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Kristin N. Youngquist

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Rristin N. Youngquist

EVALUATING COLUMBUS, GEORGIA, TREE CANOPY INTERACTIONS WITH AIR POLLUTANTS USING HIGH SPECTRAL IMAGERY AND PORTABLE PM SENSORS

A THESIS SUBMITTED TO
THE COLLEGE OF LETTERS AND SCIENCES
IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

DEPARTMENT OF EARTH AND SPACE SCIENCES

BY

KRISTIN N. YOUNGQUIST

COLUMBUS, GA
2018

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EVALUATING COLUMBUS, GEORGIA, TREE CANOPY INTERACTIONS WITH AIR POLLUTANTS USING HIGH SPECTRAL IMAGERY AND PORTABLE PM SENSORS

## By

Kristin N. Youngquist

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Columbus State University
May 2018


#### Abstract

Trees provide environmental, economic, and social advantages in urban areas. Knowing the extent and location of tree canopy in a municipality is an important step in quantifying these benefits. Spatial and temporal tree canopy analysis was performed for the city of Columbus, Georgia, by categorizing the National Agriculture Imagery Program (NAIP) aerial imagery for 2005, 2010 and 2015 into tree versus non-tree land cover type using unsupervised classification procedures. Air pollution removal rates from the i-Tree program were applied to this evaluation providing an estimate of the city's tree air quality benefits. The city's canopy overall has remained steady at $52 \%$ of the 38,143 hectares that compose the municipality for the years 2005 ( $89 \%$ accuracy), 2010 ( $93 \%$ accuracy) and 2015 ( $93 \%$ accuracy). Percent tree canopy within the city's 53 census tracts ranged from 13 to $75 \%$. Tree loss due to development in south central, north, and north-eastern areas was offset by forest regrowth, having been cleared prior to 2005. These trees remove 1,700 tonnes of five critical air pollutants $\left(\mathrm{CO}, \mathrm{NO}_{2}, \mathrm{O}_{3}, \mathrm{PM}_{2.5}, \mathrm{PM}_{10}\right.$, and $\mathrm{SO}_{2}$ ) and sequester 256,000 tonnes of $\mathrm{CO}_{2}$ annually, based on i-Tree's first-order valuations.

Since trees influence fine particulate matter $\left(\mathrm{PM}_{2.5}\right)$ and the health impacts of $\mathrm{PM}_{2.5}$ are great, a second study was conducted to better understand how tree stand formation controls PM 2.5. Three portable, fine PM sensors (AirBeams) were used among three tree canopy configurations (dense tree buffer, $n=5$; small tree line, $n=6$; and $U$-shaped, $n=4$ ) to determine if stand design effects $\mathrm{PM}_{2.5}$ concentrations in open areas near trees. AirBeams were evaluated and found to have reliability, ease of use, repeatability among units, and stability across the study period. Overall results between open and tree concentrations were not significantly different. Site by site observations indicated that dense tree buffers (3 of the 5 sites) trap $\mathrm{PM}_{2.5}$ resulting in higher tree particulate concentrations in the buffer zone and small tree lines ( 5 sites) had no


effect on $\mathrm{PM}_{2.5}$. U-shaped tree stands interactions are dependent on location of the open area within the tree stand in relation to notable PM sources. While wind direction played a role in particulates reaching sampling locations, proximity to and type of PM source had the largest impact on local $\mathrm{PM}_{2.5}$ concentrations.

Urban canopy cover recommendations are made so cities can benefit from ecosystem services that trees provide, but simply adding trees does not mean these benefits are fully utilized. Tree type, tree design, and tree placement, i.e. in available space and proximity to pollution source, need to be considered. Utilizing high spectral imagery and low-cost, portable sensors can help cities determine the best tree placement and design to aide in air pollution reduction.

INDEX WORDS: tree canopy, high spectral resolution, particulate matter, AirBeam, unsupervised classification, aerial imagery, remote sensing

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## ABBREVIATIONS

BAM - $b$-attenuation analyzer
EPA - Environmental Protection Agency
GIS - Geographic Informational Systems
GSD - Ground Sample Distance
NAIP - National Agricultural Imagery Program
PM - particulate matter
$\mathrm{PM}_{2.5}-\mathrm{PM}<2.5 \mu \mathrm{~m}$ in diameter
$\mathrm{PM}_{10}-\mathrm{PM}>2.5 \mu \mathrm{~m}$ and $<10 \mu \mathrm{~m}$ in diameter
TEOM - Tapered Element Oscillating Microbalance analyzer
UFORE - Urban Forest Effects

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A thesis submitted to the College of Letters and Sciences in partial fulfillment of the requirements for the degree of MASTER OF SCIENCE

DEPARTMENT OF EARTH AND SPACE SCIENCES

By
Kristin N. Youngquist
2018

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Date

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Date

## INTRODUCTION

Trees provide many benefits in urban areas, such as improving air quality, sequestering carbon dioxide (Nowak \& Crane, 2002), filtering water (Booth, 2005), and decreasing urban heat islands (Bolund \& Hunhammar, 1999). These environmental benefits also have health advantages, like improving senior longevity (Takano, Nakamura, \& Watanabe, 2002), lowering the number of autism cases (Wu \& Jackson, 2017), and lowering mortality with cleaner air (Tiwary, 2009). People value trees mostly for their shade, air quality improvements, and "calming effects" (Lohr, Pearson-Mims, Tarnai, \& Dillman, 2004). The economic gains to a city can include everything from lower crime rates (Kuo \& Sullivan, 2001) to increased housing prices that generate property tax revenues (Anderson \& Cordell, 1988; Donovan \& Butry, 2010).

Researchers have taken different approaches to understanding the values of trees. Topdown approaches involve quantifying trees regionally by classifying high spectral imagery into landcover classes including tree canopy cover (Nowak, 2012). Canopy is defined as the area of land covered by tree leaves, trunks, and branches as seen from an aerial perspective (Northern Research Station, 2017). Once canopy is analyzed, models can be applied to the findings to estimate tree benefits (McPherson \& Simpson, 2002; Nowak \& Crane, 2000). Conversely, field studies aimed at quantifying tree benefits in a locale are preferred, especially when few field studies exist to support models that apply air quality values to trees (Pataki et al., 2011; Setälä, Viippola, Rantalainen, Pennanen, \& Yli-Pelkonen, 2013).

While all ecosystem services and economic attributes provided by trees are important, this research focuses on the removal of air pollutants by trees. The first investigation looks at the value of applying broad level air quality assessment to cities using high spectral canopy analysis and air pollutant removal rates, obtained from the i-Tree Tool (www.i-Tree.org), for Columbus,

Georgia, a municipality in western Georgia, USA. The air pollutant removal rates using the iTree Tool are based on first-order approximations, with environmental and meteorological data from one location often accounting for several counties in a region. As such, local research should assist in determining services and possible disservices of tree placement or removal practices (Nowak \& Greenfield, 2008; Nowak et al., 2014). While other limitations exist in using the i-Tree model, fine particulate matter $\left(\mathrm{PM}_{2.5}\right)$ is the one pollutant that poses additional specific limitations. The i-Tree model's $\mathrm{PM}_{2.5}$ uses a positive removal rate in counties with low wind and a negative removal rate (meaning increase in $\mathrm{PM}_{2.5}$ ) in counties with high wind and low rain (Hirabayashi, 2014). Trees are a temporary resting location for $\mathrm{PM}_{2.5}$, and local weather conditions, especially wind and precipitation, can resuspend particles into the air or bring to the ground (Nowak et al., 2014). As a result, it was determined that the second part of this research would focus on tree and fine particulate matter interactions by tree buffer arrangement, as this interaction is more complex than other air pollutants removed from the air column by trees.

Particulate matter (PM) is among the six criteria air pollutants regulated by the Environmental Protection Agency (EPA) under the National Ambient Air Quality Standards (NAAQS) as part of the Clean Air Act (Girard, 2014). PM 2.5 causes major health related issues when inhaled (Hemon \& Fechner, 2014), and has been linked to over 100,000 deaths annually in the United States (Fann et al., 2012).

## Study Goals and Scope

As the city of Columbus was the first city in the state to become Tree City USA certified (and has remained so for 39 years; GFC, 2012), maintaining a working knowledge of the tree canopy and its services (or disservices) in the community is vital. The goal of this research is to pair spatial and temporal analysis of canopy with air quality monitoring to quantify tree benefits
and aide in future tree planning for the city of Columbus. The final product will contain: a thematic tree canopy map and percentage breakdown of tree canopy by census tract for 2005, 2010 and 2015; tree canopy change over the ten-year period; a first-order estimation of Columbus air quality benefits; and the results of a field study examining tree effects on local PM2.5 levels within tree canopy stands and adjacent open areas.

## CHAPTER 1 - SPATIAL AND TEMPORAL CANOPY COVER ANALYSIS

### 1.1 Introduction

Municipalities for decades have focused on vegetative planning to improve water filtration, reduce air pollutants, support economic growth, and abate climate change (Howard, 1965; Miller, 1988; Platt, Rowntree, \& Muick, 1994; Young, 2010; Escobedo, Kroeger, \& Wagner, 2011; Roy, Byrne, \& Pickering, 2012). Urban planning often incorporates these ecosystem services into local urban design with vegetation in mind, but determining what to account for, whether air pollution abatement, social improvements, or economic values take priority, is complex (Thomas \& Geller, 2013). Knowing the amount and location of tree canopy in an urban environment is a mandatory first step as municipalities plan for future development.

The term canopy, for the purposes of this research, means the area of land covered by tree leaves, trunks, and branches as seen from an aerial perspective (Northern Research Station, 2017). US cities and counties produce Urban Tree Canopy (UTC) assessments using high spectral aerial or satellite imagery to classify land cover thereby ascertaining tree canopy amount and distribution. The USDA Forest Service's Northern Research Station and the University of Vermont's Spatial Analysis Laboratory created procedures and have assisted cities in developing UTC assessments to help with urban tree planning (Northern Research Station, 2017).

Municipalities use similar procedures by classifying high spectral imagery to assess tree canopy spatially and temporarily in order to enhance "green" planning. As an example, Atlanta, Georgia, completed a UTC assessment using satellite imagery (2-foot pan-sharpened, 4-band data) through the Georgia Tech Center for Geographic Information Systems in 2014. That assessment determined the city had 47.9 percent canopy cover in 2008 (Giarrusso \& Smith, 2014).

Land cover classification using high spectral imagery is a top-down approach to determine tree canopy versus the bottom-up approach used when surveying individual trees in an area. Each approach has its advantages and disadvantages, with the top-down approach being the best approach for assessing amount and location of trees in larger areas the size of municipalities (Nowak, 2012). The use of imagery to assess different land cover types is based on the idea that dissimilar objects, like water, vegetation, and roads, have unique spectral signatures because they reflect and absorb wavelengths of electromagnetic radiation (EM) differently (Kachhwaha, 1983; Keranen \& Kolvoord, 2014). For example, water absorbs red and near-infrared wavelengths ( $0.76-0.90 \mu \mathrm{~m}$ ), while vegetation reflects these wavelengths ( $0.63-$ $0.90 \mu \mathrm{~m}$ ). This difference allows the two land types to be distinguished using multispectral imagery and image analysis programs, like ESRI ArcGIS (Fox, 2015). Multispectral imagery is composed of three to seven bands of pixels with values 0 to 255 , lower values are darker and higher values are lighter. Each band represents either visible or infrared wavelength ranges, i.e. for Landsat images band 1 is visible blue ( 0.45 to $0.52 \mu \mathrm{~m}$ ), band 2 is visible green $(0.52$ to 0.60 $\mu \mathrm{m})$, band 3 is visible red ( 0.63 to $0.69 \mu \mathrm{~m}$ ), band 4 is near infrared ( 0.76 to $0.90 \mu \mathrm{~m}$ ), band 5 is short-wave infrared $1(1.55$ to $1.75 \mu \mathrm{~m})$, band 6 is thermal infrared ( 10.4 to $12.5 \mu \mathrm{~m}$ ), and band 7 is short-wave infrared 2 ( 2.08 to $2.35 \mu \mathrm{~m}$ ). These bands are combined and analyzed based on known spectral signatures of objects to classify an area of concern (Keranen \& Kolvoord, 2014; Fox, 2015).

Once a municipality's tree canopy is known, ecosystem services (i.e. air quality, water filtration, and reduction of urban heat) can be estimated using tree models, like i-Tree Tools (online tools and software developed by US Forest Service, Davey Tree Expert Company, National Arbor Day Foundation, Society of Municipal Arborists, International Society of

Arboriculture, and Casey Trees) and ArcGIS based CITYGreen (software developed by American Forests with rates based on Urban Forest Effects (UFORE) methods, an earlier version of i-Tree). These models estimate UTC effects on air pollutant removal and carbon dioxide sequestration and storage. These removal rates were established through modeling the combination of tree canopy across the United States, leaf area index values, pollution removal rates by trees given local pollutant concentrations, and pollutant deposition rates based on local meteorological data. For i-Tree, the monetary value of these ecosystem services was applied based on health incidences and associated costs that would be avoided with pollutant removal (Nowak, Hirabayashi, Bodine, \& Greenfield, 2014). The UFORE model took a similar approach, but used fewer cities and applied monetary values based on prevented health and tourism loss (Nowak \& Crane, 2000).

The i-Tree Tool are a good starting point for tree planning and quantifying associated benefits of city trees. The i-Tree Tool incorporates data from across the United States and assesses removal rates for five of the six criteria air pollutants (carbon monoxide - CO , nitrogen dioxide - $\mathrm{NO}_{2}$, ozone $\mathrm{O}_{3}$, particulate matter - broken into $\mathrm{PM}_{2.5}$ and $\mathrm{PM}_{10}$, and sulfur dioxide $\left.\mathrm{SO}_{2}\right)$. The model also applies sequestration and storage rates for carbon dioxide $\left(\mathrm{CO}_{2}\right)$. Empirical studies quantifying tree impacts on air quality are limited (Pataki et al., 2011), and models projecting tree reductions of air pollutants range from 0.13 percent for $\mathrm{PM}_{2.5}$ removal in urban settings to 0.51 percent for ozone removal in rural settings (Nowak et al., 2014). Other research has quantified the ability of trees to reduce air pollutants, but the focus is on only one or two criteria air pollutants (reviewed in Nowak et al., 2014). The air pollutant removal rates using the i-Tree Tool are based on first-order approximations, with environmental and meteorological data from one location often accounting for several counties in a region. One

Italian study found good agreement when i-Tree ozone removal rates were compared to local level field measurements (Morani et al., 2014).

The Natural Resources Spatial Analysis Laboratory conducted a Georgia Land Use Trends analysis including tree cover for the state of Georgia. Landsat satellite data ( $30 \mathrm{~m} \times 30 \mathrm{~m}$ resolution) was used to create GIS databases for the state with an overall accuracy of 85 percent for years $1974,1985,1991,1998,2001,2005$, and 2008 (Kramer, 2016). The study found an eight percent tree canopy loss in Muscogee County between 1991 and 2005 (GFC, 2012). The city of Columbus (consolidated with Muscogee County, Georgia) did not have a recent assessment of tree canopy nor a high resolution assessment needed for city wide tree planning.

Maintaining a working knowledge of the Columbus city tree canopy and its services (or disservices) in the community is important given the potential environmental implications. This research seeks to fill the knowledge gap regarding the city's tree canopy through spatial and temporal analysis of its UTC. The goal of this study is to assess the city of Columbus tree canopy and estimate its associated air quality benefits. The knowledge gained will aide in providing sound recommendations to the city on advantageous locations for future tree planting and removal and will enhance planning and policies concerning development with vegetation in mind.

Disparity in tree canopy can be found in a look at the spectral imagery of Columbus, Georgia. It is visibly apparent that a greater, healthier canopy exists in the northern portion of the area. The National Agriculture Imagery Program (NAIP) imagery is a rich green color above highway 80 (denoted in red in Figure 1). Conversely, tree canopy is scarce in the downtown industrial area (the portion of the city that appears greyish-white in the mid-west portion of the image). This contrast in percent canopy is consistent with the American Forests
recommendations for ideally 15 percent canopy in downtown and industrial and 50 percent canopy in suburban residential areas (American Forests, 2002). When disparity in canopy exists across the city, the environmental benefits of the urban trees are also unequal city-wide. Tree benefits are applied at a small scale given the spread of atmospheric conditions and sources of air pollutants in urban settings (Nowak \& Greenfield, 2008; Tyrväinen, Pauleit, Seeland, \& de Vries, 2005).

This research intends to answer the following question: will aerial imagery analysis, quantifying tree canopy spatially and temporally, highlight large tree canopy and air quality benefit disparities over time across the city of Columbus? It is hypothesized that a disparity will exist between tree canopy within the study domain, with northern areas of the municipality having the most canopy and downtown having least canopy, resulting in disproportionate air quality benefits across the city. Additionally it is hypothesized that the tree canopy will decrease over the time period examined.


Figure 1. City of Columbus service region (excluding Fort Benning) 2015 1-meter, 4-band NAIP natural color image with inset map showing location of Columbus, Georiga.

### 1.2 Methods

1.2.1 Study Area - Columbus is located along the western border of Georgia, USA
(Figure 1 inset, $32^{\circ} 29^{\prime} 32^{\prime \prime} \mathrm{N}, 84^{\circ} 56^{\prime} 25^{\prime \prime} \mathrm{W}$ ). The city and county (Muscogee) governments are consolidated, therefore, the area of the city is the County land area of 56,045 ha $(138,490$ acres). Part of the Fort Benning Army base is located in southeastern Muscogee County. Excluding this portion of the County ( $17,902 \mathrm{ha}$ ), the city of Columbus has a land area of 38,143 ha ( 94,253 acres). The landscape to the north-northeast is dominated with agriculture and pine forest found throughout the southeastern United States, while the south-southwestern landscape is urban. Columbus is the second most populous municipality in Georgia with population of 189,885 in 2010 (U.S. Census Bureau, 2010).
1.2.2 High-Resolution Imagery - The 2010 and 2015 tree canopy were analyzed using the 1-meter ground sample distance (GSD) spatial resolution, 4-band National Agricultural Imagery Program (NAIP; 1m x 1m spatial resolution) imagery of Muscogee County. The 2005 tree canopy was analyzed using 2-meter GSD spatial resolution, 3-band NAIP imagery, as this is what was available. NAIP produces digital orthoimages roughly biannually (Georgia imagery exists for years 2001-2002, 2005-2007, 2009-2010, 2013, 2015, and 2017; USDA, 2017) by aerially photographing agricultural regions during the growing season, usually between July and September. The 1-meter GSD spatial resolution, available for free through the USDA program, offers the best resolution publicly available for Columbus in recurrent years, and it is, therefore, the best available imagery of the city accessible to city planners and other researchers for future tree canopy analysis. The 2005 NAIP imagery was obtained through the Columbus City Planning Department in compressed county mosaic format (Figure 2A). The 2010 city NAIP imagery was obtained from the U.S. Department of Agriculture Farm Service Agency, Aerial

Photography Field Office in Digital Ortho Quarter Quad (DOQQ) tiles format containing 25 separate DOQQ files (Figure 2B). The 2015 NAIP imagery was available online to download via the Aerial Photography Field Office in compressed county mosaic format (Figure 1). All three were projected in the UTM coordinate system, North American Datum of 1983.


Figure 2. City of Columbus natural-color image A) 2005 2-meter spatial resolution, 3-band NAIP and B) 2010 1-meter spatial resolution, 4-band NAIP.

Imagery classification was conducted using ESRI ArcGIS 10 software. NAD 1983 State Plane Georgia West FIPS 1002 Feet was used as the projected coordinate system as requested by the city of Columbus GIS Division. The city service boundary shapefile was used to clip Fort Benning from the imagery. Imagery was gathered at different times of day and on different days. The 2010 imagery was flown between two separate months. As a result, shadows, which
complicate classification, are at different angles in different sections. Recognizing flight pattern reduces this potential classification error. Quarter quadsacre closely followed the flight pattern used to gain the imagery. For this reason, the clipped city image was split using the DOQQ shapefiles to reduce classification error. The 2010 imagery was provided in 25 DOQQ tiles, so analyzing each separately was the most effective analysis technique (Figure 3A). For the 2015 imagery, DOQQ shapefiles were combined into four large images to group based on similar topographical sections (e.g. urban versus forest) and to reduce processing time (Figure 3B). The 2005 imagery, as received, was not cleanly mosaiced with north-south alignment issues across the image (Figure 3C highlights this issue). To reduce error, this imagery was cut along these mosaiced sections and analyzed in 10 sections (Figure 3D).


