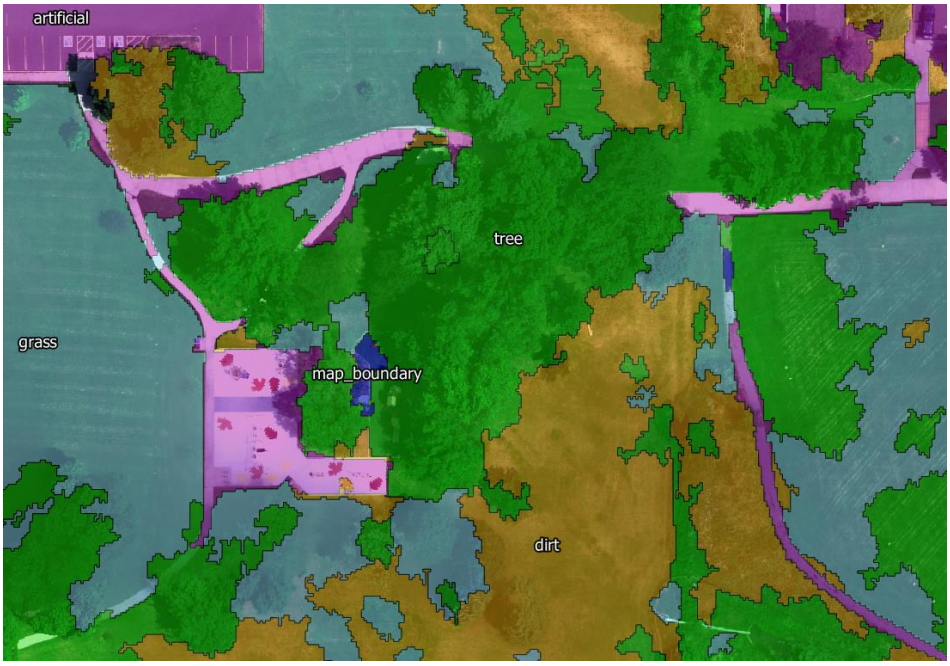


Figure 3 - Initial results from Machine Learning object classification.

Subsequent Progress. Progress in Machine Learning routines comes as the result of adding more information about an object as well as selecting the most accurate classification routine. These routines have been developed and studied for their success (or failure) to address the unique nature of objects of

interest. For example, some routines account for object "texturing" during the classification process while others weigh other mathematical features between the spectral bands. The results in Figure 2 indicate that significant improvement was needed for feature detection and delineation before more sophisticated classifications for inventory analysis become practical. Figure 4 represents continued improvements to the processing and subtle improvements in large object identification.

Figure 4 - Progression of Machine Learning routines to improve object identification accuracy.