Figure 3. A) 2005 NAIP Columbus natural-color image showing an area of misalignment. The sections used to analyze B) 2005 , C) 2010 , and D) 2015 NAIP imagery.
1.2.3 Tree Canopy Image Classification - For larger areas that an analyst is not fully acquainted with, performing unsupervised classification can reduce error (Rozenstein \& Karnieli, 2011). Therefore, for each section of the NAIP imagery, an unsupervised iso cluster classification process was conducted clustering the image bands (3-band for 2005, 4-bands for 2010 and 2015) into 40 classes. The 40 classes were visually interpreted and assigned labels of tree or non-tree (see Appendix A for iso cluster values by year). Postprocessing procedures involved mosaicing the classified sections into one raster of the whole city. The Majority Filter and Boundary Clean tools were used to clean the image by filling in areas of no data and smoothing the edges of tree and non-tree clusters (Keranen \& Kolvoord, 2014). This approach yielded three classified thematic maps spatially showing tree canopy across Columbus, Georgia, in 2005, 2010, and 2015.
1.2.4 Classification Accuracy Analysis - A simple random sampling scheme with a sample size of 500 reference points for each year (i.e. 1,500 total points) was used to assess accuracy. Using multinomial probability theory, the following equation was used to determine sample size:

$$
\mathrm{N}=\frac{B \pi_{i}\left(1-\pi_{i}\right)}{b_{i}^{2}},
$$

where $B$ is the upper $\alpha / \mathrm{k}$ percentile of chi square distribution with 1 degree of freedom, $k$ is number of classes (2), $\alpha$ is acceptable error (0.05), $\pi_{i}$ is the proportion of trees in the classification ( 0.52 ), and $b_{i}$ is confidence interval and precision ( 0.05 ). The multinomial model and simple random sampling satisfy assumptions of the kappa statistic (K-hat), which is used to calculate the significance of the error matrix table generated during the accuracy assessment (Congalton, 1991). Using this method, 1,500 reference points (500 for each of the three thematic classification rasters being assessed) were randomly generated using the Create Radom Points
tool in ArcGIS (Figure 4). All three years were assessed at each point with a separate value applied for each year based on landcover type in that particular year. Assessing all 1,500 points for all three years increases sample size, which in turn increases confidence in the classifications (Dicks \& Lo, 1990).


Figure 4. Position of 1,500 randomly generated reference points used to check accuracy of classified thematic maps with in the Columbus, Georgia, service region.

The reference imagery data used to access classification accuracy for 2005, 2010, and 2015 was Google Earth ${ }^{\mathrm{TM}}$ imagery. This tool was selected over actual ground truthing at the physical location because landcover changes rapidly. Google Earth ${ }^{\mathrm{TM}}$ serves as a good reference tool as the imagery within the tool has high-resolution and offers the historical images needed for assessment (Congalton, 1991; Olofsson et al., 2014). The history bar within Google Earth was utilized to access imagery from 1993 to 2017 for the region. The tool allows for rotating views, viewing imagery from different angles, and street view, which helped in determining tree versus non-tree when shadows were prominent. All years of imagery available (1993, 2003, 2005, $2006,2007,2009,2010,2011,2012,2014,2016,2017)$ were used to assess the accuracy of the
classification, especially the years before and after those of interest (i.e. 2005, 2010, 2015), as described in Olofsson et al. (2014).

All 1,500 reference points were manually assessed using Google Earth ${ }^{\mathrm{TM}}$ and given a value of 1 for tree and 2 for non-tree. The Extract Values to Points tool was used in ArcGIS to compare reference points to the classification raster for each of the three years (see Appendix 1, Table 4). Accuracy was then assessed using the error matrix table and corresponding Kappa coefficient (Congalton, 1991).
1.2.5 Spatial and Temporal Analysis - The Spatial Analysis tools in ArcGIS (Price, 2014) were used to determine percent tree canopy of the 53 census tracts using the 2015 US Census TIGER tract shapefile for the city of Columbus service region. A comparison of tree canopy change over time by tract was conducted and assessed by evaluating percent change by census tract between the three classified thematic maps. Changes within tracts were further evaluated to determine cause of any differences found, i.e. tree loss due to development and timber harvesting or gains due to tree plantings.
1.2.6 Air Quality Benefit Analysis - The i-Tree Tool was used in conjunction with the tree classification results to estimate urban tree canopy tree canopy air quality benefits. This tool applies average air pollutant removal rates and monetary values based on county level data. These county level rates were determined by combining tree canopy analysis, leaf area index (LAI) values, pollution removal rates by trees given local pollutant concentrations, and pollutant deposition rates based on local meteorological data (Nowak et al., 2014). The 2001 National Land Cover Database was used to determine tree cover and percent of cover that was evergreen, while the LAI values were found using the MODIS/Terra global Leaf Area Index product. Tree removal of air pollutants was determined using a statistical model that combined total tree cover,
evergreen percentage, LAI, local weather, and local air pollutant concentration data (Hirabayashi, 2014). Monetary value was estimated based on health incidences and associated costs that would be avoided with pollutant removal (Nowak et al., 2014). Table 1 contains the removal rates derived using this process for Columbus, Georgia.

Table 1. Tree air pollution annual removal rates and related monetary values for Columbus, Georgia, using i-Tree, developed by USDA Forest Service (Nowak et al., 2014).

| Pollutants <br> (Removed annually) | Removal Rate <br> (tonnes/hectare-year) | Monetary Value <br> $(\$ /$ tonnes $)$ |
| :---: | :---: | :---: |
| CO | 0.0016 | $\$ 463.91$ |
| $\mathrm{NO}_{2}$ | 0.0105 | $\$ 145.57$ |
| $\mathrm{O}_{3}$ | 0.0560 | $\$ 774.98$ |
| $\mathrm{PM}_{10}(2.5-10 \mu \mathrm{~m})$ | 0.0126 | $\$ 2,068.42$ |
| $\mathrm{PM}_{2.5}(<2.5 \mu \mathrm{~m})$ | 0.0036 | $\$ 35,253.35$ |
| $\mathrm{SO}_{2}$ | 0.0025 | $\$ 40.25$ |
| $\mathrm{CO}_{2 \text { seq }}$ | 13.0 | $\$ 39.00$ |
| $\mathrm{CO}_{2 \text { stor** }}$ | 282.5 | $\$ 39.00$ |

### 1.3 Results

1.3.1 Classification Accuracy Assessment - A 93 percent overall accuracy was found for the 2010 and 2015 classifications, while the 2005 classification had an accuracy of 89 percent (Table 2). The user and producer accuracy are the same for both tree and non-tree for the 2010 thematic map, so error was spread evenly between error of omission and commission (Table 2). The user accuracy (error of commission) for trees, i.e. the percent of trees correctly classified, is highest in the 2015 classification at 95 percent, with 2005 also being good at 92 percent. The kappa statistics for all three years is relatively high showing good agreement between reference data and thematic map data after accounting for agreement by chance. User accuracy for nontree is 4 percent lower than tree for 2015 and 6 percent lower for 2005 classifications. The producer accuracy (error of omission) for trees, i.e. the percent of pixels correctly labelled as trees, is 3 percent lower for tree versus non-tree for the 2015 classification and 4 percent lower
for 2005. In summary, the 2015 and 2005 classifications represent actual referenced trees better than non-trees, while the percent of pixels correctly labelled as non-tree is higher.

Table 2. Error matrices for 2005, 2010, and 2015 classifications containing user and producer accuracy, k statistics ( 78,86 , and 87 percent respectively), and overall accuracy ( 89,93 , and 93 percent respectively) results.

|  | 2015 Accuracy Assessment |  |  |  | 2010 Accuracy Assessment |  |  |  | 2005 Accuracy Assessment |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Ref |  |  |  |  | rence ata |  |  | Refe |  |  |  |
| Thematic Map Data | Tree | Non- <br> Tree | Map <br> Total | User's Accuracy | Tree | Non- <br> Tree | Map <br> Total | User's Accuracy | Tree | Non- <br> Tree | Map <br> Total | User's Accuracy |
| Tree | 751 | 36 | 787 | 95\% | 735 | 53 | 788 | 93\% | 716 | 62 | 778 | 92\% |
| Non-Tree | 64 | 649 | 713 | 91\% | 53 | 659 | 712 | 93\% | 103 | 619 | 722 | 86\% |
| Reference <br> Total | 815 | 685 | 1500 |  | 788 | 712 | 1500 |  | 819 | 681 | 1500 |  |
| Procedure's <br> Accuracy | 92\% | 95\% |  |  | 93\% | 93\% |  |  | 87\% | 91\% |  |  |
|  | $\begin{gathered} \text { Overall Accuracy = } 93 \% \\ \text { K-hat }=87 \% \end{gathered}$ |  |  |  | $\begin{gathered} \text { Overall Accuracy = } 93 \% \\ \text { K-hat }=86 \% \end{gathered}$ |  |  |  | Overall Accuracy $=\mathbf{8 9} \%$ <br> K-hat $=\mathbf{7 8 \%}$ |  |  |  |

1.3.2 Spatial and Temporal Dynamics of Tree Canopy Coverage - In 2015 and 2010,
the city of Columbus tree canopy covered 52 percent of the area, equivalent to 19,815 and 19,809 ha ( 48,964 and 48,949 acres), respectively. In 2005, the tree canopy made up 53 percent of landcover, equivalent to 20,012 ha ( 49,453 acres).

In 2015 the tree canopy cover in the 53 census tracts ranged from 13 to 75 percent of land cover. The range was 10 to 75 percent in 2010 and 9 to 73 percent in 2005 (Figures 5 and 6). While the overall canopy coverage for Columbus remained steady (2005-2015), the change over time within certain tracts and in certain areas of the city is notable (Figure 7). In 2005, 5 tracts had less than 20 percent canopy. This number dropped to 2 tracks with less than 20 percent canopy in 2015. The number of tracks with 20 to 39 percent canopy changed from 18 in 2005 to 26 in 2015. The tracts within the 40 to 59 percent canopy range decreased from 24 in 2005 to 21 in 2015. The tracks with the highest canopy ( 60 percent and over) decreased from 6 in 2005 to 4
in 2015 (Figure 6, see Appendix A for Table 5 summarizing by tract tree canopy and Table 6 by tract air quality benefits).


Figure 5. City of Columbus thematic tree canopy map for A) 2005, B) 2010, and C) 2015.


Figure 6. Percent tree canopy by census tract: A) 2005 ranging from 9 to 73 percent UTC, B) 2010 ranging from 10 to 75 percent UTC, and C) 2015 ranging from 13 to 75 percent UTC.


Figure 7. City of Columbus tree canopy change by census tract between 2005 and 2015. Light green represents losses ( 22 tracts) and dark green represents gains ( 13 tracts) in canopy over the ten-year period.
1.3.3 Air Quality Benefit Analysis - Approximately, $\$ 4$ million in health-related savings can be attributed to the removal of 1,700 tonnes ( 1,900 tons) of pollutants annually by trees (Table 3). $\$ 10$ million of savings is due to 256,000 tonnes ( 282,000 tons) of carbon dioxide sequestered annually by Columbus trees (Table 4). Additionally, the 20,000 hectares (49,000 acres) of trees store 5.6 million tonnes ( 6.2 million tons) of carbon dioxide valued at $\$ 218$ million (i.e. this is a long-term value).

Table 3. Columbus, Georgia, tree air quality benefits using USDA Forest Service i-Tree tool (Nowak et al., 2014).

| Pollutants <br> (Removed <br> annually) | 2015 <br> Columbus <br> Removal <br> (tonnes/yr) | 2015 <br> Monetary <br> Value (\$/yr) | 2010 <br> Columbus <br> Removal <br> $($ tonnes/yr) | 2010 <br> Monetary <br> Value (\$/yr) | 2005 <br> Columbus <br> Removal <br> (tonnes/yr) | 2005 <br> Monetary <br> Value (\$/yr) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CO | 31 | $\$ 14,394$ | 31 | $\$ 14,389$ | 31 | $\$ 14,537$ |
| $\mathrm{NO}_{2}$ | 209 | $\$ 30,449$ | 209 | $\$ 30,440$ | 211 | $\$ 30,753$ |
| $\mathrm{O}_{3}$ | 1106 | $\$ 857,419$ | 1106 | $\$ 857,157$ | 1117 | $\$ 865,982$ |
| $\mathrm{PM}_{10}(2.5-10 \mu \mathrm{~m})$ | 248 | $\$ 512,863$ | 248 | $\$ 512,706$ | 250 | $\$ 517,985$ |
| $\mathrm{PM}_{2.5}(<2.5 \mu \mathrm{~m})$ | 73 | $\$ 2,564,998$ | 73 | $\$ 2,564,212$ | 73 | $\$ 2,590,614$ |
| $\mathrm{SO}_{2}$ | 50 | $\$ 1,999$ | 50 | $\$ 1,998$ | 50 | $\$ 2,019$ |
| Total Criteria Air <br> Pollutant Removal | 1,717 | $\$ 3,982,122$ | 1,717 | $\$ 3,980,902$ | 1,732 | $\$ 4,021,891$ |

Table 4. Columbus, Georgia, tree carbon dioxide sequestration and storage using USDA Forest Service i-Tree tool (Nowak et al., 2014).

| Pollutants <br> (Removed <br> annually) | 2015 <br> Columbus <br> Removal <br> (tonnes/yr) | 2015 <br> Monetary <br> Value (\$/yr) | 2010 <br> Columbus <br> Removal <br> (tonnes/yr) | 2010 <br> Monetary <br> Value (\$/yr) | 2005 <br> Columbus <br> Removal <br> (tonnes/yr) | 2005 Monetary <br> Value $(\$ / y r)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{CO}_{2 \text { seq }}$ | 256,300 | $\$ 9,995,634$ | 256,221 | $\$ 9,992,572$ | 258,860 | $\$ 10,095,460$ |
| $\mathrm{CO}_{2 \text { stor }}$ | $5,583,416$ | $\$ 217,751,913$ | $5,581,706$ | $\$ 217,685,205$ | $5,639,177$ | $\$ 219,926,585$ |

Air quality benefits across Columbus are best visualized by applying the removal rates to trees within each census tract (Figures 8 and 9). Trees in the northern portion of the city (tracks $101.07,108.02,102.03,102.01$, and 103.01) remove the largest tonnage of air pollutants per unit area. The trees in the downtown areas (the southwestern portion of the city) remove the least, with the midtown trees removing slightly higher amounts of pollutants. This trend matches the tree canopy across Columbus. Air pollution removal rates through the i-Tree Tool are calculated based on tree coverage.


Figure 8. Annual air pollution removal by census tract. Numbers (except 11 and 25) represent tracts with largest air pollution removal. Numbers 111 and 25 represent tracts with lowest pollution removal.


Figure 9. Annual $\mathrm{CO}_{2}$ sequestration by census tract ranging from 1.7 to 9.7 tonnes/hectare. Dark blue represents tracts with largest and light blue the least sequestration.

### 1.4 Discussion

1.4.1 Classification Accuracy Assessment - The lower accuracy seen in the 2005 data is due to the NAIP imagery having a spatial resolution of 2-meters and only 3-bands. Using 4-band imagery allows for greater distinction between water and vegetation, both of which can have a greenish hue especially when water has high nutrient content. Water is not reflective, but rather absorbs EM radiation in the near-infrared (band 4) while healthy vegetation is very reflective in this band (Fox, 2015). Additionally, the 2005 iso cluster rasters had lower resolution with larger clusters covering multiple landcover types, i.e. trees, buildings, and road were in one clustered pixel group. Given these constraints, the 2005 NAIP imagery was more difficult to analyze, which increased error.

The main source of error in the 2010 and 2015 classification rasters was due to performing an iso cluster unsupervised classification. Distinguishing shadows between those
concealing trees and those concealing non-tree landcover was difficult as these were combined in at least one iso cluster class for most clipped sections. Often iso cluster classes combined tree and non-tree features. For example, tree and non-tree vegetation share at least one or two iso cluster classes in each clipped section because spectral signatures for grass, bushes, and trees can overlap. Reclassifying these classes as only tree or non-tree increased error. Unfortunately, all classification processes have error whether computer generated, as with unsupervised classification, or human error, as seen with the supervised classification process due to lack of familiarity with the region being analyzed (Rozenstein \& Karnieli, 2011). The accuracy of the 2010 and 2015 classifications is good compared with other classifications of NAIP imagery found in literature (Davies et al., 2010; Li et al., 2014; Moskal, Styers, \& Halabisky, 2011). Also of note, the 2010 NAIP imagery had added error with clouds covering a field of trees in the northeast portion of the image.

### 1.4.2 Spatial and Temporal Dynamics of Tree Canopy Coverage - The ideal canopy

 cover for an urban area as stated by the American Forests Urban Forest Program is 40 to 60 percent for forested states like Georgia (Leahy, 2017). The city of Columbus falls well within this range when the city is considered as a whole, possessing 52 percent canopy cover between 2005 to 2015. The 200-hectare difference between 2010, 2015 and 2005 is negligible when classification error is considered. While the aggregate canopy cover did not change over that time period, the canopy within the 53 census tracts did change over time. These results highlight the city's recent development and forestry practices.The greatest loss in canopy over the ten-year period occurred in the lower middle census tracts (Figure 7). Based on interpretations of classification changes over time and changes seen during the error check, there are two main reasons for tree loss: development and removal of
residential trees. The majority of the UTC loss seen over time was associated with development. In many cases, trees were cleared between 2005 and 2010, but buildings and pavement were not in place until after 2010. These areas of development have lower canopy cover to start with, and, therefore, the tree loss leaves a greater impression than areas with greater percent canopy. The increase in impervious surfaces in these areas affects to air quality too, as roads and businesses increase vehicle traffic to these areas. Ornamental trees are often planted at new businesses and shopping areas, but these trees are smaller than the mature trees removed during construction. Ornamental trees, like crape myrtles (Lagerstroemia indica L.), have small leaf area indexes and mature tree heights, which makes them poorly suited for reducing air pollutants (McPherson, Simpson, Peper, \& Xiao, 1999; Yang, Chang, \& Yan, 2015).

Census tract 25, the area between the Chattahoochee river and south of Highway 280 containing the Columbus Civic Center (Figure 8), had the second smallest tree canopy for all three years. This tract experienced a 9 percent gain in tree canopy between 2005 and 2015 because the city arborist and local tree organizations focused on tree plantings in this area (S. Jones, personal communication, October 27, 2017). Based on a thorough examination of the area and discussions with the city arborist, little can be done to further improve tree canopy in this area unless businesses get involved, even with a canopy cover of only 18 percent in 2015. Much of the land is owned by the city in the form of public parks with ball fields and parking lots. The remainder of the tract is private property.

Other tree canopy gains over the ten-year period are due in large part to tree growth on forestry lands previously cleared for timber. This growth was evident in the northeast corner of Columbus (Figure 5). Another noteworthy area is the northeast tract, known as Midland (tract 101.07). While this area has experienced little overall change in canopy between 2005 and 2015,
a lot has changed in canopy location across this large census tract. The most eastern portion of the tract has many pine tree farms that were harvested around 2005 and have since been replanted. The western to middle portion of this tract has experienced a lot of development with the expansion of neighborhoods and businesses at the expense of tree canopy. While the forest regrowth offset the losses due to development, another timber harvest would reduce tree canopy for this area and the city as a whole. Due in part to the city tree ordinance enacted in 2002, Columbus maintained marginal loss of trees despite large gains in impervious surfaces. Key to the reduction of tree loss is the mandate that requires new business developments plant trees in parking lots.

When adding trees to an urban environment, planning often focuses on location and types of trees to best provide the ecosystem services trees offer. Attention should be given to utilizing as many of tree benefits as possible in addition to air pollution reduction, like water management, social and recreational values, and noise reduction (Miller, Hauer, \& Werner, 2015; Grey, 1996; Jim, 2004). City owned property, i.e. parks, city buildings, monuments, cemeteries, and right of ways, lacking tree coverage is the first priority for planting locations (Grey, 1996). Columbus has done a good job of managing trees in many of these areas, but downtown municipal buildings lack appreciable tree canopy. In the Columbus downtown area, cemeteries, the medical center, and businesses comprise the land available for planting trees. Increasing trees in these vegetation sparse areas will involve educating businesses on the value of trees.