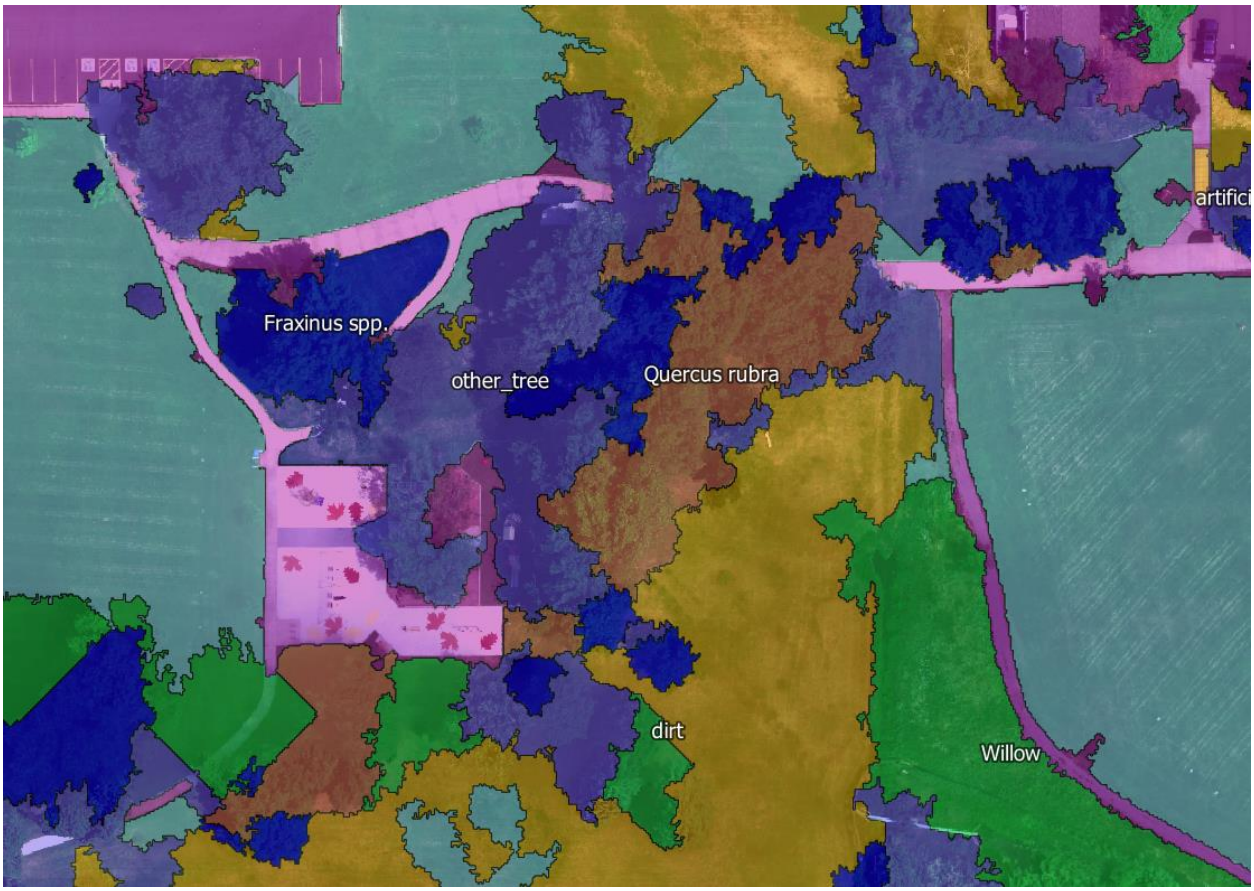


Figure 5 - Progression of tree object detection and initial species identification.

Further Progress. Improvements in the Machine Learning approach to aerial inventories indicates that with enough input data for object model development, improvements in object identification accuracies will enable faster, more accurate, and less costly aerial inventories of urban forests. Additionally, the same input data can be used for other analysis efforts such as canopy studies for heath and potential infestations as well as diversity studies for overall urban forest health studies (Figure 6)

Figure 6 - Initial test effort final results to improve Machine Learning routines to address Urban Forest Aerial Inventory studies.

Denver Species Classifications. Figure 7 depicts the early results of a machine learning algorithm to identify tree species in the City and County of Denver (Berkeley neighborhood). Work in Denver, Boulder and elsewhere allowed the team to refine its algorithms for the difficult work of identifying species in the City and County of Denver – a dense urban area with many confounding surfaces on the ground.