When compared with 5 other counties and their associated major cities in the Southeastern United States, Muscogee County has the best canopy cover (Table 5). However, the urban portion of Columbus only has more canopy cover than Montgomery, Alabama. As

Chatham is located on Georgia's coast, it's land cover is 32 percent water, which reduces land available for tree plantings (Plan-It Geo, 2015). The five counties viewed for comparison, except for Chatham, Georgia, have the same trend as Muscogee County: they all possess greater canopy cover than their major cities. This alludes to the idea that air pollutants are most likely being produced in areas with lower numbers of trees to reduce the pollution. Charlotte, North Carolina, has similar population density over land area as Columbus, but Charlotte has a greater canopy cover as compared to the urban portion of Columbus. This suggests that Columbus can improve its tree canopy in the developed portions of the city.

Table 5. U.S. Southeastern counties' populations, areas, and canopy coverage.

| County <br> (Major City) | 2010 <br> County <br> Population | City \% of <br> County <br> Population | City <br> Population/ <br> Hectare | City \% of <br> County <br> Land Area | County <br> $\%$ <br> Canopy | City \% <br> Canopy | Study <br> Year |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Muscogee <br> (Columbus), GA | 189,885 | 84 | 8.9 | 47 | 52 | 37 | 2015 |
| Mechlenburg <br> (Charlotte), NC | 919,628 | 80 | 9.6 | 53 | 50 | 46 | 2008 |
| Guilford <br> (Greensboro), $\mathrm{NC}^{2}$ | 488,406 | 55 | 7.9 | 20 | 50 | 38 | 2007 |
| Chatham <br> (Savannah), $\mathrm{GA}^{3}$ | 265,128 | 52 | 5.2 | 21 | 36 | 44 | 2013 |
| Tri-county area <br> (Montgomery), $\mathrm{AL}^{4}$ | 363,597 | 57 | 5.2 | 8 | 47 | 34 | 2002 |
| Hamilton <br> (Chattanooga), $\mathrm{TN}^{5}$ | 336,463 | 50 | 4.5 | 25 | N/A | 51 | 2008 |

1 American Forests, 2010b; 2 Cusimano, Bardsley, Ashton, \& Hill, 2009; 3 Plan-It Geo, 2015;
4 American Forests, 2004; 5 American Forests, 2010a
1.4.3 Air Quality Benefit Analysis - Spatially, the city tree canopy differs greatly from north to south. The census tracts (101.07, 102.03, 102.01, and 103.03) north of highway 80 and tract 108.02 (second most eastern tract below 101.07) are considered the northern portion of the city. These four and tract 108.02 (previously Fort Benning land) are not as developed as the rest of the city, containing mainly forest and agriculture landcover. These five tracts comprise 53 percent of the area for the city of Columbus. Only 16 percent of the Columbus population
resides in this northern portion of the city. The remaining 48 tracts make up the other 47 percent of the land in the southern portion of the municipality. This distinction, north versus south, separates the mainly urban, developed portion of Columbus (south) from the agricultural, rural portion (north).

The north portion of Columbus contains two-thirds the city tree canopy. Not surprisingly these 5 tracts experience the most air quality benefits of trees ( 1,141 tonnes of air pollutant removal, 170,000 tonnes $\mathrm{CO}_{2}$ sequestered annually). If these 5 northern census tracks were removed from Columbus (leaving the urbanized portion of the city), it would only have 37 percent tree canopy capable of removing an estimated 576 tonnes of air pollutants and sequestering 86,000 tonnes of $\mathrm{CO}_{2}$ annually. Many of the city's shopping centers and businesses exist in the south central portion of the city, so most residents must travel within the southern section. Therefore, the majority of the air pollutants are being produced (via vehicles and businesses) in the portion of the city with the least number of trees.

Urban forest management involves diversifying types of trees planted and selecting trees that can remain stable, improve air quality, and not emit high amounts of volatile organic carbon (VOC). VOCs contribute to air pollution and can lead to higher particulate concentrations (Miller et al., 2015). The best tree species to reduce pollution are typically unpopular trees to use in street and residential planting (Yang et al., 2015; Simpson \& McPherson, 2011; Curtis et al., 2014; Benjamin, Sudol, Bloch, \& Winer, 1996). Conversely, popular trees, like oaks, offer great air pollutant reduction but also emit high VOCs during spring and summer seasons (Curtis et al., 2014; Bolund \& Hunhammar, 1999). This points to the need to diversify the types of trees planted across cities, prioritizing the species with the best overall performance.

The methods used here to quantify tree canopy coverage and its associated air quality benefits have limitations. Comparing city canopy cover using aerial imagery at five-year intervals may not provide adequate time to detect differences at a city-wide scale. Analysis every ten years, is better for tracking these changes. However, technological advancements are expected during a time period of ten-years, which makes comparable imagery difficult. NAIP imagery improved over the 10 years used in this analysis, from 3-band, 2 m resolution in 2005 to 4-band, 1 m resolution in 2010. Starting in 2017, three states had NAIP imagery available with 50 cm resolution. It is likely that this higher resolution imagery will be available for all states soon (USDA, 2017). Satellite imagery is also improving, offering better resolution and more bands than NAIP (WorldView-2: 0.5m resolution with 8 bands). However, these satellite images are not free, like NAIP.

Meneguzzo, Liknes, and Nelson (2013) found the unsupervised approach to NAIP imagery classification overestimates tree clusters as compared with object based image analysis (OBIA) and better reflects photo-interpreted results compared to ground-based or bottom-up approaches. Ground surveying trees in a city on a block by block approach is often the next step after quantifying canopy using high spectral imagery (Miller et al., 2015). Tree surveys are helpful in identifying tree health, height, and type, which better assists in planning at a street level.

Since the i-Tree Tool is a first-order assessment of air pollutant removal associated with trees, it is not possible to estimate the degree of accuracy and variability associated with its predictions. The developers of i-Tree acknowledge that there are limitations in using this method (Nowak et al., 2014). Removal rates are calculated in part based on air pollution concentrations and meteorological data, which are gathered at county and regional levels. For
example, $\mathrm{SO}_{2}, \mathrm{PM}_{2.5}, \mathrm{O}_{3}$, and meteorological data were retrieved from data collected at the Columbus Airport (AQS Site ID: 13-215-0008), which is centrally located in Muscogee County. PM 10 data was collected at Cusseta Road Elementary school (AQS Site ID: 13-215-0011) in south Columbus. $\mathrm{NO}_{2}$ and CO data were collected near Atlanta, Georgia, (AQS Site ID: 13-0890002) approximately 145 km away from Columbus (EPA, 2015). Thus, the removal rates for $\mathrm{SO}_{2}, \mathrm{PM}_{2.5}, \mathrm{PM}_{10}$ and $\mathrm{O}_{3}$ are better applied at the city scale, given the data used to determine these rates was obtained within Columbus, as compared to the removal rates for $\mathrm{NO}_{2}$ and CO . Vehicles and energy production are main sources of $\mathrm{NO}_{2}$ and CO emissions in urban settings (Girard, 2014). As Atlanta, Georgia, is more heavily populated with more vehicles than Columbus, Georgia, relying on $\mathrm{NO}_{2}$ and CO data gathered in the Atlanta metropolitan area to create Columbus removal rates raises concerns. With fewer vehicles in Columbus, it is conceivable the pollution concentrations in the area are lower than the Atlanta area. Therefore, removal rates for these two air pollutants by trees in the Columbus area are likely overestimated. In this study, pollutant removal rates were applied at the census tract level. While useful for highlighting variation in the removal of air pollutants across the city, this approach may not accurately represent pollutant attenuation. As air pollution is generated locally, the trees in the northern portion of the city may not be removing air pollutants at the rates estimated if the air pollution does not exist in these areas.

In addition to the limitations caused by the lack of air pollutant concentration data, too few studies quantify tree reductions of air pollutants (Pataki et al., 2011; Setälä et al., 2013). This scarcity of data is a noteworthy drawback to the i-Tree model. Additionally, the $\mathrm{PM}_{2.5}$ concentrations removed by trees may be insignificant compared to the levels in the air (Witlow, 2009).

Over half the monetary savings of the five criterion pollutants found using i-Tree are attributed to $\mathrm{PM}_{2.5}$ removal (4 percent of the 1,700 tonnes of air pollutants removed annually). PM ${ }_{2.5}$ health concerns have been well researched (Sarnat, Schwartz, \& Suh, 2001; Pope III et al., 2002; Schlesinger et al., 2006; Fann et al., 2012), but the tie between trees interactions with PM2.5 and the credited health benefits has not been well researched (Pataki et al., 2011). Estimates from the i-Tree model suggest that Columbus trees offer $\$ 4$ million in health savings. This estimate may not be an accurate assessment.

As an example, consider $\mathrm{PM}_{2.5}$ and its complex interactions with trees. This relationship cannot fully be captured in a simple removal rate, even if the rate was generated using Muscogee County specific data. Other air pollutants such as $\mathrm{O}_{3}, \mathrm{NO}_{2}, \mathrm{SO}_{2}$, and CO (being gaseous) have simpler relationships with trees because they are removed from the atmosphere by leaf stomata. In contrast, temperature, wind direction and wind speed alter $\mathrm{PM}_{2.5}$ deposition and resuspension (Hemond \& Fechner, 2014; Nowak et al., 2014; Tong, Whitlow, MacRae, Landers, \& Harada, 2015). County $\mathrm{PM}_{2.5}$ removal rates vary in the i-Tree model and are positive or negative (increases in $\mathrm{PM}_{2.5}$ ) depending on county wind and precipitation conditions (Hirabayashi, 2014). While $\mathrm{PM}_{2.5}$ rates used in the model come from county specific data, the interaction with trees and $\mathrm{PM}_{2.5}$ is clearly complicated. This complex interaction between $\mathrm{PM}_{2.5}$ and local tree canopy conditions requires additional research.

While the approach employed in this research to quantify trees' air quality services has limitations, the benefit of this top-down approach in locating and determining change in canopy over time allows for city planners to develop tree plans that can improve local environmental conditions. Conducting a thorough tree benefit analysis at the street level would be ideal, but, access, time, and funding are large hinderances to this endeavor. A standard model, like i-Tree,
provides city planners with information that can be used to gain support and funding for future tree plantings. As long as caution is taken by weighing the approximated air quality reductions and monetary values in light of the model's restrictions, this approach is helpful to start conversations relating to vegetation planning at the city level.

## CHAPTER 2 - TREE ARRANGEMENT PARTICULATE MATTER TESTS

### 2.1 Introduction

Air pollution reduction benefits by trees in urban areas have been linked to health improvements (Beckett, Freer-Smith, \& Taylor, 2000; Tiwary, 2009; Nowak et al., 2014). The air quality benefits of trees for gaseous air pollutants is a simpler relationship compared to particulate pollutants because trees remove gaseous pollutants from the atmosphere through leaf stomata. In contract, trees are a temporary resting location for fine particulate matter, $\mathrm{PM}_{2.5}$. Tree interactions with particulates is dependent on weather conditions such as temperature, relative humidity, wind direction and wind speed all of which alter $\mathrm{PM}_{2.5}$ deposition and resuspension (Hemond \& Fechner, 2014; Nowak et al., 2014; Tong, Whitlow, MacRae, Landers, \& Harada, 2015; Cai et al., 2017). While studies have been conducted to better define this relationship, studies often discuss the need for testing across regional conditions (Ortolani \& Vitale, 2016; Nowak \& Greenfield, 2008; Nowak et al., 2014; Witlow, 2009). The complex interactions between trees and particulates warrants additional examination.
2.1.1 Particulate Matter and Trees - Particulate matter (PM) is among the six criteria air pollutants monitored by state agencies and regulated by the U.S. Environmental Protection Agency (EPA) under the National Ambient Air Quality Standards (NAAQS) as part of the Clean Air Act (Girard, 2014). PM is categorized by aerodynamic diameter into coarse, PM10 - 2.5 to $10 \mu \mathrm{~m}$ in diameter, and fine particles, PM2.5-2.5 $\mu \mathrm{m}$ or smaller in diameter. The residence time of PM10 is minutes to hours, being removed from the air due to gravitational settling. As a result, PM10 travels less than 100 km . PM2.5 has a residence time of days to weeks. It is often removed through dry deposition and rain and travels 100s to 1000 s of kilometers (Wilson \& Spengler, 1996). In interactions with trees, PM2.5 levels on leaves are lower than PM10 due to
gravitation deposition properties (Beckett, Freer-Smith, \& Taylor, 2000; Freer-Smith, 2005; Sæbø et al., 2012). Fine particulates are solid/liquid aerosols created through anthropogenic activities e.g., fossil fuel combustion, wildfires, steel making, and natural processes e.g., sea spray, pollen, vegetation releasing volatile organic compounds (Hemond \& Fechner, 2014; Girard, 2014). These microscopic particles are most distressing for health reasons as inhaling these aerosols can cause respiratory and cardiovascular complications (Sarnat, Schwartz, \& Suh, 2001; Pope III et al., 2002; Schlesinger et al., 2006). Inhalation of PM2.5 caused an estimated 130,000 deaths in the U.S. in 2005. For comparison, 4,700 deaths were attributed to ozone exposure in the same year (Fann et al., 2012).

Field studies monitoring $\mathrm{PM}_{2.5}$ within and near tree buffers report varying results. Several small-scale experiments in the New York City area indicate that tree buffers limit $\mathrm{PM}_{2.5}$ dispersion causing concentrations to be elevated in close proximity downwind from tree lines, while $\mathrm{PM}_{2.5}$ concentrations quickly decrease in open areas (Tong et al., 2015). The New York City study and two other studies conducted in and near Beijing found $\mathrm{PM}_{2.5}$ concentrations are higher within dense tree canopy buffer or forests as compared with open areas (Tong et al., 2015; Liu, Yu, \& Zhang, 2015; Chen et al., 2015). A Detroit, Michigan field study found vegetation barriers caused particulates to decrease more gradually beyond the tree stand than open areas (Brantley, Hagler, Deshmukh, \& Baldauf, 2014). Witlow (2013) found that particulates increased with distance behind tree stands. Another study reported that tree buffers decreased particulate matter beyond tree stands when the wind is from the direction of the road (Baldauf et al., 2008). These reported results were conducted across different weather conditions in various locations, which further points to the need for site specific analysis of tree fine particulate air quality benefits.

The EPA has a guide for designing vegetation barriers along roadways in order to reduce air pollution and recommends denser tree lines to reduce air flow and stop pollutants near the street (Baldauf, 2016). In recent years, studies have been conducted in various tree configurations. Most studies, discussed above, indicate higher $\mathrm{PM}_{2.5}$ concentrations exist within denser canopies (Tong et al. 2015; Whitlow, 2013; Tong, Chen et al. 2015). One study modelled the impact of air pollutant reduction among six tree designs finding dense tree buffers most effective (Baldauf, Isakov, Deshmukh, \& Zhang, 2016). A few studies have modelled the tunnel effect created by trees lining either side of the street, which traps pollutants between the tree lines increasing concentrations (Gromke, 2011; Cai et al., 2017). These studies investigated the trees near roadsides, concentrating on the reduction of vehicle produced pollutants. Vehicles are a main particulate pollution sources in cities, but other sources like restaurants, prescribed burns, and utility companies can also contribute to $\mathrm{PM}_{2.5}$ concentrations (Zheng et al., 2002).

Additional field studies are needed to better understand the relationships between urban tree stand arrangements and $\mathrm{PM}_{2.5}$ concentrations, especially accounting for local $\mathrm{PM}_{2.5}$ sources and atmospheric conditions.
2.1.2 PM $_{2.5}$ Instrumentation - Fine particulate matter as regulated by the EPA is monitored by states using in situ continuous monitors that are accurate and expensive equipment, e.g, the Tapered Element Oscillating Microbalance (TEOM) and $b$-attenuation monitoring (BAM) analyzers (EPA, 2013). These monitors are located in larger cities across the U.S. (EPA, 2015), and are designed to measure regional PM levels. Air pollution across cities is heterogeneous, depending on localized interactions of $\mathrm{PM}_{2.5}$, weather, and vegetation, and small portable sensors can be beneficial in identifying areas of focus and concern. Low-cost, portable PM sensors can be used to bridge the gap in knowledge between regional particulate data and
neighborhood level exposure to pollutants. However, caution should be taken when using these portable devices due to accuracy and reliability concerns (Jiao et al., 2016; Lewis \& Edwards, 2016; Rai et al., 2017; Snyder et al., 2013; Wang et al., 2015; Manikonda, Zíková, Hopke, \& Ferro, 2016).

The EPA encourages cities to study air quality at several locations using a variety of sensors to assess local air quality conditions (EPA - Smart City Challenge, Green Cities project). With advances in sensor technology, people can monitor their local air quality by operating a personal, portable PM device. While not promoting specific equipment, the EPA has supported these efforts by providing agency research on portable PM devices and data regarding how individuals and communities can use these devices to facilitate urban planning (EPA - Air Sensor Toolbox).

The Community Air Sensor Network (CAIRSENSE) project was conducted by the EPA and Georgia Environmental Protection Department to assess the accuracy of a few of these lowcost particulate matter devices including the AirBeam. The AirBeam is a low-cost portable fine particulate matter sensor developed in 2013. In CAIRSENSE, three AirBeams were tested for 168 days and compared to federal equivalent method (FEM) monitors. The results indicated mid-level agreement ( $\mathrm{r}=0.65-0.66$; Jiao et al., 2016). This result was comparable to another low-cost PM device, the Dylos ( $\mathrm{r}=0.63-0.67$ ). Notably, CAIRSENSE found a strong association among the three AirBeam devices tested (e.g. $r=0.99$; Jiao et al., 2016). Another recent study compared AirBeam performance to reference instruments in field tests and found similar results (AirBeams to each other: $\mathrm{r}^{2}=0.99$, to GRIMM $11-\mathrm{R} \mathrm{r}^{2}=0.66$ to 0.71 ; Mukherjee, Stanton, Graham, \& Roberts, 2017). While the AirBeam has mid-level agreement to FEM, these devices have utility as portable field devices when conducting comparative studies.
2.1.3 Study Goals - This research project investigated the question of the relative relationship of $\mathrm{PM}_{2.5}$ concentrations within varying tree canopy types versus adjacent open areas. The AirBeams provide a useful tool to address this question. Since the complex relationship between trees and particulate matter is dependent on local factors (e.g., particulate sources, weather conditions), this research presents an opportunity to test the efficacy of AirBeams in the field at different locations and under different atmospheric conditions. Thus, one question posed by this research is whether a portable, low-cost monitoring device (specifically AirBeams) can be used to effectively compare $\mathrm{PM}_{2.5}$ among differing tree canopy configurations? Based on previous AirBeam studies (Jiao et al., 2016; Mukherjee et al., 2017), it is hypothesized that the devices will be sufficient for measuring relative relationships among tree canopy configurations, but they will not be accurate for quantifying actual $\mathrm{PM}_{2.5}$ concentrations in the field. As such, the first goal of this research is to assess the field capabilities of the AirBeam.

The PM 2.5 concentrations within open areas will be compared to adjacent tree buffers composed in the following tree arrangements: dense tree buffer (width $>45 \mathrm{~m}$ ), small tree line (width $<30 \mathrm{~m}$ ), and U -shaped tree arrangement (Figure 10). The following question will be addressed in this approach: Do open areas near PM sources differ in PM 2.5 concentrations as compared with adjacent tree stands of various configurations? It is hypothesized the dense tree stands will have higher $\mathrm{PM}_{2.5}$ concentrations than adjacent open areas, small tree line $\mathrm{PM}_{2.5}$ concentrations will have no appreciable difference to adjacent open areas concentrations, and the U-shaped tree arrangements will have highest relative concentrations of $\mathrm{PM}_{2.5}$ within the open areas adjacent to the trees. Columbus has average low wind speeds, $\mathrm{PM}_{2.5}$ should be trapped by dense trees and disperse less in open areas along streets. Therefore, the primary goal of this
study is to examine the relationship between $\mathrm{PM}_{2.5}$ and trees by investigating varying tree canopy configurations.


Figure 10. Picture of neighboring open areas and an example of A) dense tree buffer, B) small tree line, and C) U-shaped tree arrangement with examples of open (blue arrows) and tree (orange arrows) sample locations. (Images taken in 2017 via Google Earth ${ }^{\mathrm{TM}}$.)