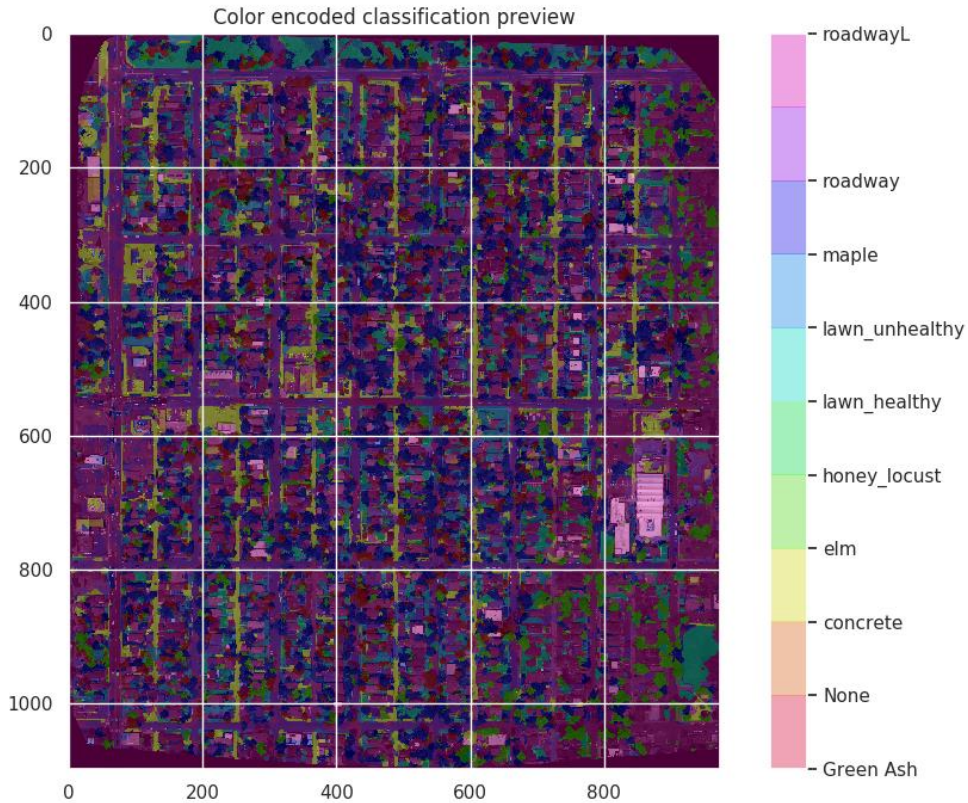


Figure 7. Depiction of Denver's Berkeley neighborhood after a machine learning algorithm was trained to identify vegetation and infrastructure.

Plant Health Assessments (PHAs). The team continues to refine its PHA tools, with a goal towards incorporating it into large-scale inventories. 2018 results showed good correlation again with the Denver 2015 tree inventory, despite many trees looking haggard due to very low winter and seasonal moisture. The team suspects that 2019 will be the last year our results can be reliably compared to the 2015 inventory, due to weather and time passage.

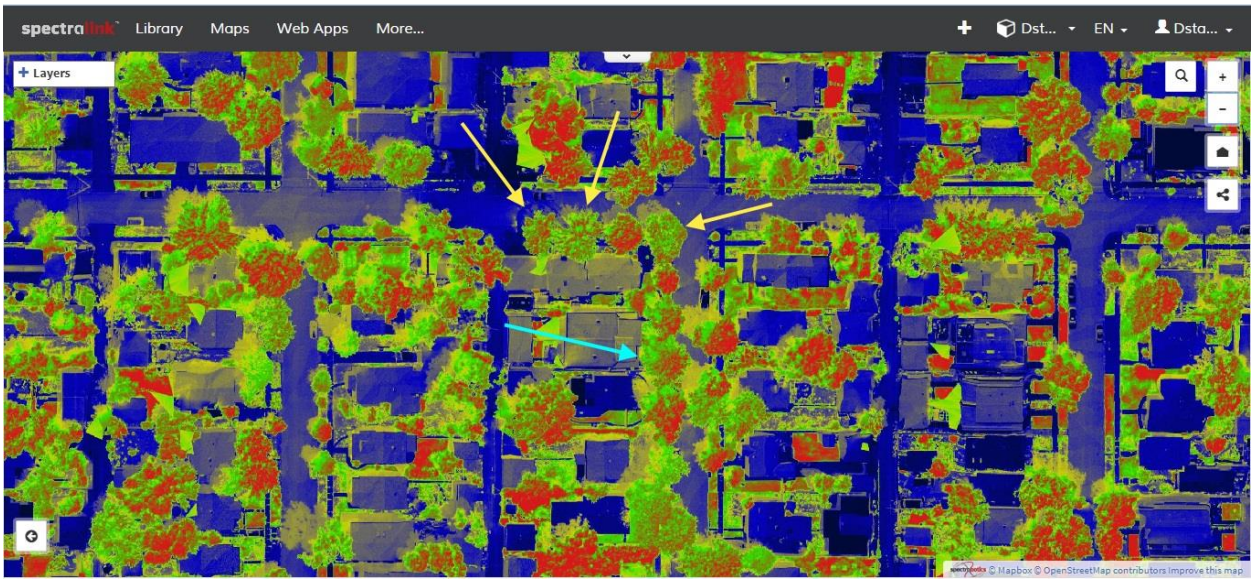


Figure 8. Examples of training trees used to validate tools, vegetation indices and machine learning algorithms.