### 2.2 Methods

### 2.2.1 Study City Atmospheric Conditions and PM Sources - Columbus, Georgia, is

located along the western border of the state ( $32^{\circ} 29^{\prime} 32^{\prime \prime} \mathrm{N}, 84^{\circ} 56^{\prime} 25^{\prime \prime} \mathrm{W}$ ). The Fort Benning Army base is located to the southeast of the city. This city has an annual precipitation of 46 inches (NWS, 2017). Maximum monthly temperatures range from $57^{\circ} \mathrm{F}$ to $92^{\circ} \mathrm{F}$ and monthly minimum temperatures from $36^{\circ} \mathrm{F}$ to $73^{\circ} \mathrm{F}$ (lows in January and highs in July and August). Monthly relative humidity stays close to the annual mean of 65 percent, peaking at 71 percent in August with low of 62 percent in February and March (NCEI, 2017a). The city has mean winds speeds of $2.5 \mathrm{~m} / \mathrm{s}$ with highest winds, $2.9 \mathrm{~m} / \mathrm{s}$, in the winter months. Mean wind direction is variable throughout the year, with the highest frequency of winds from the east (Figure 11; NCEI, 2017a). Climatological data used in this study was retrieved from the weather station located at the Columbus Metropolitan Airport (WBAN: 93842, Lat/Long 32.5161 ${ }^{\circ},-84.9422^{\circ}$ ).

The city's high annual precipitation and low annual wind speed should be conducive for $\mathrm{PM}_{2.5}$ to
be trapped by trees and brought to the ground rather than resuspended into the air (Hirabayashi, 2014).


——Wind Speed $<5 \mathrm{~m} / \mathrm{s}$<br>- Wind Speed 11 to $15 \mathrm{~m} / \mathrm{s}$

—Wind Speed 6 to $10 \mathrm{~m} / \mathrm{s}$
$\rightarrow$ Wind Speed $>15 \mathrm{~m} / \mathrm{s}$
Figure 11. Columbus wind rose (data from 2007 to 2016) indicating highest frequency of winds from the east. Wind direction frequency is marked by the 2 and 4 percent circles.

Fort Benning is located to the southeast of Columbus. Many of the city's worst air quality days occur during controlled wildfire burns at Fort Benning. These burns increase $\mathrm{PM}_{2.5}$ concentrations, among other pollutants. Several studies have monitored the air pollution at increasing distances around Fort Benning (Achtemeier, 2011; Baumann, 2005; Liu, 2010; Odman, 2012) because this pollution impacts the region. Like other cities, vehicles, residential wood burning, and meat cooking are main sources of fine particulate matter (Reff et al., 2009; Zheng, Cass, Schauer, \& Edgerton, 2002), which have more localized influence as compared to the prescribed burns.
2.2.2 Instrumentation - In order to quantify $\mathrm{PM}_{2.5}$, this research utilized the AirBeam (Figure 12A). This device employs a Shinyei PPD60PV particle sensor and Bluetooth to transmit data through a smart phone app called AirCasting (Android app, Figure 12B) or a website (aircasting.org/map). The AirBeam can record data while mobile or in fixed position. The AirBeam reports $\mathrm{PM}_{2.5}\left(\mu \mathrm{~g}-\mathrm{m}^{-3}\right)$, temperature $\left({ }^{\circ} \mathrm{F}\right)$, percent relative humidity, and sound level (decibels) every second, minute, or hour in real time (Heimbinder \& Besser, 2014). The Shinyei PPD60PV particle sensor uses the light scattering method to count particulates that cross the path of the encased infrared light (Figure 13). This particle sensor has a concentration measurement range of 0.5 to $300 \mu \mathrm{~g}-\mathrm{m}^{-3}$ (Shinyei Technology Co., Ltd). The AirBeam has an output resolution of $0.0001 \mu \mathrm{~g}-\mathrm{m}^{-3}$ when recording at 1 -minute intervals and $0.01 \mu \mathrm{~g}-\mathrm{m}^{-3}$ when recording at 1 -second intervals (Heimbinder \& Besser, 2014). The data were sent from the app to email in comma-delimited format and converted to an Excel spreadsheet for analysis. The AirBeams each have a unique serial number recorded with the data to assist in quality assurance. Additionally, the devices and corresponding phones were labeled 1, 2, and 3 (AirBeam 001896105818,001896105926 , and 0018961061 CE respectively) for easy identification in the field.


Figure 12. A) AirBeam diagram (Heimbinder \& Besser, 2014) and B) smart phone app example.


Figure 13. The inside of the Shinyei PPD60PV (Heimbinder, 2013).
Since temperature, relative humidity, wind speed and direction (Hemond \& Fechner, 2014; Nowak et al., 2014; Tong et al., 2015; Tai, Mickley, \& Jacob, 2010), precipitation, and change in pressure over time have been shown to account for 30 percent of the daily variability in $\mathrm{PM}_{2.5}$ in Southeastern U.S. (Tai et al., 2010), a handheld Kestrel 4000 pocket weather meter (Nielsen-Kellerman, Nelson, PA) was used to collect the ambient temperature (accuracy: $\pm 1{ }^{\circ} \mathrm{C}$; resolution: $0.1^{\circ} \mathrm{C}$ ), relative humidity (accuracy: $\pm 3 \%$; resolution: $0.1 \%$ ), and wind speed (accuracy: $\pm 0.1 \mathrm{~m} / \mathrm{s}$; resolution: $0.1 \mathrm{~m} / \mathrm{s}$ ) aligned with wind direction at each site in ten-minute intervals. The wind direction was obtained using a compass by noting direction at maximum wind speed. Field tests were performed during periods of no precipitation to protect the AirBeam units.
2.2.3 AirBeam Equivalency Tests - Following best practices (Lodge, 1988) and EPA recommendations (Williams et al., 2004) any device used for monitoring air quality should be suitably calibrated. Based on the standard reference instrument method, the AirBeams were compared with the state's TEOM continuous monitor located at the Columbus airport. Due to instrumentation differences (the TEOM has omnidirectional intake, while the AirBeam units
have unidirectional intakes), data resolution differences (TEOM has 1-hour resolution and AirBeams have 1-minute resolution), and the limited lifespan of the AirBeams (2-hour battery life), it was determined intra-unit correction (through equivalency tests conducted prior to and during field testing) would be the best standardization method.

The three AirBeams were assessed for their equivalency across a range of $\mathrm{PM}_{2.5}$ concentrations from 0 to $177 \mu \mathrm{~g}-\mathrm{m}^{-3}$ before the start of the field tests. These units were assessed for equivalency at low ranges by running the devices over the course of three days in an undisturbed room, in which the room's HVAC vents were sealed and entry into the room was limited to conducting the test. The Austin Air HealthMate Plus® (an air purifier capable of removing particulates larger than 0.3 microns) was used to reduce particulate matter within the room after small levels of smoke were allowed into the room through a small opening in the window to compare response to stimuli over time. The three units were equal distance from the opening in the window and the air purifier.

A second indoor test was conducted to compare the units' response to high particulate concentrations. This test was performed by burning a 160 g carbon fiber vinyl ester specimen in a muffle furnace at $600^{\circ} \mathrm{C}$ for 1 hour 47 minutes. The AirBeams were positioned in the fume hood 1 m above the furnace smoke stack. The fume hood was allowed to run prior to and during the burning of the carbon sample to ensure steady airflow. During this equivalency test, unit 3 disconnected from the phone app and did not record 22 minutes of data. These 22 minutes were removed from the statistical analysis for all units.

The first two tests were conducted in controlled indoor environments. The last equivalency test was conducted outdoors to assess response of the units to stimuli without the ability to control environmental factors. The AirBeams were set up outside equal distances and
downwind from an outdoor wood burning stove. Smoke was allowed to escape from the top of the stove for 5 minutes, and then the fire was squelched in the stove. The units collected data for 5 minutes before and after the smoke, and the data were assessed to determine if the units responded to the stimuli at the same time.

The Pearson product-moment correlation coefficient was computed between the three AirBeams and the state TEOM. Model II linear regression was used to assess the relationship among the three AirBeams for all equivalency tests combined. As with time-series data, autocorrelation was an issue in the results of all three equivalency tests. The appropriate lag was determined and autocorrelation corrected for each individual test (indoor test $1 \mathrm{lag}=21 \mathrm{~min}$, indoor test $2 \mathrm{lag}=4 \mathrm{~min}$, outdoor test $1 \mathrm{lag}=2 \mathrm{~min}$ ) before using one-way analysis of variance (ANOVA) to compare the results of the three units.
2.2.4 AirBeam Temperature and Relative Humidity - The AirBeam's relative humidity and temperature sensors are good indicators to ensure the devices are not overheating or oversaturated. AirBeams are programmed to shut off at 100 percent humidity (Heimbinder \& Besser, 2014) and the Shinyei PPD60PV performs best at temperatures of 0 to $45^{\circ} \mathrm{C}$ (Shinyei Technology Co., Ltd). Jiao et al. (2016) and Mukherjee et al. (2017) did not address the performance of the temperature and relative humidity sensors housed in the AirBeams. The output from these sensors were compared to Kestrel 4000 data obtained during field testing and to hourly data from the weather station at the Columbus Metropolitan Airport (WBAN: 93842) [gathered from the National Centers for Environmental Information (NCEI, 2017b)].
2.2.5 Field Test - During February 2017 (winter, leaf-free period), particulate concentrations were measured in one-hour sampling sessions at 15 study sites (Figure 14), on rain free days, along major Columbus roads (Interstate 185, Highway 80, Highway 27, and

Highway 280), near busy shopping centers, and close to restaurants that produce smoke (e.g.
Burger King). The roads that run along the study sites are considered principle arterial highways and experience average daily traffic ranging from 27,000 vehicles (Manchester Parkway) to 66,000 vehicles (Highway 80). As access to power was limited, the devices were operated for one hour to avoid exceeding the two-hour battery lifespan.


Figure 14. Field study sites with dense field buffer (green circle), small tree line (an x), and Ushaped arrangements (yellow square with $x$ ) indicated across Columbus, Georgia.

Sites were categorized as dense tree buffers $(\mathrm{n}=5)$, small tree lines $(\mathrm{n}=6)$, and U -shaped tree arrangements $(n=4)$. At eleven sites more than one location was tested so each tree arrangement type had 10 sample locations. Barriers, like fences, walls, and steep drop-offs in elevation, limited ability for more than one sample location at four sites. For each sample location two AirBeam units monitored particulate concentrations, one within the tree stand and one in the adjacent open area (Figure 10). In total, 60 sample locations (30 pairs of tree stand and open areas) were monitored.

The study sites were chosen based on proximity to major roads and busy shopping centers. The closeness to smoke producing restaurants was not accounted for in the original experimental design, and sites were not picked with this feature in mind. Each site needed a tree buffer with neighboring open area and a higher density of conifers than deciduous trees (as testing occurred during winter months). Sample locations picked within sites were based on distance from source, with first locations close to the road and successive locations set farther back as spaced allowed. Detailed pictures of each study site with marked test locations can be found in Appendix B. It should be noted that sites were not tested randomly as wind direction needed to correspond to the direction of particulate matter source and access to some sites (Haverty's, Lazyboy, Colony Bank, and the three churches) was limited to specific days and times.

At each site AirBeams were set at the height of 1.7 m , the average adult height in the U.S. (Ogden, Fryar, Carroll, \& Flegal, 2004). All three units were started at the same location close to the street, in the open area, and collected data for at least five minutes. While positioned facing the direction of the road, a compass was used to determine the unit orientation, and units remained facing this direction for the entirety of each testing session. The two units with the most similar peak and average data were identified and used for subsequent testing. The two selected units were placed within the tree buffer and adjacent open area at the same distance from the road. The units sampled for five to ten minutes at this location. Units within the tree buffer and adjacent open area were moved back farther (if space allowed) for an additional five to ten minutes. All units were moved back to the start location for the final five minutes. At each location in the open area, the Kestrel 4000 was held at approximately 1.5 m and
temperature was allowed to equilibrate before wind speed, relative humidity, and temperature data were recorded.

Aakash et al. (2017) recommends frequent recalibrations in an environment similar to study conditions when using low-cost portable devices. Therefore, the five-minute start and end PM2.5 data were used to correct for AirBeam discrepancies. The units' median values for the start/end period were calculated. A median ratio (unit 1: unit 3 and unit 2: unit 3) was then applied to the $\mathrm{PM}_{2.5}$ data recorded at each location. Unit 3 was used as the standard for comparison testing as unit 3 was used at 27 of the sampling locations for tree/open concentration monitoring. (This matches the equivalency test results as unit 3 was found to vary between unit 1 and unit 2). For the three locations in which unit 3 was not deployed, a median ratio of unit 1: unit 2 was used to correct baseline differences. While a high correlation was found during equivalency tests among the units, this added corrective measure was used to ensure the data of importance, the tree and open $\mathrm{PM}_{2.5}$ concentration data, aligned before final analysis. At three sites (the first site for each tree arrangement type), the units were corrected based on median ratio data for all sites and equivalency tests because the median ratio correction method (described above) was not employed until after testing was completed at these sites.

Columbus hourly weather from the weather station at the Columbus Metropolitan Airport (WBAN: 93842) airport for February 2017 were obtained from the National Centers for Environmental Information (NCEI, 2017b). Columbus hourly PM 2.5 concentrations for February 2017 were certified and obtained from the Georgia Environmental Protection Department - Air Branch Division. These data were used to assess if a relationship existed at city level between weather conditions and particulates. The daily averages were calculated and correlations examined between wind direction, wind speed, temperature, relative humidity, precipitation, and

Columbus PM 2.5 concentrations. Fort Benning controlled burn (Fort Benning's Smoke and Sound Archive, 2017) and regional agricultural fire (NESDIS, 2017) dates were gathered to determine if regional smoke impacted $\mathrm{PM}_{2.5}$ and study sample locations' $\mathrm{PM}_{2.5}$ concentrations.

The Columbus hourly $\mathrm{PM}_{2.5}$ concentration were also used to assess whether study sample locations' $\mathrm{PM}_{2.5}$ levels were influenced by localized sources. Each location's peak $\mathrm{PM}_{2.5}$ values less the city $\mathrm{PM}_{2.5}$ data were calculated. The results ranged from 2.0 to $92.6 \mu \mathrm{~g}-\mathrm{m}^{-3}$. Values 70 to $499 \mu \mathrm{~g}-\mathrm{m}^{-3}$ were labelled as high, 30 to $69 \mu \mathrm{~g}-\mathrm{m}^{-3}$ as medium, and below $29 \mu \mathrm{~g}-\mathrm{m}^{-3}$ as low sources. As a part of their Village Green Project, the EPA developed this scale for short-term air sensors in order to understand personal exposure to nearby air pollutants (Keating et al., 2016). This method matched what was experienced at the sites as the three high PM source locations were near local restaurants producing smoke and the one medium location occurred near a stop light with idling vehicles. These PM source level results were considered a random factor in the analysis as this was controlled for in the experimental design. The mean $\mathrm{PM}_{2.5}$ for each location (tree vs open) and by type (dense, small, U-shaped) was used in an analysis of covariance (ANCOVA) with temperature, relative humidity, the wind direction versus the AirBeam unit orientation, and wind speed as covariates. IBM SPSS Statistics (Version 25.0) computer software was used for the statistical calculations (IBM Corp., 2017).

### 2.3 Results

2.3.1 AirBeam Equivalency Tests - Two of the three AirBeams had good correlation
(Unit 1: $\mathrm{r}=0.78, \mathrm{p}=0.066$; Unit 2: $\mathrm{r}=0.85, \mathrm{p}=0.032$; Unit $3 \mathrm{r}=0.85, \mathrm{p}=0.03$ ) to the state TEOM when $\mathrm{PM}_{2.5}$ concentrations ranged from 0 to $10 \mu \mathrm{~g}-\mathrm{m}^{-3}$. The among unit equivalency tests yielded a total of 774 minutes ( 601 min for indoor test one, 85 min for indoor test two, and 88 minutes for the outdoor test) of $\mathrm{PM}_{2.5}$ data for each AirBeam. All three units showed a
significant positive relationship to each other (Figure 15; Model II Regression Units 1 \& 2: F $\mathrm{F}_{1,773}$ $=67471, r^{2}=0.989, p<0.001$; Units $1 \& 3: F_{1,773}=37019, r^{2}=0.980, p<0.001$; Units $2 \& 3$ : $\left.\mathrm{F}_{1,773}=53262, \mathrm{r}^{2}=0.986, \mathrm{p}<0.001\right)$. All three units were not statistically different from each other when comparing the mean $\mathrm{PM}_{2.5}$ among all three equivalency tests $\left(\right.$ ANOVA F $_{2,278}=$ $0.440, \mathrm{p}=0.645$ ). Overall, units 2 and 3 differed least as compared to unit 1 (Units $2 \& 3$ Tukey HSD $\mathrm{p}=0.991$; Units 1 \& 2 Tukey HSD $\mathrm{p}=0.738$; Units $1 \& 3$ Tukey HSD $\mathrm{p}=0.661$; Table 6).


Figure 15. Airbeam $\mathrm{PM}_{2.5}$ equivalency test results showing model II linear regression relationship between $A$ ) unit 1 v . unit $2, \mathrm{~B}$ ) unit 1 v . unit 3 , and C ) unit 2 v . unit 3. 1:1 line denoted by solid line for reference.


Figure 16. Equivalency test results $\mathrm{PM}_{2.5}$ mean and $95 \% \mathrm{CI}$ : A) indoor test one, D) indoor test two, C) outdoor test, and D) all tests combined.

To better understand the relationship among the units, comparisons were made among the three separate equivalency test results to determine how the units performed with various particulate concentrations and indoors versus outdoors (Table 6). The three tests varied in $\mathrm{PM}_{2.5}$ concentration ranges: indoor test one ranged from 1 to $10 \mu \mathrm{~g}-\mathrm{m}^{-3}$, indoor test two ranged from 30 to $177 \mu \mathrm{~g}-\mathrm{m}^{-3}$, and the outdoor test ranged from 17 to $155 \mu \mathrm{~g}-\mathrm{m}^{-3}$. No statistically significant difference was found between the average $\mathrm{PM}_{2.5}$ estimates for the three units for the first indoor
test $\left(\right.$ ANOVA $\left.\mathrm{F}_{2,81}=2.322, \mathrm{p}=0.105\right)$, the second indoor test $\left(\right.$ ANOVA F $_{2,62}=2.562, \mathrm{p}=$ 0.086 ), and the outdoor test (ANOVA $\left.F_{2,131}=0.927, p=0.398\right)$. Units 1 and 3 varied less at lower concentrations (4 percent difference) versus higher concentrations ( 20 percent difference). The pairwise relationship results were similar between the first indoor test and the outdoor test. Units 1 and 3 have a 4 percent mean difference for the outdoor test (Figure 16).

Table 6. Equivalency test results for AirBeams' PM2.5 mean, 95\% CI, and Tukey HSD p-values indicating no significant difference between $\mathrm{PM}_{2.5}$ concentration means of the three units.

|  | Indoor Test 1 <br> $(\mathrm{n}=28)$ |  | Indoor Test 2 <br> $(\mathrm{n}=21)$ |  |  | Outdoor Test <br> $(\mathrm{n}=44)$ |  |  |  | Combined <br> $(\mathrm{n}=93)$ |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Units | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Mean | 3.2 | 4.1 | 3.3 | 80.9 | 86.5 | 99.1 | 26.5 | 31.7 | 27.6 | 31.8 | 35.8 | 36.4 |
| $\pm 95 \% \mathrm{CI}$ | $\pm 0.5$ | $\pm 0.7$ | $\pm 0.6$ | $\pm 12.1$ | $\pm 10.6$ | $\pm 11.4$ | $\pm 6.1$ | $\pm 5.3$ | $\pm 5.1$ | $\pm 7.0$ | $\pm 7.0$ | $\pm 8.0$ |
| Unit 1 |  | 0.120 | 0.955 |  | 0.777 | 0.078 |  | 0.407 | 0.966 |  | 0.738 | 0.661 |
| Unit 2 |  |  | 0.209 |  |  | 0.284 |  |  | 0.557 |  |  | 0.991 |

2.3.2 AirBeam Temperature and Relative Humidity - For average relative humidity, all three AirBeam units, the Kestrel and the City data were not significantly different (ANOVA F4,89 $=2.425, \mathrm{p}=0.054$; Table 7). The mean relative humidity for unit 3 was significantly different (at an $\alpha=0.1$ threshold) because it was 15 percentage points lower than Kestrel and City data and 7 percentage points lower than units 1 and 2 . For temperature, a statistically significance difference was found (ANOVA $\mathrm{F}_{4}, 89=2.425, \mathrm{p}=0.001$ ). Units 1,2 , and 3 showed mean temperatures that were $4^{\circ} \mathrm{C}$ and $5^{\circ} \mathrm{C}$ higher than the Kestrel and City, respectively (Figure 17).

Table 7. Relative humidity and temperature results: Kestrel, City, and AirBeams' mean, 95\% CI, and Tukey HSD p-values.

| Relative Humidity (\%) |  |  |  |  |  |  |  |  |  | Temperature $\left({ }^{\circ} \mathrm{C}\right)$ |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Kestrel | City | Unit 1 | Unit 2 | Unit 3 | Kestrel | City | Unit 1 | Unit 2 | Unit 3 |  |  |  |  |
| Mean | 45 | 45 | 37 | 37 | 30 | 21 | 20 | 25 | 25 | 25 |  |  |  |  |
| $\pm 95 \% \mathrm{CI}$ | $\pm 8.6$ | $\pm 9.0$ | $\pm 7.0$ | $\pm 7.1$ | $\pm 7.0$ | $\pm 1.8$ | $\pm 1.6$ | $\pm 2.8$ | $\pm 2.1$ | $\pm 2.6$ |  |  |  |  |
| Kestrel |  | 1.000 | 0.553 | 0.531 | 0.074 |  | 0.951 | 0.090 | 0.102 | 0.080 |  |  |  |  |
| City |  |  | 0.631 | 0.609 | 0.098 |  |  | 0.013 | 0.016 | 0.012 |  |  |  |  |
| Unit 1 |  |  |  | 1.000 | 0.785 |  |  |  | 1.000 | 1.000 |  |  |  |  |
| Unit 2 |  |  |  |  | 0.821 |  |  |  |  | 1.000 |  |  |  |  |



Figure 17. Hourly mean and $95 \%$ CI of A) relative humidity and B) temperature for Kestrel, City, and the three AirBeam units.
2.3.3 Field Test - The temperature obtained using the Kestrel 4000 during the field testing period ranged from 12.1 to $28.6^{\circ} \mathrm{C}$ with mean of $21.2{ }^{\circ} \mathrm{C}$, the relative humidity varied from 19.4 to 87.1 percent with mean of 51.1 percent, and the wind direction was variable at speeds of 0 to $5.1 \mathrm{~m} / \mathrm{s}$ with a mean of $1.6 \mathrm{~m} / \mathrm{s}$. The temperature, relative humidity, wind direction in relation to unit orientation, and wind speed were assessed using linear regression and found to account for little variation in $\mathrm{PM}_{2.5}$ across all locations $\left(\mathrm{r}^{2}=0.110, \mathrm{~F}_{4,23}=0.712, \mathrm{p}=\right.$ 0.592). Therefore, the Kestrel obtained weather data were not included in the rest of the analysis.

The $\mathrm{PM}_{2.5}$ concentrations differed across PM source level $\left(\mathrm{F}_{2,52}=41.635, \mathrm{p}<0.001\right)$. The tree stand arrangements also differed significantly (ANCOVA F2,52 $=3.939, \mathrm{p}=0.026$ ). No difference in $\mathrm{PM}_{2.5}$ was found in open areas versus trees ( 0.9 percent difference) across all sites (ANCOVA $\mathrm{F}_{1,52}=0.003, \mathrm{p}=0.956$ ). Dense tree buffers differed as compared to small tree lines (43 percent difference; Tukey HSD $\mathrm{p}=0.001$ ) and U -shaped arrangements ( 31 percent
difference, Tukey HSD $p=0.018$ ). However, small tree lines and U-shaped arrangements showed no differences in mean $\mathrm{PM}_{2.5}$ (Tukey HSD $\mathrm{p}=0.633$ ). Dense tree buffers had higher PM 2.5 concentrations in trees versus open areas with a mean difference of $1.6 \mu \mathrm{~g}-\mathrm{m}^{-3}$. In contrast, small tree lines (mean difference of $0.1 \mu \mathrm{~g}-\mathrm{m}^{-3}$ ) and U -shaped (mean difference of 1.7 $\mu \mathrm{g}-\mathrm{m}^{-3}$ ) arrangements had higher $\mathrm{PM}_{2.5}$ concentrations in open areas versus trees (Figure 18). This interaction was not statistically significant $\left(\mathrm{F}_{2,52}=0.716, \mathrm{p}=0.493\right)$. Sample location details used in the analysis, including PM2.5 corrected data and weather data, are located in Appendix B, Table 7.


Figure 18. Comparison of the open and tree $\mathrm{PM}_{2.5}$ concentrations mean and $95 \% \mathrm{CI}$ within dense tree, small tree line, and U-shaped tree stands.

The Columbus city weather and $\mathrm{PM}_{2.5}$ data for February 2017 were also analyzed to better understand the city's particulates in relation to atmospheric conditions. During February 2017, the city experienced 20 days with particulate concentrations less than $12 \mu \mathrm{~g}-\mathrm{m}^{-3}, 7.4$ days with $12.1-35.4 \mu \mathrm{~g}-\mathrm{m}^{-3}, 12$ hours with $35.5-55.4 \mu \mathrm{~g}-\mathrm{m}^{-3}$, and 2 hours with $55.5-150.4 \mu \mathrm{~g}-\mathrm{m}^{-3}$. All 24-hour averages were below $12 \mu \mathrm{~g}-\mathrm{m}^{-3}$, except for 5 days (February 5, 6, 11, 14, and 18), where concentrations were between $12.1-35.4 \mu \mathrm{~g}-\mathrm{m}^{-3}$, with the highest being $27.3 \mu \mathrm{~g}-\mathrm{m}^{-3}$ on February $18^{\text {th }}$.

Winds from the south or east bring fine particulate concentrations to the city during Fort Benning controlled burns. Fort Benning conducted controlled burns on February 1st, 11th, 17th, 24th, and $25^{\text {th }}$ when winds were predicted to be from the north and west (Fort Benning's Smoke and Sound Archive, 2017). Overnight between February $17^{\text {th }}$ and $18^{\text {th }}$ the wind direction shifted, and winds from the southeast brought smoke into the Columbus area. This phenomenon was observed through an increase in $\mathrm{PM}_{2.5}$ concentrations and the highest concentrations all month. Rain occurred later on the day of the $18^{\text {th }}$ and reduced airborne particulates. An increase in PM 2.5 concentrations on February $11^{\text {th }}$ could also be linked to Fort Benning prescribed burns. The remaining three 24 -hour periods (February 5, 6, and 14) were most likely due to agricultural burning in other parts of the state (NESDIS, 2017). No field test days overlapped agricultural burning dates, and three test days took place on the same day as controlled burns (February $1^{\text {st }}$, $17^{\text {th }}$, and $24^{\text {th }}$ ). The city hourly $\mathrm{PM}_{2.5}$ ranged from 0.7 to $11.9 \mu \mathrm{~g}-\mathrm{m}^{-3}$ with a mean of $5.7 \mu \mathrm{~g}-\mathrm{m}^{-3}$ during the hours when field testing occurred. Regional agriculture and Fort Benning fires were not found to contribute to field test particulate levels.

When Fort Benning prescribed burn data were removed, statistically significant correlations were found between city hourly $\mathrm{PM}_{2.5}$ concentrations and the following city weather variables: wind speed $(\mathrm{r}=-0.253, \mathrm{p}<0.001)$, relative humidity $(\mathrm{r}=-0.080, \mathrm{P}=0.043)$, temperature $(\mathrm{r}=0.134, \mathrm{p}=0.001)$, and precipitation $(\mathrm{r}=-0.093, \mathrm{p}=0.018)$. When daily averages for the month of February 2017 were calculated, the city $\mathrm{PM}_{2.5}$ correlated positively with temperature $(\mathrm{r}=0.460, \mathrm{p}=0.024)$ and negatively with relative humidity $(\mathrm{r}=-0.433, \mathrm{p}=$ 0.035). No correlation was found with daily city $\mathrm{PM}_{2.5}$ and wind speed $(\mathrm{r}=0.166, \mathrm{p}=0.438)$. These findings suggest the daily changes in Columbus city $\mathrm{PM}_{2.5}$ concentrations could be attributed to daily temperature and relative humidity fluctuations (Figure 19).


Figure 19. Average hourly data variability in Columbus February $2017 \mathrm{PM}_{2.5}$ as compared to A) relative humidity ( RH ) and B ) temperature.

### 2.4 Discussion

2.4.1 AirBeam Performance - The stability, reproducibility, and reliability are concerns when using low-cost PM sensors (Rai et al., 2017). The three AirBeam units were assessed for these three factors during the equivalency evaluations and throughout the field study. Stability refers to the performance of the sensors remaining constant over a period of several months (Rai et al., 2017). The stability of the units was determined based on the change in unit median ratio between units over the course of the research. The median ratio for all tests for unit 1 : unit 3 was 1.17 and for unit 2: unit 3 was 0.93 . At the beginning of the equivalency testing period (October 2016), the median ratios were 1.01 (unit $1: 3$ ) and 0.92 (unit 2:3). At the start of the field testing median ratios were 1.03 and 0.91 (February 2017), and at the end of the field study they were 1.22 and 0.85 , respectively. The change in the median ratio may be due in part to units not being cleaned during the testing period. The makers of the particle sensor inside the AirBeam suggest a lifespan of two to three years for the sensor if it is cleaned properly (Shinyei Technology Co., Ltd.). Jiao et al. (2016) found a change in response with "days of use" for the AirBeams they tested over 168 days. Given the small change in median ratio from beginning to end, the

AirBeams were found to be stable for the short time period of use. Longer testing sessions could prove problematic if particles collect on sensors over time.

Reproducibility is the difference in measurements found between similar devices (Rai et al., 2017). As $\mathrm{PM}_{2.5}$ concentrations increased, the differences among the three units also increased. While at lower levels all three units did not differ greatly, and units 1 and 3 corresponded most closely. Units 1 and 2 correlated best at higher levels. Correlations among the units were the same in the field study as with equivalency tests. Particulate levels were low at many study sites with average concentrations of $12 \mu \mathrm{~g} / \mathrm{m}^{3}$ for all locations. Units 1 and 3 were found to be closer in mean and peaks, and, therefore, were used in tandem at half the study locations. As seen in the equivalency tests, the three units had the same response to stimuli and were found to have high reproducibility. These findings match the two studies previously conducted in regards to the high correlation found between AirBeam units (Jiao et al., 2016; Mukherjee et al., 2017).

The relative humidity and temperature sensors within each unit were used as an additional means to determine sensor reliability. The relative humidity and temperature sensors housed within the units were used as a gauge to ensure the units would not shut off, as AirBeams are programed to shut off at 100 percent relative humidity (Heimbinder and Besser 2014) and do not operate outside the temperature range of 0 to $45^{\circ} \mathrm{C}$ (Shinyei Technology Co., Ltd). The AirBeams' internal temperature and relative humidity were determined to not interfere with unit performance in the present study. The maximum relative humidity reading of all three units was 80 percent recorded on unit 2. The maximum temperature reading was $38^{\circ} \mathrm{C}$ and the minimum reading was $12^{\circ} \mathrm{C}$, both measured on unit 1 . The comparison between the AirBeams, Kestrel, and City weather data suggest that these sensors should not be used when collecting local
weather data. For example, all three units' mean temperatures were 17 percent higher than Kestrel and 22 percent higher than City mean temperatures. The AirBeams' black casing may account for the higher average temperatures seen in each unit as compared with the Kestrel and City data. Using the units during the summer in Columbus, Georgia, could prove problematic as temperatures average $33^{\circ} \mathrm{C}$ in July and August (NCEI, 2017a) leading to a greater probability of exceeding the acceptable AirBeam internal temperature range.

The utility of the AirBeam $\mathrm{PM}_{2.5}$ sensors for extended deployments and over multiple seasons with varying temperatures has yet to be established. One additional problem is the need to tether the device to a cell phone with a data plan to record data in the field. However, the AirBeams' high correlations, short-term stability, and reliability make these units legitimate sensors for the field studies. These units have limitations in data accuracy and usable temperature ranges, but the practicality of these devices is in their portability and ease of use. Field assistants were trained in less than five minutes to use the units and the accompanying cell phone app. The only complication occurred when field assistants did not save data properly. These features were found to be valuable when conducting the field study tests at multiple locations.
2.4.2 Fine Particulate Matter and Trees - The relationship between $\mathrm{PM}_{2.5}$ and trees was statistically insignificant for all tree versus open sample pairs. While not significant, isolating by tree design found results similar to other studies. In this study, small tree lines had no impact on particulate levels as compared to surrounding open areas. This finding parallels the results of Hagler et al. (2012) that roadside buffers less than 10 m did not hinder particle transport beyond the vegetative barrier. Tong et al. (2015), Whitlow (2013), Liu et al. (2015) and Chen et al. (2015) found $\mathrm{PM}_{2.5}$ concentrations were higher in dense tree buffers versus neighboring open
areas. While this study found no significance between all open versus dense tree buffer sample sites, it did find higher $\mathrm{PM}_{2.5}$ concentrations in dense field sample locations as compared with other tree configurations. Overall the small difference between open and tree concentrations when using active monitors is consistent with the observations of Setälä et al. (2013).

For dense tree arrangements, the trees trap nearby $\mathrm{PM}_{2.5}$ keeping particulates from leaving these tree barriers after being intercepted by the trees. Three locations used in this study did not have this relationship dynamic. For the Havertys and Lazyboy sites, $\mathrm{PM}_{2.5}$ was essentially the same in the trees $\left(\mathrm{m}=6.6 \mu \mathrm{~g}-\mathrm{m}^{-3}\right)$ and the open $\left(\mathrm{m}=6.9 \mu \mathrm{~g}-\mathrm{m}^{-3}\right)$. These locations were tested in the same sampling session because these sites are located near the same high traffic shopping center. The notable differences versus the other seven locations was the lower than anticipated traffic volumes, $3^{\circ} \mathrm{C}$ higher temperature, and $\mathrm{PM}_{2.5}$ that was $12 \mu \mathrm{~g}-\mathrm{m}^{-3}$ lower than the other dense field locations. It is not possible to determine whether the higher open $\mathrm{PM}_{2.5}$ concentrations is a confounding variable of these three locations, that, when removed, would make the overall dense tree buffer configuration results significant. Four of the dense field sites had a second location at farther distance from PM source. At each of these sites, a decrease in particulate concentration was measured with distance from PM source in both open and tree locations.

One dense tree location, the Manchester bike park, had the highest overall particulate matter concentrations of the entire study (tree $\mathrm{m}=39.8 \mu \mathrm{~g}-\mathrm{m}^{-3}$ and open $\mathrm{m}=34.1 \mu \mathrm{~g}-\mathrm{m}^{-3}$ ). This location is located near a traffic stop, and cars and trucks were idling at the stop light with wind direction coming from the direction of this source during the sampling session. An increase in $\mathrm{PM}_{2.5}$ is expected with idling vehicles, especially diesel trucks (Girard, 2014; Reff et al., 2009). The city $\mathrm{PM}_{2.5}$ was $8.5 \mu \mathrm{~g}-\mathrm{m}^{-3}$ during the test. Two other testing sessions (not used in statistical
analysis due to partial loss of data) at this location, saw the same relationship of higher particulates in the trees versus open areas at lower $\mathrm{PM}_{2.5}$ levels ( 5.8 and $5.4 \mu \mathrm{~g}-\mathrm{m}^{-3}$ ). The sessions with data loss were conducted at low traffic periods, so this may account for the difference in particulate levels among sessions.

Another dense tree site located on Williams Road near the I-185 exit 12 on/off ramp had relatively elevated particulate levels (average of tree $\mathrm{m}=17.0 \mu \mathrm{~g}-\mathrm{m}^{-3}$ and open $\mathrm{m}=15.3 \mu \mathrm{~g}-\mathrm{m}^{-3}$ ). This site (Figure 10A) offered the perfect dense field set-up with dense trees to the east of a cleared open area and across the street from two gas stations. The slightly elevated PM2.5 in the area was thought to be due to proximity to these gas stations and idling traffic. The winds were calm for the majority of the testing session with the exception of the start. The lower winds could also lead to a build-up of pollution in the area (Tai et al., 2010).

The small tree line arrangement overall saw no statistical difference in tree $\mathrm{PM}_{2.5}$ concentrations versus open $\mathrm{PM}_{2.5}$ concentrations. The smaller number of trees in these arrangements are not able to noticeably reduce the fine particulate matter in the air. One site (the CSU softball field site) experienced high PM source levels, and open $\mathrm{PM}_{2.5}$ concentrations were $2.9 \mu \mathrm{~g}-\mathrm{m}^{-3}$ higher than tree concentrations. This may be a feature of this location. Tall pine trees populated the site. Wind direction aligned to bring smoke from a local Burger King to this site. Smoke from a meat cooking restaurant is higher in the air column, and the tree tops should intercept some of the particulate pollution. The parts of Columbus that have small tree line arrangements are shopping centers with meat cooking restaurants. As discussed in Chapter 1, often smaller ornamental trees frequent these areas as compared with the trees found at this site. The CSU softball site, with additional testing, could serve as a case study example of how tall
trees within small tree line designs can reduce fine particulate concentrations, which may influence the types of trees planted near restaurants that produce smoke.

While no relationship was found between field measured weather parameters and particulates, the city $\mathrm{PM}_{2.5}$ and city temperature, relative humidity, and wind speed were found to have a significant correlation. This weather-particulate interaction at the city level could help explain some of the findings at sample locations. The direction of relationship found between city $\mathrm{PM}_{2.5}$ concentrations and city temperature, relative humidity, and wind speed are consistent with Tai et al. (2010) findings for Southeastern U.S. and point to organic carbon (OC) and elemental carbon (EC) in the atmosphere. OC and EC are mainly caused by combustion of fossil fuels, which is consistent with Fort Benning controlled burns, vehicles, and smoke from restaurants as sources of particulates. Additionally, the daily decrease of particulates from morning to afternoon might explain the higher levels of particulate matter found at Cascade Hills Church (small tree line site) during the only sampling session that took place in the morning. All three locations sampled at the church averaged $12 \mu \mathrm{~g}-\mathrm{m}^{-3}$ the morning tested with relatively high traffic conditions ( 83 vehicles per minute), but two previous tests conducted in the afternoon measured particulate levels below $3 \mu \mathrm{~g}-\mathrm{m}^{-3}$ with higher traffic conditions ( 99 vehicles per minute).

The U-shaped tree arrangement also had no statistically significant difference between tree and open area particulate concentrations. At all PM source levels open area concentrations were higher by $1.7 \mu \mathrm{~g}-\mathrm{m}^{-3}$ when compared with tree concentrations. Not all study sites constituted ideal U-shaped tree stand arrangements, making city-wide generalizations difficult. However, the All Saints Presbyterian Church (Figure 10C) could be considered an almost perfect U-shaped tree stand with idling cars and diesel trucks at the opening of the U being the main
source of particle pollution. The average $\mathrm{PM}_{2.5}$ at this site was low, but high winds (the highest recorded throughout the entire field study at $5.1 \mathrm{~m} / \mathrm{s}$ ) from the direction of the road brought an increase in particulate levels to the open area as compared to the trees. While sampling at the second location, the winds increased from 2.9 to $11 \mathrm{~m} / \mathrm{s}$. Unit 2 was left at the start/end location approximately 35 m from the road. Unit 1 was positioned 85 meters from the road in the open area, and unit 3 was the same distance in the tree line. With the increase in winds the particulate level also increased. This was seen with particulate levels peaking in series four times, first at unit 2 and 25 to 37 seconds later at unit 1 . This dynamic of flowing through the opening of the U and not the trees highlights the impact the right wind direction and wind speed can have on particulate levels in this tree arrangement.