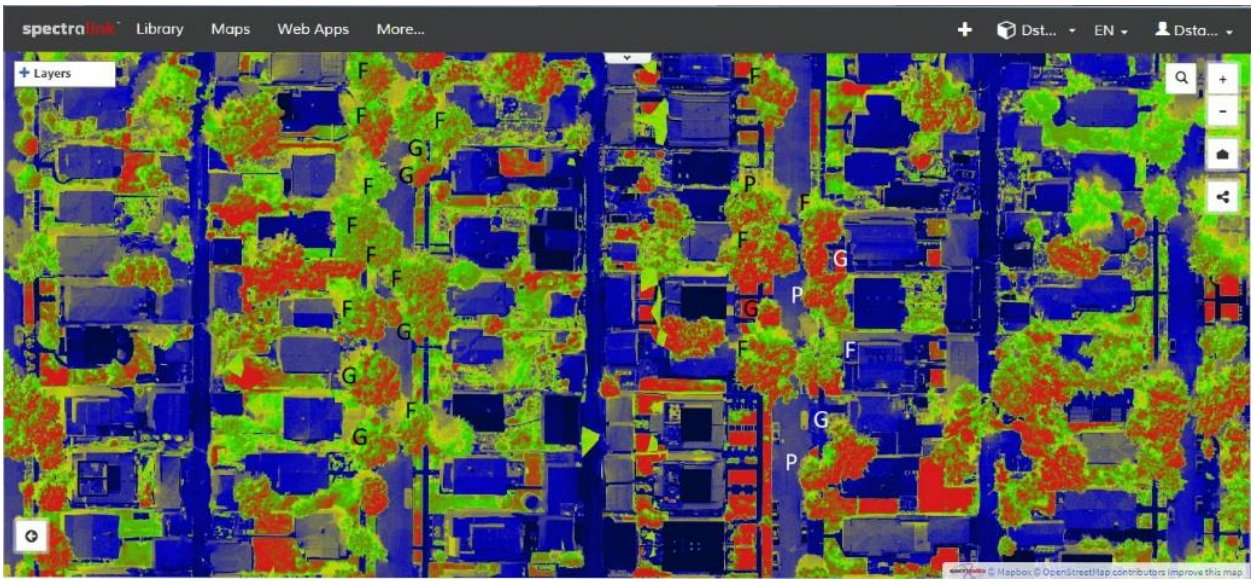


Figure 9. Comparison of Denver inventory condition class with the team's current version of its Plant Health Assessment tool. A qualitative assessment shows good correlation. Quantitative assessments are difficult at this time as it is unclear how the inventory classifications were obtained for each tree. Additional quantitative learning is needed to develop this tool to highest accuracy with respect to the formal inventory.

CONCLUSION

Our innovative Machine Learning algorithms currently in late-stage development will soon be able to segment urban canopy for species identification and Canopy Cover Assessments in the City and County of Denver (and elsewhere) with a high degree of accuracy. As of this report, our Canopy Cover Assessment development is close to being as accurate as other published studies (within ~10%, as outlined in the report body). We expect that soon we will be able to identify individual tree species with multispectral sensors to approximately 80-85% accuracy – as good or better than several methods of ground-based inventory.

Our goals for 2019 include collecting data for the first tests of urban forest aerial inventories, including using our machine learning algorithms for canopy cover assessments, species identification, and integrating existing formulas to estimate DBH by crown size and species.

Being able to monitor and accurately identify species on private land will go a long way to assist urban forest managers in monitoring and controlling large-scale pest and disease infestations like EAB. Knowing precisely where a disease front is can potentially save urban forest managers time and money in the future, and give decision-makers confidence that effectively combatting a pest or disease can be cost-effective.

Appendix B
Canopy Cover Analyses with Machine Learning Algorithms

The team performed Canopy Cover Analyses (CCAs) on data from both manned aircraft and UAS collected in Denver, CO, USA, using machine learning algorithms for the entire process. The results are mixed, with the manned aircraft analysis achieving ~80% accuracy and the UAS analyses achieving ~90% accuracy.

Due to lower image resolution from **aircraft imagery**, (Figure 1) the ability of the algorithms to accurately detect tree canopy and segment trees from buildings, lawn, hardscape and groundcover is approximately 80% accuracy after the first phase of algorithm development and testing, with some areas better than average and a few areas with slightly less accurate coverage (Figure 1, see Appendix A for more information). Given that this is likely one of the first attempts at using Machine Learning for urban forest CCA, this is seen as a good result and the team will continue to refine the algorithms to achieve greater accuracy.

Figure 1. Comparison of UAS and manned aircraft images. The manned aircraft has ~33% less resolution and has more atmospheric obscuration, as explained in the main document text.