Two other U-shaped sites (Colony Bank and the corner of University Avenue and Manchester Expressway) were located across the street from restaurants that produced smoke during testing sessions. Wind direction was from the direction of these sources, and, consequently, these sites experienced high $\mathrm{PM}_{2.5}$ concentrations. The Colony Bank site is also located near a shopping center parking lot. The U-shaped opening points towards this parking lot, while a small tree line exists directly opposite the restaurant. The Colony Bank site had the same average $\mathrm{PM}_{2.5}$ levels ( $14.6 \mu \mathrm{~g}-\mathrm{m}^{-3}$ ) in the trees and open areas with a slightly elevated level in the trees $\left(22.1 \mu \mathrm{~g}-\mathrm{m}^{-3}\right)$ as compared to the open $\left(21.9 \mu \mathrm{~g}-\mathrm{m}^{-3}\right)$ when smoke was present. Conversely, at the corner of University Avenue and Manchester Expressway the U opens towards the restaurant. The average particulate concentrations were higher in the trees $(12.9 \mu \mathrm{~g}$ -$\left.\mathrm{m}^{-3}\right)$ versus the open $\left(8.1 \mu \mathrm{~g}-\mathrm{m}^{-3}\right)$ being $8.5 \mu \mathrm{~g}-\mathrm{m}^{-3}$ higher in the trees over the open area when smoke was present. A bike path runs through the U-shaped opening at this site, meaning higher particulate levels are experienced by people using this path for recreation when the restaurant is
cooking meat. The difference between the two sites demonstrates how the right (or wrong) alignment of trees to PM source impacts particulate levels. The city of Columbus has several of these U-shaped tree designs because often only trees necessary for development are cleared in order to save tree canopy. This tree arrangement becomes problematic when it is located in areas where people frequent, like parks, and a PM source is near.

Every site, even those closely located (i.e. Manchester bike park and the corner of University Avenue and Manchester Expressway), has different localized PM sources that contribute to particulate levels. As discussed in methods and results sections, these localized sources must be controlled for in order to compare tree stands across the city. It is important to note these PM sources beyond controlling for background though. A study conducted in southeastern United States cities found wood combustion made up 25 to 66 percent, diesel exhaust 14 to 30 percent, meat cooking operations 5 to 12 percent, and vehicle exhaust 0 to 10 percent of the OC PM 2.5 concentrations (Zheng et al., 2002). The portion of fine particulate matter caused by vehicles in Atlanta, Georgia, has decreased due to vehicular emission regulations (Vijayaraghavan et al., 2012). The low wind speeds in Columbus cause vehicle particulate pollution to remain in the vicinity of the roads. This concept could be seen with low particulate levels at most locations near areas of high traffic (sample locations were greater than 15 m from the road), except those mentioned already as being located near smoke producing restaurants or heavy idling traffic with diesel trucks and cars.

Smoke producing restaurants were the sources of high PM in this study. Smoke from restaurants were found to pass through sampling areas within minutes. These higher concentrations plumes ( 73 to $93 \mu \mathrm{~g}-\mathrm{m}^{-3}$ ) can impact people in sensitive groups such as those with respiratory issues (EPA, 2016b). A study conducted in Los Angeles found meat cooking
establishments contribute 21 percent of the $\mathrm{OC} \mathrm{PM}_{2.5}$ concentrations in the city (Rogge, Hildemann, Mazurek, Cass, \& Simoneit, 1991). Reducing pollution at the source is the best way to combat it, but cities have shown little will to regulate restaurant emissions (Murphy, 2015; Chaudhury, 2015). Taller trees can assist in blocking the spread of smoke from these point sources, as seen at the Colony Bank and CSU softball field sites. Future studies should focus on this dynamic looking at height of trees near smoke producing restaurants as well as distance to source.

This field study test had limitations. The testing took place for one month, only encompassing one season of the year. The study, while city wide, was on a small scale based on the number of locations visited. The small sample size limits the ability to apply findings beyond specific sites tested. The use of the Kestrel 4000 and its limitations may be the main reason for the insignificant statistical relationships seen between $\mathrm{PM}_{2.5}$ and weather conditions measured at each site. The Kestrel 4000 is not capable of determining wind direction. Wind speed and direction were variable and Kestrel sampling was not continuous, rather a sample point method was employed. Continuous weather monitoring with similar sample resolution as the AirBeam is needed to assess if localized weather influenced $\mathrm{PM}_{2.5}$ concentrations.

The time of year offers some complications as deciduous trees had shed their leaves before this study took place. Leaf absorption of ultrafine particulates is limited (Hemond \& Fechner, 2014). Fine and ultrafine particulates settle on leaves through deposition. $\mathrm{PM}_{2.5}$ levels on leaves are lower than $\mathrm{PM}_{10}$ due to gravitation deposition properties (Beckett et al., 2000; Freer-Smith, 2005; Sæbø et al., 2012). Conifers are better at capturing particulate matter due to leaves having a waxy coating, (Sæbø et al., 2012), high leaf area index, and no annual loss (Yang et al., 2015). Broadleaf trees have the second greatest capacity to capture airborne particles
(Beckett et al., 2000; Yang et al., 2015). All study sites had conifers trees (site pictures in Appendix B show sites during leaf-off season). Focusing on locations that had more conifer tree species during the winter makes findings specific to study locations during the one season. A Beijing study comparing forest $\mathrm{PM}_{2.5}$ concentrations to open area concentrations found the same higher concentrations in forests during leaf-off periods (Liu et al., 2015), while Cai et al. (2017) found higher deposition levels in urban settings in winter months. The composition and main sources of fine particulate matter can change throughout the year, with more wood combustion in the winter and higher biogenic VOC in the summer (Tai et al., 2010; Malm, Schichtel, Pitchford, Ashbaugh, \& Eldred, 2004). These changes could have an impact on tree-particulate interactions throughout the year in addition to leaf-on vs leaf-off differences (Cai et al., 2017).

Additional field study tests need to be conducted to determine the appropriate level of tree services in reducing $\mathrm{PM}_{2.5}$ taking into account various localized particulate sources. The insignificant statistical findings between open and tree $\mathrm{PM}_{2.5}$ concentrations point to the low ability of conifer trees at these study locations to trap particulates during the winter season. A larger sample size, across multiple seasons will help in determining if similar findings are significant annually and city-wide for the city of Columbus. Dense tree barriers may reduce $\mathrm{PM}_{2.5}$ concentrations in other seasons. Additionally, taller trees may assist in the reduction of airborne smoke particulates from nearby restaurants. The results of this study highlight the need to focus on various tree configurations in relation and distance to different particulate sources when considering utilizing trees as a deterrent to particulate pollution. Low-cost, portable sensors, like the AirBeam, can aide in determining neighborhoods with higher relative $\mathrm{PM}_{2.5}$ concentrations and identify sources, as well as, assist in determining appropriate tree design and placement to reduce pollution.

## DISCUSSION

When looking at air quality benefits, the $\mathrm{PM}_{2.5}$ results found using the i-Tree model in Chapter 1 should be discussed with respect to the results of the $\mathrm{PM}_{2.5}$ field tests conducted in Chapter 2. The field tests (i.e. Chapter 2) can better characterize the interactions between trees and $\mathrm{PM}_{2.5}$ on a site by site level and facilitate generalizations regarding if the PM removal associated monetary savings are valid for the Columbus area. The field study documented higher particulate levels in treed versus adjacent open areas in seven of the ten dense field sample locations tested. On average, the observed difference was not great $\left(1.6 \mu \mathrm{~g}-\mathrm{m}^{-3}\right)$. The greatest variation in $\mathrm{PM}_{2.5}$ was measured at the Manchester bike park, the area with highest average particulate levels for the whole study.

Most of the northern portion of Columbus consists of dense fields of tree. Census tracts 103.02 (Bradley Park area, south of 102.01), 33.01 (area northwest of the I-185, highway 280 intersection), 105.02, and 105.01 (to the west of 108.02) are less developed with higher tree canopy percentages and dense tree buffers are the main type of tree arrangement (See Figure 8 or Appendix A, Figure 2 to locate tracts). Assuming the i-Tree Tool removal rates are accurate, these nine tracts contain 14,516 ha ( 35,871 acres) of canopy that could potentially remove 15 tons of particulates (or 18 percent of the original overall city removal of this pollutant) during Columbus winters (i-Tree Tool removal rate was adjusted to account for the field study being conducted during leaf-off period). The notion this removal rate is valid for these areas hinges not only on dense tree stands trapping particulates, but also on particulate pollution being the same in these nine tracts as it is for the whole city. This rate depends of pollution levels gathered at the Columbus Airport. Witlow (2009) argues localized particulate concentrations differ from those detected by regional monitors. These nine tract areas are less populated with less traffic
and meat cooking restaurants, and, therefore, the fine particulate levels may not be as high as those near the airport. Regional fires may contribute to particulate pollution in these mainly northern tracts with the right wind direction. However, based on the tested conducted during controlled burns at increasing distance from Fort Benning by Baumann (2005) and Liu (2010), the smoke from Fort Benning controlled burns will likely disperse before significantly impacting these areas.

The remaining 44 census tracts contain residential, business, and shopping neighborhoods with various tree arrangements. $\mathrm{PM}_{2.5}$ removal by trees is not as accurate in these areas using the i-Tree Tool. Additionally, if the results from the field study hold, U-shaped tree stands have open areas with elevated particulate pollution, and small tree stands would not impact this pollution. Therefore, the areas of the city with the greatest population would not observe trees reducing particulate levels.

In addition to limitations previously discussed, the applicability of the field test results relative to the i-Tree $\mathrm{PM}_{2.5}$ removal rates is questionable. The field study took place over the course of one month (February), while the i-Tree removal rates are annual rates. Simply adjusting the rate to cover one season, as above, does not account for the change in particulate levels, sources, and trees across all seasons. While Columbus, GA, experiences similar wind conditions throughout the year, other seasonal factors such as tree leaf off, weather, and fine particulate matter variations were not taken into account in this research. One big difference between summer and winter seasons is the existence of more leaves on trees to intercept particulates. Trees emit more volatile organic carbons during the summer, which increases ozone and can lead to eventual increase in particulates within and around trees (Yang et al.,
2015). These seasonal dynamics could change the interactions observed between trees and particulates in the field study.

Neither studies' results unequivocally conclude that trees abate $\mathrm{PM}_{2.5}$ in Columbus. Additional research is needed to assess the effectiveness of trees for reducing particulates specifically as tree planting activities relate to particulate reduction. Researchers have argued that planting trees solely for the purposes of improved health from reduced particulates is in "vain", and that government funds should be used to reduce pollutants at their source (Whitlow et al., 2014). While this argument is valid, as discussed in Chapter 2, not all pollutant sources are regulated at the source. A telling example is the lack of desire to control pollutants from meat cooking restaurants (Murphy, 2015). Trees also help cities in other ways, like cooling air temperatures, reducing storm water runoff, and improving health not related to air quality (Pataki et al., 2011). Therefore, the aim of tree planting should be to provide maximum total benefits of the services offered by trees as a whole and not simply their ability to remove particulate pollution.

In this research, the ability of trees to reduce air pollutants was assessed using high spectral analysis that quantified tree canopy and its associated benefits. The overall the canopy for Columbus, Georgia, at 52 percent, meets the criterion set by the American Forests Urban Forest Program for ideal urban canopy cover (Leahy, 2017), but the variations in percent cover across the city leaves the impervious downtown, business, and shopping center areas lacking in good canopy cover. Urban canopy cover recommendations are made so cities can benefit from the ecosystem services trees provide, but simply adding canopy does not mean these benefits are fully utilized. Tree placement, tree type, and tree design need to be considered, and the latter often is not when considering urban vegetation plans.

The city's high tree canopy cover is estimated to remove 1,900 tons of criterion air pollutants and sequesters 282,000 tons of carbon dioxide annually. The high spectral imagery analysis highlighted large tree canopy and air quality benefit disparities over time across the city of Columbus. Areas of highest removal of gaseous air pollutants is dependent on location of trees. These are the northern sections of the city, which also have fewer air pollutant sources. Higher pollution and a lower number of trees in more urban areas of the city (downtown and shopping centers) lead to lower pollution removal.

This research utilized a low-cost, portable particulate sensor to analyze the interactions between fine particulate matter and tree stand designs. AirBeams are affordable (\$250/unit) and easy to use. Accurate, more expensive equipment, is not feasible for studies of this scale and length or reasonable for citizen use. The three units tested in this study effectively measured PM 2.5 variations at multiple sample locations. The unestablished stability of the AirBeam over extended periods and its temperature restraints limits usability for longer testing periods.

AirBeams and other portable sensors allow simple, city-wide field studies to be performed. Use of more affordable sensors leads to more measurements by more people, which in turn yields big data with incredible potential. Open access to big data allows for new possibilities in understanding the environment. The possibilities, given advancements in portable sensors, are wide, and can be very valuable in understanding air quality as it relates to many aspects of an urban setting at localized levels.
$\mathrm{PM}_{2.5}$ has more complex interactions with trees than other air pollutants and removal is dependent on local PM sources, weather conditions, and tree design. Small tree lines have no discernable impact on $\mathrm{PM}_{2.5}$ concentrations and dense tree buffers trap $\mathrm{PM}_{2.5}$ resulting in slightly higher tree particulate concentrations as compared to open areas. U-shaped tree stand
interactions with particulates depended on location of the open area within the tree stand in relation to notable PM sources. Overall, in the winter, trees had little impact on particulate concentrations as compared with open areas. While the city of Columbus has, on average, low wind speeds, wind direction played a key role in particulates reaching sampling locations. Future tree plantings and removal should take note of areas with lower tree canopy as well as paying attention to tree arrangement and proximity to PM sources to better assist in the removal of air pollutants. Also, as the dense tree buffer arrangements trap pollution particles, the clearing of fields of trees should be seen as impeding the removal of $\mathrm{PM}_{2.5}$ along with other air pollutants.

Given the limitations of the study conducted, future research is needed to better understand the relationship between tree stand arrangements and fine particulate matter involving more sample locations across multiple seasons. Research should also focus on alternative fine particulate sources in addition to that from vehicles, like restaurants that produce smoke. Using portable monitoring devices to assess smoke fallout and interception by placing sensors in trees of varying height would be useful in determining tree height effect on local pollution produced by restaurants. Research is lacking in this area, and more portable sensors allows for more methods to asses these interactions.

## LITERATURE CITED

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## APPENDICES

## APPENDIX A - COLUMBUS TREE CANOPY ANALYSIS SUPPLEMENTAL DATA

Table 1. 2005 iso cluster values and reclassified values for 10 clipped sections.

|  | Section Names Used to Identify |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Midland East | Midland Middle | Midand West | Smith_River | Smith | Midde_NW (Fortson) | Middle_NE (Fortson) | Middle_S (ColumbusS) | NCol_SW | SCol_SW |
| 150 Cluster Name: | isocluster25 | isocluster23 | isocluster27 | isocluster59 | isocluster63 | isocluster 73 | isocluster75 | isocluster71 | isocluster79 | isocluster81 |
| Values | New Value | New Value | New Value | New Value | New Value | New Value | New Value | New Value | New Value | New Value |
| 1 | 2 | 2 | 2 | 1 | 2 | 1 | 1 | 1 | 1 | 1 |
| 2 | 2 | 2 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 |
| 3 | 1 | 1 | 1 | 2 | 2 | 1 | 1 | 1 | 1 | 1 |
| 4 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 | 1 |
| 5 | 1 | 1 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 1 |
| 6 | 2 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 | 1 |
| 7 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 | 1 |
| 8 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 | 2 |
| 9 | 1 | 1 | 1 | 2 | 1 | 1 | 2 | 1 | 2 | 2 |
| 10 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 2 | 2 | 2 |
| 11 | 1 | 1 | 2 |  | 1 | 1 | 1 | 1 | 2 | 2 |
| 12 | 1 | 1 | 1 |  | 1 | 1 | 1 | 1 | 2 | 2 |
| 13 | 1 | 1 | 1 |  | 1 | 2 | 2 | 2 | 2 | 2 |
| 14 | 1 | 1 | 1 |  | 1 | 1 | 2 | 2 | 2 | 2 |
| 15 | 1 | 2 | 1 |  | 1 | 1 | 1 | 2 | 2 | 2 |
| 16 | 1 | 1 | 1 |  | 1 | 2 | 2 | 2 | 2 | 2 |
| 17 | 1 | 1 | 2 |  | 1 | 2 | 1 | 2 | 2 | 2 |
| 18 | 1 | 1 | 1 |  | 2 | 2 | 2 | 2 |  |  |
| 19 | 1 | 1 | 1 |  | 1 | 2 | 2 | 2 |  |  |
| 20 | 1 | 2 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 21 | 1 | 1 | 1 |  | 1 | 2 | 2 | 2 |  |  |
| 22 | 2 | 1 | 1 |  | 1 | 2 | 2 | 2 |  |  |
| 23 | 2 | 1 | 1 |  | 1 | 2 | 2 | 2 |  |  |
| 24 | 2 | 1 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 25 | 2 | 1 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 26 | 2 | 1 | 1 |  | 1 | 2 | 2 | 2 |  |  |
| 27 | 2 | 1 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 28 | 2 | 1 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 29 | 2 | 2 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 30 | 2 | 1 | 2 |  | 2 | 2 | 2 | 2 |  |  |
| 31 | 2 | 2 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 32 | 2 | 2 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 33 | 2 | 2 | 2 |  | 1 | 2 | 2 | 2 |  |  |
| 34 | 2 | 2 | 2 |  | 2 | 2 | 2 | 2 |  |  |
| 35 | 2 | 2 | 2 |  | 2 | 2 | 2 | 2 |  |  |
| 36 | 2 | 2 | 2 |  | 2 | 2 | 2 | 2 |  |  |
| 37 | 2 | 2 | 2 |  | 2 | 2 | 2 | 2 |  |  |
| 38 | 2 | 2 | 2 |  | 2 | 2 | 2 | 2 |  |  |
| 39 | 2 | 2 | 2 |  | 2 | 2 | 2 | 2 |  |  |
| 40 | 2 | 2 | 2 |  | 2 | 2 | 2 | 2 |  |  |

Table 2. 2010 iso cluster values and reclassified values for 20 clipped sections.