The **UAS imagery** provided the Machine Learning algorithms much higher resolution and noticeably clearer data. The result of this increased resolution is that the initial CCAs in Denver achieved ~90% accuracy after the first phase of algorithm development and testing (Figure 2 and body text). The team is confident these results can be improved, and has set a work goal of accuracy improvement for the

2019 flight season, including using CCA output for the development of aerial inventories (more on this topic in Appendix A).

Figure 2. Early result of a Canopy Cover Assessment from personed aircraft data showing varying accuracy due to reduced resolution (as outlined in the body of the report).

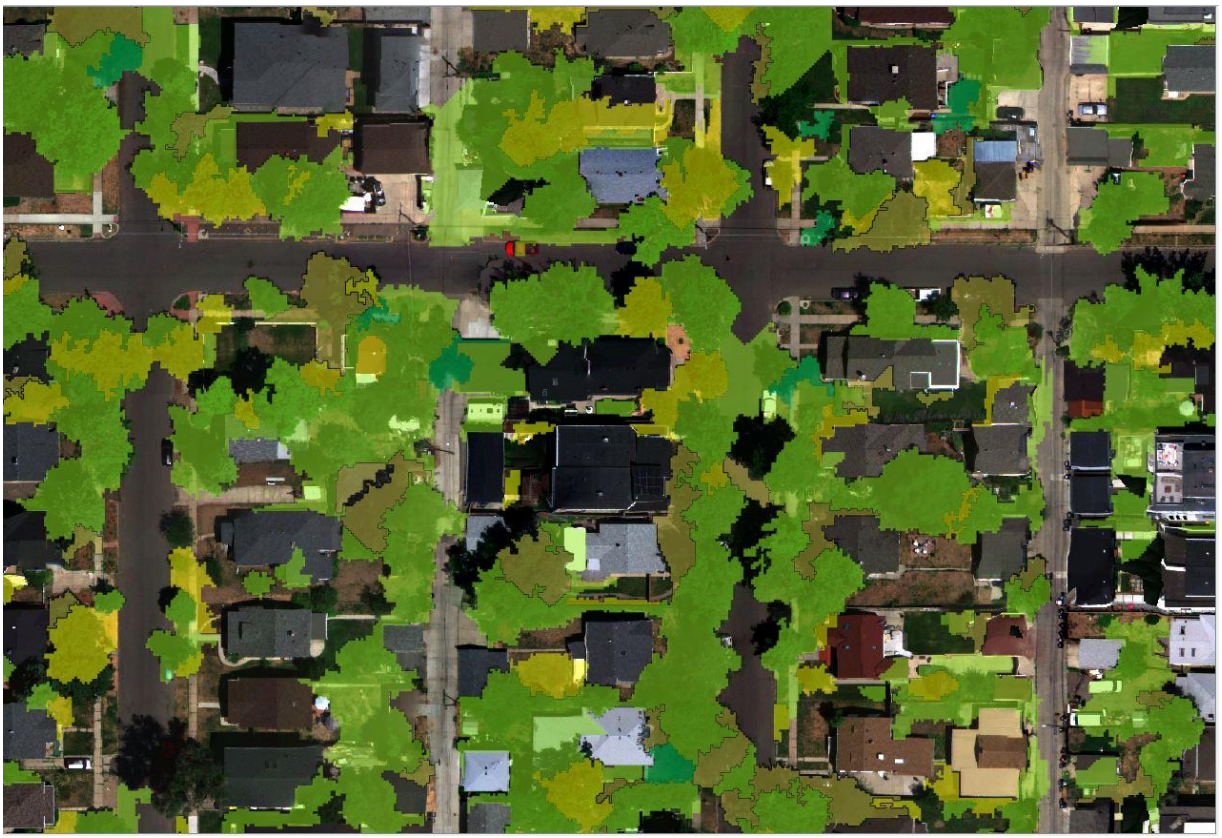


Figure 3. Most recent iteration of our Canopy Cover Analysis process. Several groups of species (not individual species) are shown by the different colors and canopy delineation accuracy is much higher in this most recent processing run.

One useful tool that can be used across City departments is obtained by converting the CCA into a shapefile for Geographic Information Systems (GIS) software, such as that used by the City and County of Denver. Converting canopy cover data to a shapefile allows GIS technicians the ability to overlay canopy data on other layers for additional analysis:

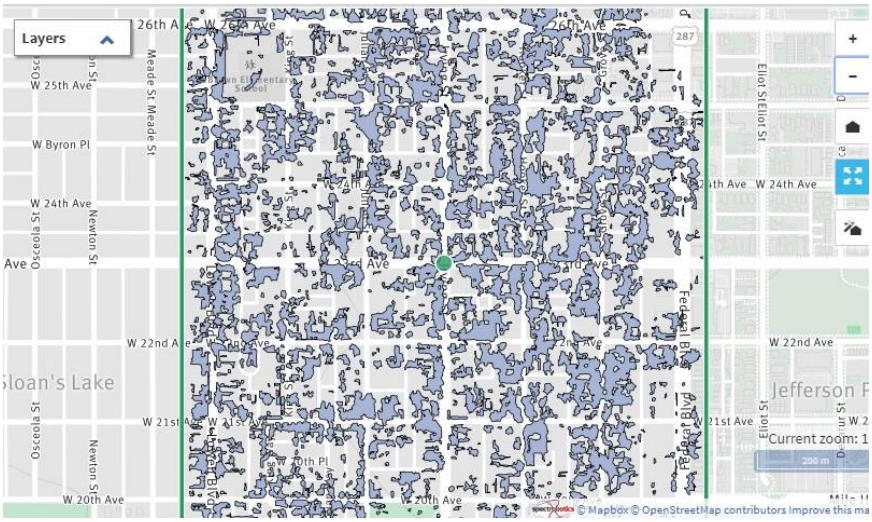


Figure 4. Shapefile of tree canopy cover – on private parcels and public lands – overlaid on a street map.

Efforts are ongoing to incorporate machine learning algorithms for CCAs into all data collected or obtained – UAS, personed aircraft, even high-resolution satellite data – to train the algorithms to highest accuracy in order to ensure the City and County of Denver can assess canopy cover using any tool at its disposal.

Appendix C
Early Detection of Emerald Ash Borer (EAB)

The team did not find EAB in the UAS collection area in the City and County of Denver. The manned aircraft sensors were not capable of collecting the bands needed for the specialized tool developed for early-onset EAB detection. The team analyzed approximately 300 drone-flown ash trees in Denver (in DBH classes over 12 inches). Given the number of trees infested with EAB in the team's datasets, we are confident that we can identify EAB in a tree canopy and that EAB is not in the areas where there are UAS data.

Fine-tuning of the tool the team developed in 2017 to detect early onset EAB has allowed for more refined analysis in areas where EAB is present. For example, the team can now detect trees treated by injection for EAB. Detection of distinct Phases of Early Onset EAB is possible in other areas as well, including Gunbarrel, Longmont and Superior in Boulder County.