Table 3. 2015 iso cluster values and reclassified values for 4 clipped sections.

|  | Section Names Used to Identify |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Columbus | Midland, Upitoi, Ochillee | Fortson South | SmithFortson N |
| Iso Cluster Name: | columbus_40 | midupi_40 | fortsonS_40 | smithfort_40 |
| Values | New Value | New Value | New Value | New Value |
| 1 | 2 | 2 | 2 | 2 |
| 2 | 2 | 2 | 2 | 2 |
| 3 | 2 | 2 | 2 | 2 |
| 4 | 1 | 2 | 1 | 2 |
| 5 | 1 | 2 | 1 | 2 |
| 6 | 1 | 2 | 1 | 2 |
| 7 | 1 | 1 | 2 | 2 |
| 8 | 1 | 1 | 1 | 2 |
| 9 | 1 | 1 | 1 | 2 |
| 10 | 1 | 1 | 1 | 1 |
| 11 | 1 | 1 | 1 | 1 |
| 12 | 1 | 1 | 1 | 1 |
| 13 | 1 | 1 | 1 | 1 |
| 14 | 1 | 1 | 1 | 1 |
| 15 | 2 | 1 | 1 | 1 |
| 16 | 2 | 1 | 2 | 1 |
| 17 | 2 | 1 | 1 | 1 |
| 18 | 2 | 1 | 2 | 1 |
| 19 | 2 | 1 | 2 | 1 |
| 20 | 2 | 1 | 2 | 1 |
| 21 | 2 | 1 | 2 | 1 |
| 22 | 2 | 1 | 2 | 1 |
| 23 | 2 | 1 | 2 | 1 |
| 24 | 2 | 1 | 2 | 1 |
| 25 | 2 | 2 | 2 | 1 |
| 26 | 2 | 2 | 2 | 1 |
| 27 | 2 | 2 | 2 | 1 |
| 28 | 2 | 2 | 2 | 2 |
| 29 | 2 | 2 | 2 | 1 |
| 30 | 2 | 2 | 2 | 2 |
| 31 | 2 | 2 | 2 | 2 |
| 32 | 2 | 2 | 2 | 2 |
| 33 | 2 | 2 | 2 | 2 |
| 34 | 2 | 2 | 2 | 2 |
| 35 | 2 | 2 | 2 | 2 |
| 36 | 2 | 2 | 2 | 2 |
| 37 | 2 | 2 | 2 | 2 |
| 38 | 2 | 2 | 2 | 2 |
| 39 | 2 | 2 | 2 | 2 |
| 40 | 2 | 2 | 2 | 2 |



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 2086545.97 937955．824 c $2089024.80 \quad 9300757577$ 2059141.07 894497．231高范

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啇 $2049671.56 \quad 934193.781$



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| 944716.249 |



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|  | cid |  |  |  | 5205 | 2010 |  | POINT_X | POINT_Y |  |  |  |  |  |  |  |  | POINT_X | PIINT_Y |  |  |  |  |  |  | 2010 |  | polint_ | PO |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0 | 1 |  | 1 | $\stackrel{2}{2}$ | 1 | 1 | ${ }_{2}^{2153933,34}$ | ${ }^{\text {928316396 }}$ | 779 | 9 | 1 | 1 | 1 | 2 | 1 | 1 | ${ }^{2035673393}$ | ${ }^{9332422488}$ | ${ }^{820}$ | 0 | 2 | 2 | 2 | 2 | 2 | 2 | ${ }^{2041392304}$ | 91077.4894 |
|  | 0 | 1 | 1 | 1 | 1 | 1 |  | 21855215 | 92925.34 | 780 |  | 1 | 1 | 1 |  | 2 | 1 | 2040587.2 | 93413185 | 821 | 0 | 2 | 2 | 2 |  | 2 |  |  | 910427.7932 |
|  | 0 | 1 | 2 | 2 | 1 | 1 | 1 | 2053229.07 | 889234558 | 781 | 10 | 1 | 1 | 1 | 1 | 1 | 1 | 205322998 | 925683225 | 82 | 0 | 2 | 2 | 2 |  | 2 |  | 207354.733 | 889556286 |
|  | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2046873.12 | 89778.121 | 782 | 20 | 2 | 2 | 2 | 2 | 2 | 2 | 208129595 | 930459387 | ${ }_{823}$ | 0 | 1 | 1 | 1 | 1 | 2 | 1 | 2033515.629 | 9287258816 |
| 74 | 0 | 2 | 2 | 2 | 2 |  | 2 | 2039834.62 | 97716.718 | 783 | - |  | 1 | 2 |  | , |  | 205724281 | 897053238 | ${ }^{82}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 20412838 | 935500, 3429 |
|  | 0 | 2 | 2 | 2 | 2 | 2 | 1 | 2039890.93 | 929535.391 | 784 | , | 2 |  | 1 | 2 | 1 | 2 | 208955.48 | 92614.254 | 825 | 0 |  | 2 | 2 |  | 1 |  | 206837.871 | 900950.2485 |
|  | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 209337.12 | 93610.716 | 785 | 5 | 2 | 2 | 2 | 2 | 2 | 2 | 2046558.478 | 875377308 | 826 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2000352432 | 93015259718 |
|  | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 203736848 | 92254,688 | 788 | 0 | 1 | 2 | 2 | 1 | 2 | 2 | 2067337.18 | 9452189319 | 827 | - | 1 | 1 | 1 | 1 | 1 | 1 | 206945.551 | 9302833303 |
|  | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 204000118 | 897012163 | 787 |  | 2 | 2 | 2 | 2 | 2 | 2 | 205799388 | 905932242 | ${ }^{82}$ | 0 | 1 | 1 | 1 |  | 1 |  | 2076333.498 | 939029.5486 |
|  |  |  |  | 2 |  | 2 | 2 | 2055059,32 | 91611607 | 788 |  |  |  |  | 1 | 1 | 1 | 2100562.26 | 930050.115 | 829 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2035500.705 | 92744.4313 |
| 748 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 204527.54 | ${ }^{927705.756}$ | 789 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 204056167 | 91256,004 | ${ }^{83}$ | 0 | 2 | 2 | 2 | 2 |  | 2 | 2050722169 | 887997.3045 |
|  | 0 | 1 | 1 | 2 | 1 | 2 | 2 | 202804.68 | 932837.866 | 790 |  | 2 | 1 | 1 |  | 1 | 1 | 20331125 | 93478.632 |  |  | 2 | 2 |  |  |  |  | 2003501568 | 912957.6751 |
|  |  | 2 | 2 |  | 2 | 2 | 2 | 2025855.27 | 93457.244 | 791 |  | 2 | 2 | 2 |  | 2 | 2 | 21532235 | 92995.7. |  |  | 2 | 2 |  |  |  |  | 204537.156 | 839365.3612 |
| 751 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 202824337 | 94826123 | 792 | 20 | 1 | 1 | 2 | 1 | 1 | 2 | 20641122 | 885502 | ${ }^{33}$ | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2056647.052 | 880468.1088 |
| ${ }_{52}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 222866073 | 938815209 | 793 | 0 | 1 | 1 | 1 | 1 | 1 | , | 2090073.18 | 92229309 | ${ }^{334}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 206656.529 | 933590.1254 |
|  |  | 1 |  |  |  | 1 | 2 | 204090163 | 940336046 | 794 |  | , |  | 1 | 1 | 1 |  | 20138957 | 98043.098 |  | 0 | 2 | 2 |  |  |  | 2 | 2049807.206 | 928281932 |
| ${ }^{54}$ | 0 | 2 |  |  |  | 2 |  | 206037.55 | 87977.494. | 795 |  |  |  |  | 1 | 1 | 2 | 2048973.12 | 94420.069 | ${ }^{936}$ | 0 | 2 | 1 | 1 | 2 | 1 | 1 | 2084169.485 | 9077119545 |
| ${ }^{55}$ | 0 | 2 | 2 | 2 | 2 | 2 | , | 2044700.7 | 90311.497 | 796 | 0 | 1 | 1 | 1 | 1 | 1 | , | 206558488 | 89235.208 | 837 | 0 | 1 | 2 | 1 | 1 | 2 | 1 | 2059024.932 | 9477328877 |
| ${ }^{566}$ |  | 2 | , |  | 1 | 1 | 1 | 2099664.46 | 90747502 | 797 | 0 | 2 |  | 1 | 2 | 1 |  | 208709 | 91841.0.53 | ${ }^{838}$ |  | 2 | 2 |  |  |  |  | 2077550.022 | 92274.0077 |
|  |  |  |  |  | 2 | 1. |  | 2055013.04 | 907952689 | 798 |  | 1 |  |  |  | 1 |  | 20508456 | 88580.31 |  |  |  | 2 |  |  |  |  | 2078067.374 | 915216.697 |
| 58 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2053330.01 | 905503883 | 799 | 0 | 1 | 1 | 1 | 2 | 1 | 1 | 20500235 | 940003 | 840 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 206731.573 | 885230.6762 |
| 159 | 0 | 2 | 2 |  | 2 | 2 | 2 | 204905169 | 92284.091 | 300 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 205455331 | 94177.018 |  | 0 | 1 | 2 | 2 |  |  |  | 2131532115 | 9284597864 |
|  |  | 2 |  |  | 2 | 1 | 1 | 2045645.77 | 944383895 | 801 | - | 1 | 2 | 2 | 1 |  | 2 | 204155192 | 971720 | ${ }^{84}$ | 0 |  | 1 |  |  |  |  | 2055923.854 | 937310.6497 |
|  | 0 | 1 | 1 | 1 | + | 1 | 1 | 2078557.23 | 88670.915 | 802 | 20 | 1 | 1 | 1 | 1 | 2 | 1 | 2058805 | 8923010 | 843 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2045240.1 | 9397584795 |
| 762 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 213774249 | 92716.97 | ${ }^{803}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 208571.48 | 93557.033 | 944 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 200601155 | 9356462389 |
|  |  |  | 1 |  | I | 1 | 1 | 204132944 | 929815.809 | 304 |  | 1 | + |  | 1 | , | 1 | 2084077.16 | 933202.241 | 945 | 0 | 1 | 1 |  | 2 |  |  | 2111295.783 | 933904,1982 |
| 164 |  | 1 |  |  | 1 | 1 |  | 2118510.62 | 93052243 | 805 |  | 1 | 1 | 2 | 1 | 1 | 2 | 20942317 | 927477.6 |  | 0 | 2 | 1 | 1 |  | 1 | 1 | 20519895 | 887802113 |
| 765 | 0 | 2 | 2 | 2 | 2 | 1 | 2 | 2054789.01 | 896664.353 | 806 | - | , | 1 | 1 | 2 | 1 | 1 | 2099825 | 93509159 | ${ }^{84}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2079593212 | 90125, 4463 |
|  |  |  |  | 1 | I | 2 | 1 | 207938639 | 938610.374 | 807 | 0 |  |  | 2 | 1 |  | 2 |  | 93013368 |  | 0 | 2 | 2 | 2 |  |  |  | 208898338 | 9208028897 |
|  | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2067077.27 | 909383.602 | ${ }^{808}$ |  | 1 |  |  |  |  | 2 | 209383 | 92827. |  |  | 2 |  |  |  |  |  | 2054276.395 | 892249,1564 |
| 768 | 0 |  | 2 | 2 | 2 | 2 | 2 | 204956271 | 939893885 | 309 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 204700878 | 90817.958 | ${ }^{950}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 202887.729 | 90779883343 |
|  | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 204592245 | 900051407 | 810 | 0 | 1 | 1 |  | 1 |  | 1 | 2055924.7 | 89590.432 | 87 | 0 | 1 | 1 | 1 | 1 |  |  | 2088611186 | 5120961642 |
|  | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 205421226 | 917437.874 | 811 | - | 2 |  | 2 | 2 |  | 2 | 20759994 | 93327.82 | ${ }^{252}$ | 0 | 1 | 1 | 1 |  | 1 |  | 2036919.78 | 92868,40018 |
| 71 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 204235167 | 946602678 | 812 | 0 |  | , | 1 | 1 | 1 | 1 | 2018214 | 94028.9 | ${ }^{953}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2028293007 | 993364.526 |
|  | 0 | 2 | 2 | 2 | , | 2 | 2 | 207579.55 | \$56853,79 | ${ }^{813}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2055124.0 | 87568279 | ${ }^{954}$ | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2053300.473 | 91564,3402 |
|  | 0 | 2 | 2 | 2 | 2 | , | 2 | 20676106 | 91927.01 | ${ }^{14}$ | - | 2 |  | 2 | 1 | 1 | 2 | 2083545.84 | 90772.147 | 855 | 0 | 1 | 1 | 1 | 1 |  | 1 | 2053575.526 | 877544,7915 |
| 74 | 0 | 1 | 2 | 2 | 1 | 2 | 2 | 209779932 | 926599976 | 315 | 0 |  | 2 | 1 | 2 | 1 | 1 | 2067977.33 | 938569.32 | ${ }^{256}$ | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2040835.547 | 91664.8275 |
| 775 | 0 |  | 1 | 1 | 2 | 1 | 2 | 2084512 | 907787.382 | 816 |  | 1 | 1 | 1 | 1 | 1 | 1 | 21302714 | 22680 | 857 | 0 | 1 | 1 | 1 | 1 | 2 | 1 | 20932 | 9233629159 |
|  | 0 | 2 | 2 | 2 |  | 2 | 2 | 2069484.81 | 9062062 | 817 | - | 1 | 2 |  | 2 |  | 1 | 288470.77 | 91870.3 | ${ }^{258}$ | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 208479.367 | 0689328 |
|  | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 202713954 | 936792522 | 918 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2052564.6 | 892983,752 | ${ }^{959}$ | 0 | 1 | 2 | 2 | 1 | 2 | 2 | 205053146 | 90213 |
|  |  |  |  |  |  |  |  |  |  | 819 | 0 |  |  |  |  |  | 1 |  |  | 880 |  | 1 |  |  |  |  |  |  |  |


|  | CID | GT05 |  |  | 2005 | 2010 | 2015 | Point-X | POINT_Y |  | cid | GT05 | 6T10 |  |  | 2010 | 2015 | POINT_X | PIINT_Y |  |  |  |  |  | 2005 | 2010 | 2015 | Point_X | Point |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  | 1 | 1 | 1 | 206753809 | 932254748 |  |  |  |  |  |  |  |  | 20192915 | 945533619 |  |  |  |  |  |  |  |  |  |  |
|  | 0 | 1 | 1 | 2 | 1 | 1 | 2 | 211655.97 | 935045203 | 903 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 20650493 | 88956.667 | 944 | 0 | 1 | 1 | 1 | 2 | 1 | 1 | 203122.95 | 9372 |
| 863 | 0 | 1 | 1 | 1 | 1 | 1 | 2 | 215216.64 | 9323036.596 | 904 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 20799595 | 916005.51 | 945 | 0 | 2 | 2 | 2 | 2 | 2 | 1 | 211322202 | 955382, |
| 864 | 0 | 1 | 1 | 1 | 1 | 2 | 1 | 2073920.69 | 91561.578 | 905 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 21093196 | 934969.416 | 946 | 0 | 1 | 1 | 1 |  | 1 |  | 2077526.56 | 91264,4 |
|  | 0 |  | 1 |  | 1 |  | 1 | 207800817 | 896930.936 | 906 | 0 | 1 | 1 | 1 | 1 | 1 | 12 | 208430728 | 91897.965 | 947 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2089533087 | 91880.58 |
| ${ }^{668}$ | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 205075978 | 875996.245 | 907 | 0 | - | 2 | 2 | 2 | 2 | 2 | 2064087.48 | 88300.323 | 948 | 0 | 2 | 2 | 2 | 1 | 1 | 1 | 208544.441 | 909390.412 |
| 887 | 0 |  | 2 | 2 | 2 | 2 | 2 | 204682.04 | 830063.842 | 908 | 0 |  | 2 | 1 | 1 | 2 | 1 | 2066477.818 | 89864.548 | 949 |  | 1 | 1 |  |  |  |  | 2138614.75 | 932294 |
| 989 | 0 |  | 1 |  | 1 |  | 1 | 20501638 | 949049633 | 909 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 207904.12 | 93357.834 | 950 | 0 |  |  | 2 |  | 1 | 2 | 204067.726 | 91956 |
|  |  | 1 | 1 | 1 | 2 | 1 | 1 | 208473564 |  | \% | 0 | 1 | 1 | 1 | 1 | 1 | 12 | 20652553 | 92883.3 | 951 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2082112327 | 912123.36 |
| 870 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 206644167 | 912644.833 | 91 | 0 | 2 | 2 | 2 | 2 | 2 | 1 | 20482924 | 924899 | 952 | 0 |  | 2 | 1 |  |  | 1 | 204187.042 | (1319 |
| 871 | 0 | 1 | 2 | 1 | 2 | 2 | 1 | 2079350.66 | 901822073 | 912 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2055196.6 | 97739.653 | 953 | 0 |  | 2 | 2 | 2 | 2 | 1 | 204523.593 | 91422 |
|  |  |  | 2 | 2 |  | 2 | 2 | 2131515.45 | ${ }^{92296141}$ |  |  |  |  |  | 2 | 2 | 2 | 205256 | 91023708 | 954 | 0 | 1 |  |  |  |  | 1 | 206886 | 89069.7 |
| 873 | 0 | 2 | 1 | 1 | 2 | 1 | 1 | 2009566.65 | 94123.115 | 94 | 0 | 2 | 2 | 2 | 1 | 2 | 2 | 204334143 | 912959971 | 955 | 0 | 2 | 1 | 1 | 1 | 1 | 1 | 211731.658 | \%23 |
|  |  |  | 1 | 1 | 1 | 2 | 2 | 2033775.29 | 93222393 | 915 |  | 2 | 2 | 2 | 2 |  | 2 | 205759672 | 901392935 |  |  |  |  |  |  |  |  | 209136.557 |  |
|  | 0 | 2 | 2 | 1 | 2 | 2 | 1 | 205404.5 | 902998.49 | 916 | 0 |  | 2 |  | 1 | 1 | 2 | 20390974 | 93670.13 | 957 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 205782 |  |
| 878 |  | 1 | 1 | 1 | 1 | 1 | 1 | 209554,04 | 92384999 | 917 | - | 1 | 1 | 1 | 1 | 1 | 1 | 211509.96 | 936344 | 958 | 0 |  | 1 | 1 |  | 1 |  | 205549 |  |
|  | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2095430.04 | ${ }^{923249.51}$ | 918 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 206512.53 | 88277.424 |  | 0 | 1 | 2 | 1 |  | 2 | 1 | 2055124.924 | ช316816 |
| 878 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2088233.85 | 93122,999 | 919 | 0 | 1 | 1 | 1 | 2 | 1 | 1 | 207595137 | 905497.712 | 960 | 0 | 1 | 1 | 1 | 1 |  |  | 2118939.993 | 93561488 |
|  |  |  |  |  |  |  |  | 27361236 | 928831169 |  | 0 | 1 | 1 |  | 2 | 1 | 1 | 2048819 | 86094.332 |  | 0 |  | 2 | 2 |  | 2 | 2 | 205432 | 95131205 |
| 880 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 202214169 | ${ }^{924674.59}$ | 右 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2000384.7 | 91537.094 | 962 | 0 | 1 | 1 | 1 | 1 | 1 |  | 20555 | 765 |
|  |  | 2 | 2 | 2 | 2 | 2 | 2 | 204429894 | 8908618988 | 922 | 0 | 1 | 1 | 1 | 1 |  | 1 | 2078380.49 | 93033.358 |  |  | 2 | 2 |  |  |  |  | 206326 | 922982 |
|  | 0 | 1 | 1 | 2 | 1 | 1 | 2 | 2130224.45 | 93630.12 | 923 | 0 | 1 | 1 | 1 | 2 | 1 | 1 | 2048006.12 | 924010551 | 964 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 204297 | 897855. |
|  |  | 1 | 1 | 1 | 1 | 1 | 1 |  | 935 | 924 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2087565.6 | 91326.113 | 955 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 208850137 | 87934 |
| 884 | 0 | 1 | 1 | 1 | 1 | 2 | 1 | 203929948 | 93907604 | 925 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 207763.11 | 91562389 |  | 0 | 1 | 1 |  | 1 |  | , | 2023816.423 |  |
| 895 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2093515.54 | 92893, 493 | 926 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2058786.72 | ${ }^{2941158}$ | 967 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2035646 | 92835. |
|  |  |  | 2 |  | 2 |  | 2 |  | 91850.62 |  | 0 | 1 | 1 |  | 1 | 1 | 2 |  | 899331131 | 968 | 0 | 2 | 2 | 2 |  | 2 | 2 | 2535 |  |
| 887 | 0 | 2 | 2 |  | 2 | 2 | 2 | 2050075.97 | 90738, 175 | 928 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2046779.17 | 94834727 | 969 | 0 | 1 | 2 | 1 | 1 | 2 |  | 208554.788 | 934047 |
|  | 0 | 2 | 2 | 2 | 2 | - | 2 | 207507197 | 90355676 | 929 | 0 | 1 |  | 1 | 1 |  | 1 | 210037.05 | 94020139 | 970 | 0 |  | 2 |  |  |  |  | 207909 |  |
|  |  |  | 1 | 1 | 1 | 1 | 1 | 2037037.16 | 93152.441 | 930 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 204334.46 | 94320.5 | 971 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 206983.682 | 89599 |
| 890 |  |  | 1 | 1 | 1 |  |  | 20525252 | 93174 |  | 0 | 1 | 2 | 2 | 2 | 2 | 2 | 2053794.18 | 923919.5 | 972 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 208651.384 | 85591 |
| 291 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 20422992 | 946247.534 | 932 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2022519 | 92603792 |  | 0 | 2 | 2 |  |  |  | 2 | 2061233165 |  |
| $892$ | 0 | 1 | 2 | 2 | 1 | 2 | 2 | 205619295 | 90556134 | 933 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 205052154 | 89378.607 | 974 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 206932237 |  |
|  |  | 1 |  |  | 1 |  |  |  |  | 934 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 205912 | 92885 | 975 | 0 | 1 |  |  |  |  |  | 20533 |  |
| 894 | 0 | 2 | 2 |  | 2 | 1 | 2 | 202370918 | 94121185 | 935 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2055210.91 | 934187643 | 976 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 20622 |  |
| 395 |  | 1 | 2 | 2 | 1 | 2 | 2 | 206399924 | 944198389 | 936 | 0 | 1 | 1 | 1 | 1 | 1 | 12 | 27072245 | 914698.13 | 977 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2019773139 |  |
|  |  | 2 |  | 2 | 2 | 2 | 2 | 207888 |  | ${ }^{937}$ | 0 | 1 |  |  | 1 | 1 | 1 | 203189066 | 9374724 | 978 | 0 |  | 2 | 2 |  | 2 | 2 | 2075596.799 |  |
| ${ }^{89}$ | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 20548203 | 920745.1 | 938 | 0 | 1 | 2 | 2 | 1 | 2 | 2 | 208986823 | 920847. | 979 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 178 |  |
| ${ }^{998}$ | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2029565.35 | 99745.13 | 939 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 20888279 | 90534.7 | 980 | 0 | 1 | 1 | 1 | 2 | 1 |  | 201755.924 |  |
|  |  |  |  |  |  |  |  |  |  | 940 | 0 |  |  |  | 1 |  | $120$ |  |  |  | 0 |  |  | 2 | 2 | 2 | 2 |  |  |
|  |  |  |  | 2 |  |  | 2 |  |  |  | 0 |  |  |  | 1 |  | $120$ |  |  | 932 | 0 |  |  | 2 | 2 | 2 | $2$ |  |  |
|  |  |  |  |  |  |  |  | 206770611 | 898167839 | 942 |  | 2 |  |  |  |  |  | 20441246 |  | 983 |  |  |  |  |  |  |  |  |  |







Figure 1. City of Columbus tree canopy change by census tract between: A) 2005 and 2010 and B) 2010 and 2015. Dark green represents canopy gains and light green represents loss in canopy over time.