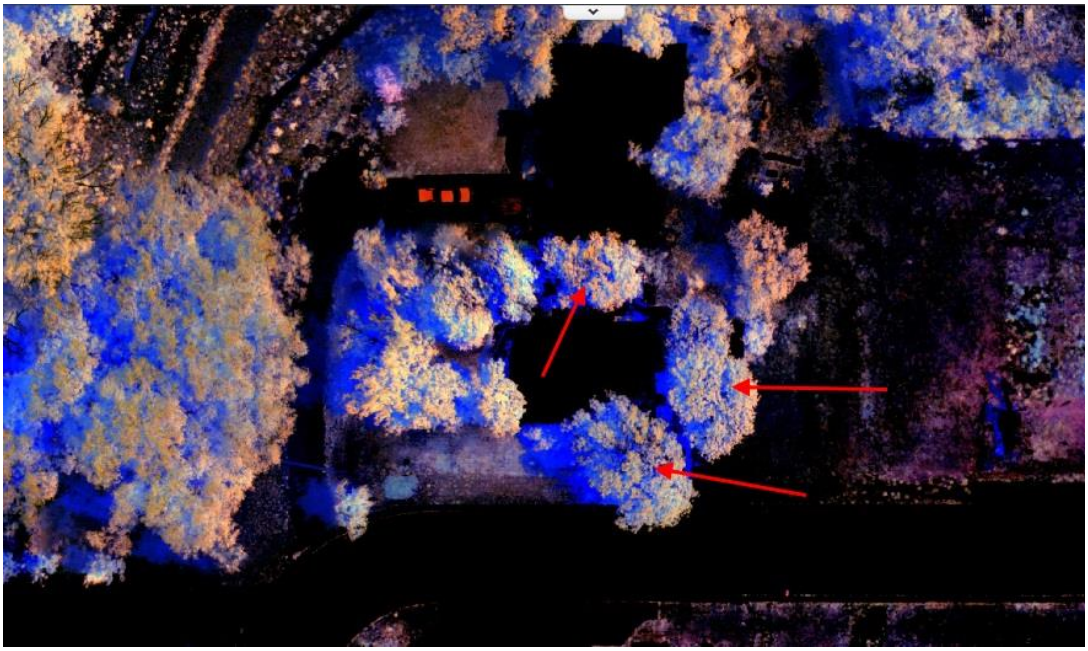


Figure 1. Residence in Superior with very early EAB (arrows) on private property

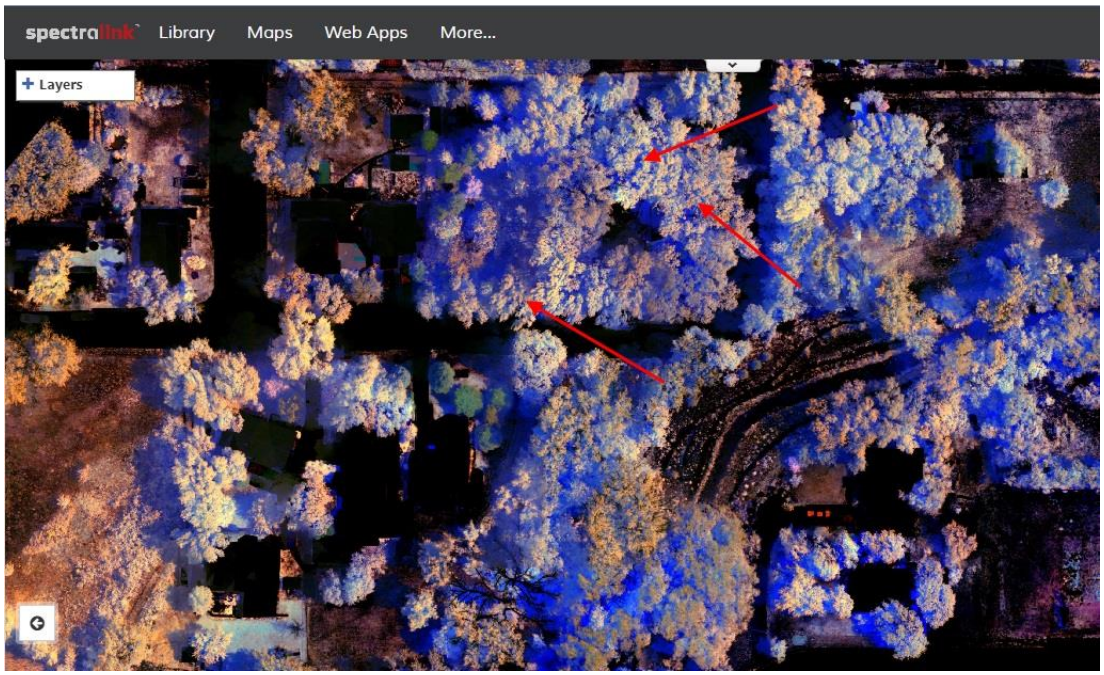


Figure 2. Residence in Superior with treated ash trees. Arrows indicate EAB hits on private property trees that have been treated. The team spoke to the property owner and got confirmation of treatment.

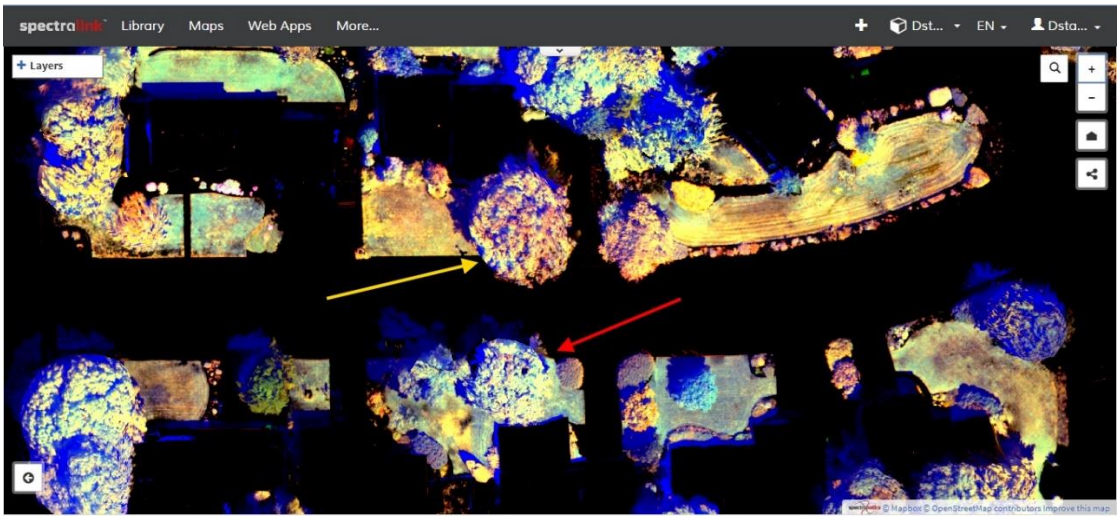


Figure 3. Residences in Longmont with front yard trees hit by EAB. Yellow arrow is a treated tree, red arrow is untreated at the time of imaging. The bottom tree may be the earliest hit ash the team has imaged.

Figure 4. Residence in Longmont with back yard tree with an early hit by EAB (red arrow). The team spoke with the homeowner and the tree was not treated at the time of imaging. This image indicates the value of imaging the entire area to accurately track the disease front. Artefacts are from the machine learning algorithm learning process and the EAB Detection Tool including groundcover in the background.

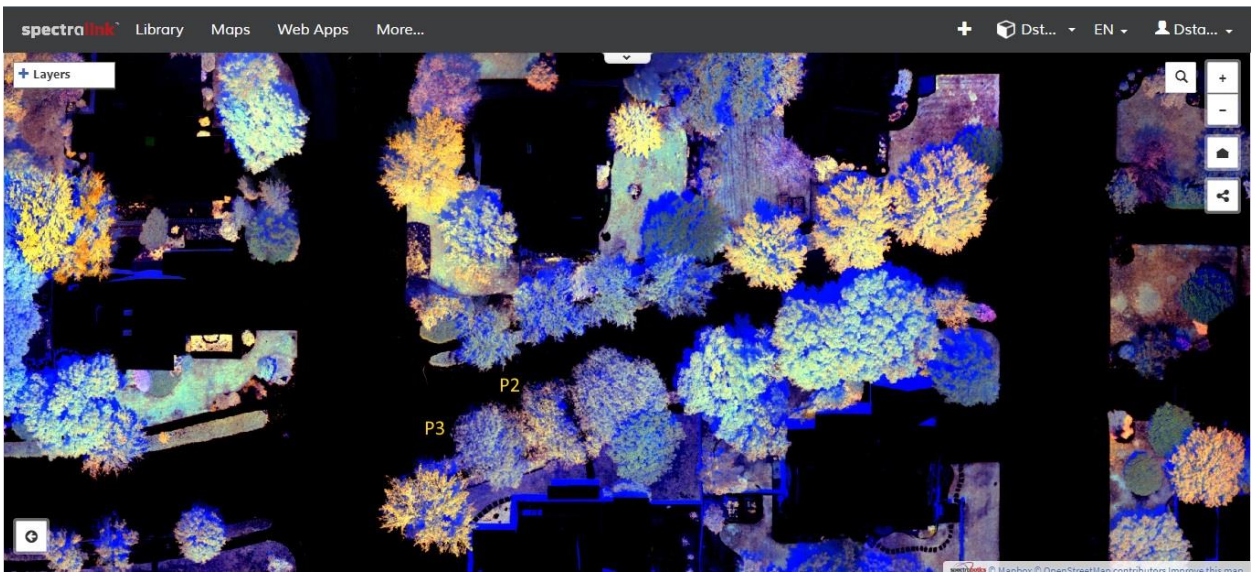


Figure 5. Street trees in Gunbarrel (with yellow Phase designations) hit by EAB. The trees were marked by the County as ready to be 'adopted' so are assumed to be untreated at the time of imaging. The P2 and P3 designations are tree condition expressed as 'phase of attack'. Further explanation above in text. Odd tree coloration of other species is due to the nature of the tool developed to detect EAB and its "re-coloration" of reflectance values.

The ability of urban forest managers to precisely track EAB on both public and private property is an invaluable tool to gain time and save money in the fight to preserve urban ash trees. As of the date of this report, we believe we are still the only team to be able to consistently detect EAB before woodpeckers. The City and County of Denver should continue to use all tools at its disposal to detect and mitigate this unprecedented pest outbreak, in order to best protect and preserve urban forest benefits for Denver residents and stakeholders.