Figure 2. Muscogee County, Georgia, census tract reference map - 2010 census (from census.gov).

Table 5. City of Columbus census tract percent tree canopy detail.

| FID | NAME | $\begin{gathered} 2005 \\ \% \text { Tree } \end{gathered}$ | $\begin{gathered} 2010 \\ \% \text { Tree } \end{gathered}$ | $\begin{gathered} 2015 \\ \% \text { Tree } \end{gathered}$ | $\begin{aligned} & \text { Difference } \\ & \text { ' } 05 \text { to ' } 10 \\ & \hline \end{aligned}$ | $\begin{aligned} & \text { Difference } \\ & \text { '10 to ' } 15 \\ & \hline \end{aligned}$ | Difference '05 to '15 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 104.01 | 46 | 33 | 41 | -13 | 8 | -6 |
| 1 | 101.06 | 49 | 37 | 41 | -12 | 4 | -8 |
| 2 | 102.04 | 43 | 35 | 40 | -8 | 5 | -3 |
| 3 | 102.05 | 37 | 28 | 32 | -9 | 4 | -6 |
| 4 | 102.03 | 59 | 57 | 58 | -2 | 1 | -1 |
| 5 | 103.01 | 63 | 67 | 64 | 4 | -3 | 2 |
| 6 | 102.01 | 73 | 75 | 75 | 2 | 0 | 2 |
| 7 | 101.07 | 63 | 70 | 66 | 7 | -4 | 2 |
| 8 | 101.04 | 44 | 42 | 40 | -2 | -2 | -5 |
| 9 | 106.06 | 31 | 37 | 37 | 6 | 0 | 6 |
| 10 | 10 | 50 | 36 | 37 | -14 | 1 | -13 |
| 11 | 105.01 | 63 | 48 | 49 | -15 | 1 | -14 |
| 12 | 104.02 | 27 | 21 | 24 | -6 | 3 | -3 |
| 13 | 105.02 | 49 | 44 | 47 | -5 | 3 | -2 |
| 14 | 12 | 56 | 41 | 50 | -15 | 9 | -6 |
| 15 | 112 | 38 | 32 | 42 | -6 | 10 | 4 |
| 16 | 14 | 14 | 21 | 27 | 7 | 6 | 13 |
| 17 | 8 | 35 | 32 | 37 | -3 | 5 | 2 |
| 18 | 114 | 28 | 28 | 34 | 0 | 6 | 6 |
| 19 | 3 | 21 | 20 | 27 | -1 | 7 | 5 |
| 20 | 9 | 41 | 30 | 34 | -11 | 4 | -6 |
| 21 | 111 | 11 | 10 | 13 | -1 | 3 | 2 |
| 22 | 28 | 36 | 30 | 39 | -6 | 9 | 3 |
| 23 | 22 | 49 | 34 | 42 | -15 | 8 | -8 |
| 24 | 23 | 43 | 35 | 43 | -8 | 8 | 1 |
| 25 | 18 | 16 | 19 | 24 | 3 | 5 | 8 |
| 26 | 29.01 | 53 | 40 | 44 | -13 | 4 | -9 |
| 27 | 107.01 | 46 | 43 | 45 | -3 | 2 | -1 |
| 28 | 20 | 36 | 23 | 28 | -13 | 5 | -8 |
| 29 | 106.02 | 52 | 37 | 35 | -15 | -2 | -17 |
| 30 | 21 | 56 | 43 | 40 | -13 | -3 | -16 |
| 31 | 11 | 60 | 42 | 49 | -18 | 7 | -11 |
| 32 | 33.02 | 48 | 44 | 41 | -4 | -3 | -7 |
| 33 | 32 | 29 | 25 | 27 | -4 | 2 | -2 |
| 34 | 107.03 | 43 | 32 | 31 | -11 | -1 | -12 |
| 35 | 29.02 | 31 | 24 | 26 | -7 | 2 | -4 |
| 36 | 107.02 | 52 | 40 | 37 | -12 | -3 | -15 |
| 37 | 30 | 44 | 36 | 44 | -8 | 8 | 0 |
| 38 | 27 | 24 | 23 | 29 | -1 | 6 | 4 |
| 39 | 25 | 9 | 13 | 18 | 4 | 5 | 9 |
| 40 | 24 | 16 | 17 | 22 | 1 | 5 | 6 |
| 41 | 108.02 | 56 | 71 | 69 | 15 | -2 | 12 |
| 42 | 106.07 | 41 | 36 | 34 | -5 | -2 | -6 |
| 43 | 106.05 | 39 | 36 | 34 | -3 | -2 | -5 |
| 44 | 106.08 | 25 | 31 | 31 | 6 | 0 | 6 |
| 45 | 108.01 | 47 | 41 | 44 | -6 | 3 | -4 |
| 46 | 33.01 | 59 | 51 | 49 | -8 | -2 | -10 |
| 47 | 4 | 33 | 30 | 41 | -3 | 11 | 9 |
| 48 | 2 | 27 | 22 | 28 | -5 | 6 | 1 |
| 49 | 103.02 | 41 | 36 | 46 | -5 | 10 | 5 |
| 50 | 16 | 22 | 19 | 24 | -3 | 5 | 2 |
| 51 | 115 | 36 | 41 | 35 | 5 | -6 | 0 |
| 52 | 34 | 23 | 23 | 23 | 0 | 0 | 1 |

Table 6. City of Columbus census tract air quality benefits.

| FID | NAME | Area <br> (ha) | Tree <br> (ha) | Air <br> Pollutant <br> Removal <br> (kg/yr) | $\begin{gathered} \text { CO2seq } \\ (\mathrm{kg} / \mathrm{yr}) \end{gathered}$ | Air Pollutant Removal (kg/ha) | $\begin{gathered} \mathrm{CO} 2 \mathrm{seq} \\ (\mathrm{~kg} / \mathrm{ha}) \end{gathered}$ | CO2seq (tonnes/ha) | Population $2010$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 104.01 | 510 | 206 | 17,856 | 2665516 | 35.0 | 5224 | 5.2 | 6401 |
| 1 | 101.06 | 723 | 293 | 25,411 | 3793234 | 35.2 | 5249 | 5.2 | 5451 |
| 2 | 102.04 | 585 | 232 | 20,088 | 2998705 | 34.3 | 5123 | 5.1 | 6013 |
| 3 | 102.05 | 502 | 159 | 13,736 | 2050397 | 27.3 | 4081 | 4.1 | 2911 |
| 4 | 102.03 | 2955 | 1710 | 148,172 | 22118654 | 50.1 | 7485 | 7.5 | 7933 |
| 5 | 103.01 | 3502 | 2249 | 194,873 | 29090003 | 55.7 | 8307 | 8.3 | 2478 |
| 6 | 102.01 | 3201 | 2402 | 208,093 | 31063509 | 65.0 | 9704 | 9.7 | 6740 |
| 7 | 101.07 | 9197 | 6020 | 521,607 | 77863811 | 56.7 | 8466 | 8.5 | 7265 |
| 8 | 101.04 | 583 | 230 | 19,917 | 2973075 | 34.2 | 5102 | 5.1 | 6532 |
| 9 | 106.06 | 176 | 65 | 5,666 | 845789 | 32.2 | 4802 | 4.8 | 1834 |
| 10 | 10 | 492 | 182 | 15,796 | 2357956 | 32.1 | 4792 | 4.8 | 4384 |
| 11 | 105.01 | 1054 | 515 | 44,640 | 6663789 | 42.3 | 6322 | 6.3 | 6399 |
| 12 | 104.02 | 704 | 166 | 14,422 | 2152916 | 20.5 | 3056 | 3.1 | 4049 |
| 13 | 105.02 | 370 | 176 | 15,281 | 2281066 | 41.3 | 6159 | 6.2 | 1406 |
| 14 | 12 | 298 | 149 | 12,877 | 1922247 | 43.2 | 6454 | 6.5 | 3371 |
| 15 | 112 | 137 | 57 | 4,979 | 743269 | 36.3 | 5415 | 5.4 | 1942 |
| 16 | 14 | 83 | 22 | 1,889 | 281930 | 22.8 | 3402 | 3.4 | 1768 |
| 17 | 8 | 158 | 57 | 4,979 | 743269 | 31.5 | 4705 | 4.7 | 2431 |
| 18 | 114 | 148 | 50 | 4,292 | 640749 | 29.1 | 4340 | 4.3 | 2132 |
| 19 | 3 | 163 | 44 | 3,777 | 563859 | 23.1 | 3456 | 3.5 | 1741 |
| 20 | 9 | 174 | 59 | 5,151 | 768899 | 29.7 | 4431 | 4.4 | 2851 |
| 21 | 111 | 388 | 52 | 4,464 | 666379 | 11.5 | 1715 | 1.7 | 1992 |
| 22 | 28 | 171 | 67 | 5,838 | 871419 | 34.2 | 5098 | 5.1 | 2107 |
| 23 | 22 | 158 | 65 | 5,666 | 845789 | 35.9 | 5353 | 5.4 | 2795 |
| 24 | 23 | 117 | 52 | 4,464 | 666379 | 38.3 | 5718 | 5.7 | 1785 |
| 25 | 18 | 111 | 26 | 2,232 | 333189 | 20.0 | 2992 | 3.0 | 1272 |
| 26 | 29.01 | 241 | 107 | 9,271 | 1384018 | 38.5 | 5746 | 5.7 | 2878 |
| 27 | 107.01 | 627 | 279 | 24,209 | 3613824 | 38.6 | 5766 | 5.8 | 6010 |
| 28 | 20 | 215 | 61 | 5,323 | 794529 | 24.8 | 3696 | 3.7 | 3266 |
| 29 | 106.02 | 383 | 135 | 11,675 | 1742837 | 30.5 | 4547 | 4.5 | 4936 |
| 30 | 21 | 311 | 125 | 10,817 | 1614687 | 34.8 | 5195 | 5.2 | 2381 |
| 31 | 11 | 326 | 161 | 13,907 | 2076027 | 42.6 | 6362 | 6.4 | 2588 |
| 32 | 33.02 | 223 | 91 | 7,898 | 1178978 | 35.5 | 5293 | 5.3 | 2455 |
| 33 | 32 | 197 | 52 | 4,464 | 666379 | 22.7 | 3385 | 3.4 | 1744 |
| 34 | 107.03 | 552 | 170 | 14,766 | 2204176 | 26.8 | 3995 | 4.0 | 5995 |
| 35 | 29.02 | 306 | 81 | 7,039 | 1050828 | 23.0 | 3438 | 3.4 | 2249 |
| 36 | 107.02 | 482 | 178 | 15,452 | 2306696 | 32.1 | 4788 | 4.8 | 4764 |
| 37 | 30 | 189 | 83 | 7,211 | 1076458 | 38.1 | 5693 | 5.7 | 2676 |
| 38 | 27 | 376 | 107 | 9,271 | 1384018 | 24.7 | 3685 | 3.7 | 2710 |
| 39 | 25 | 272 | 48 | 4,121 | 615119 | 15.2 | 2262 | 2.3 | 2626 |
| 40 | 24 | 98 | 22 | 1,889 | 281930 | 19.2 | 2865 | 2.9 | 1581 |
| 41 | 108.02 | 1150 | 791 | 68,506 | 10226353 | 59.6 | 8895 | 8.9 | 6454 |
| 42 | 106.07 | 440 | 153 | 13,220 | 1973507 | 30.0 | 4482 | 4.5 | 5328 |
| 43 | 106.05 | 588 | 202 | 17,513 | 2614256 | 29.8 | 4447 | 4.4 | 4146 |
| 44 | 106.08 | 347 | 109 | 9,443 | 1409648 | 27.2 | 4062 | 4.1 | 4156 |
| 45 | 108.01 | 32 | 14 | 1,202 | 179410 | 37.7 | 5631 | 5.6 | 1427 |
| 46 | 33.01 | 150 | 73 | 6,353 | 948308 | 42.3 | 6313 | 6.3 | 1317 |
| 47 | 4 | 557 | 230 | 19,917 | 2973075 | 35.8 | 5339 | 5.3 | 2841 |
| 48 | 2 | 300 | 83 | 7,211 | 1076458 | 24.0 | 3583 | 3.6 | 2498 |
| 49 | 103.02 | 1251 | 581 | 50,306 | 7509578 | 40.2 | 6003 | 6.0 | 6293 |
| 50 | 16 | 228 | 55 | 4,807 | 717639 | 21.1 | 3149 | 3.1 | 2749 |
| 51 | 115 | 1370 | 476 | 41,207 | 6151190 | 30.1 | 4490 | 4.5 | 5496 |
| 52 | 34 | 176 | 42 | 3,606 | 538229 | 20.5 | 3056 | 3.1 | 2338 |

Table 7．Sampling locations details used for statistical analysis．

| 离离霖 |  | 은 | $\ldots$ | $\cong$ | $\cdots$ | $\cdots$ | 은 | ＜ | 잇 | － | － | 응 | \％ | \％ | \％ | \％ | － | 잇 | 은 | 안 | 亿 | へ | 앗 | 앙 | 2 | $\bigcirc$ | 8 | 2 | \％ | ヶ | ¢ | 子 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\bumpeq$ | $\sim$ | 아 | 안 | 안 | 안 | 안 | － | 안 | 앙 | n | ～ | 8 | 8 | $\infty$ | ¢ | ヶ | ヶ | 은 | 안 | $\cdots$ | ヘ | $\stackrel{\sim}{2}$ | $\cdots$ | 8 | 8 | \％ | ヶ | $\sim$ | $\sim$ | －1 | － |
| 荡为登 | $\cdots$ | $\stackrel{9}{2}$ | N | こ | $\left\|\begin{array}{c} 0 \\ \mathrm{~m} \end{array}\right\|$ | $\cdots$ | त | $\mathfrak{m}$ | $\begin{aligned} & 0 \\ & + \end{aligned}$ | $\bigcirc$ | $\vec{a}$ | O | $\cdots$ | $\stackrel{9}{2}$ | $\vec{\sim}$ | $\stackrel{1}{\infty}$ | $\stackrel{\rightharpoonup}{1}$ | 9 | $\left\lvert\, \begin{aligned} & n \\ & \stackrel{n}{n} \end{aligned}\right.$ | $\left\|\begin{array}{l} 0 \\ \underset{\sim}{2} \end{array}\right\|$ | $\stackrel{9}{7}$ | n＇ | n | － | d | $\left\|\begin{array}{l} n \\ \sim \\ \sim \end{array}\right\|$ | n | $\stackrel{\bigcirc}{+}$ | $\sim$ | on | $\stackrel{9}{+}$ | $\xrightarrow{9}$ |
|  |  | 1 | － | －1 | H | H | － | －1 | H | H | H | －1 | H | － | H | －1 | H | H | $\Sigma$ | － | H | H | H | H | 岃 | 它 | － | － | 1 | － | － | －1 |
|  | $\exists$ | $\square$ | $\stackrel{9}{9}$ | $\stackrel{9}{=}$ | $\stackrel{9}{=}$ | $\stackrel{9}{=}$ | $\left\|\begin{array}{c} \infty \\ \infty \\ \infty \end{array}\right\|$ | $\left\|\begin{array}{l} \infty \\ \infty \\ \infty \end{array}\right\|$ | $\begin{gathered} \infty \\ \infty \\ \infty \end{gathered}$ | $\infty$ | in | i | $\|\overrightarrow{\mathrm{C}}\|$ | $\vec{i}$ | N | $\|\stackrel{\rightharpoonup}{\mathrm{N}}\|$ | $\bigcirc$ | O－ | $\left\|\begin{array}{c} n \\ \infty \end{array}\right\|$ | $\cdots$ | $\square$ |  | $\pm$ | － | 寸 | $\dot{\sim}$ | $\left\lvert\, \begin{aligned} & \infty \\ & m \end{aligned}\right.$ | $\cdots$ | － | $\infty$ | $\cdots$ | $\cdots$ |
|  | $\cdots$ | － | 二 | 乙 | 二 | Z | Z | Z | Z | 亿 | Z | Z | Z | Z | 乙 | Z | Z | Z | Z | Z | Z | Z | － | － | i | － | Z | Z | Z | Z | Z | Z |
| $\begin{aligned} & \text { 岛 } \\ & 0 \\ & 0 \\ & 0 \end{aligned}$ | $\because$ | $10$ | $\dot{+} .$ | $\underset{0}{\mathbf{O}}$ | $\left\|\begin{array}{l} n \\ 0 \end{array}\right\|$ | $\left\lvert\, \begin{gathered} n \\ 0 \end{gathered}\right.$ | $\|n\|$ | $\left\lvert\, \begin{aligned} & n \\ & i \end{aligned}\right.$ | $\overrightarrow{\mathrm{N}}$ | $\overrightarrow{\mathrm{c}}$ | $\overrightarrow{\mathrm{m}}$ | $\cdots$ | $\vec{n}$ | － | $\cdots$ | $\vec{m}$ | $\stackrel{\sim}{\circ}$ | ${ }_{0}^{2}$ | $\overrightarrow{\mathrm{c}} \mid$ | $\overrightarrow{\mathrm{a}}$ | ～ | $\cdots$ | $\xrightarrow{-}$ | N | $\cdots$ | $\underset{i}{n}$ | $\left\|\begin{array}{r} \hat{0} \end{array}\right\|$ | $\stackrel{\sim}{\circ}$ | $0$ | $\because$ | $\bigcirc$ | $\stackrel{-}{-}$ |
|  | $\infty$ | c | g | 9 | 二 | a | － | － | $\rightarrow$ | － | $\infty$ | $\infty$ | $\infty$ | $\infty$ | － | － | $\stackrel{0}{7}$ | $\cdots$ | － | － | － | － | － | － | － | － | $\stackrel{\infty}{\sim}$ | $\stackrel{\infty}{\sim}$ | $\bigcirc$ | 0 | ก | $\underset{\sim}{2}$ |
| \% | $\left\|\begin{array}{c} \infty \\ \infty \\ \infty \end{array}\right\|$ | $\left\lvert\, \begin{aligned} & \infty \\ & \underset{\sim}{n} \end{aligned}\right.$ | $\left\|\begin{array}{c} \infty \\ n \\ n \end{array}\right\|$ | $\left\|\begin{array}{c} \infty \\ \vdots \\ \vdots \end{array}\right\|$ | $\left\|\begin{array}{l} \infty \\ \dot{4} \end{array}\right\|$ | $\left\lvert\, \begin{gathered} \infty \\ \underset{1}{2} \end{gathered}\right.$ | $\left\|\begin{array}{l} 9 \\ \stackrel{9}{0} \end{array}\right\|$ | $\begin{aligned} & 9 \\ & 6 \end{aligned}$ | $\infty$ | $\begin{gathered} \infty \\ \infty \\ 0 \end{gathered}$ | $\begin{gathered} m \\ 0 \\ 0 \end{gathered}$ | $m$ | $\left\|\begin{array}{c} T \\ \infty \\ \infty \end{array}\right\|$ | $\left\|\begin{array}{c} T \\ \infty \\ \infty \end{array}\right\|$ | $\widehat{\mathbf{o}}$ | $\begin{aligned} & \hat{e} \\ & \underset{\sim}{2} \end{aligned}$ | $\underset{\sim}{\sigma}$ | $\underset{\sim}{a}$ | $\left\lvert\, \begin{aligned} & \underset{\sim}{\lambda} \\ & \text { a } \end{aligned}\right.$ | $\left\lvert\, \begin{aligned} & \underset{~}{~} \\ & \mid \end{aligned}\right.$ | $\left\|\begin{array}{c} T_{1} \\ n \\ n \end{array}\right\|$ | $\begin{aligned} & \underset{\sim}{q} \\ & \stackrel{y}{n} \end{aligned}$ |  | $\begin{array}{\|c} \text { din } \end{array}$ | O- | $\begin{aligned} & 0 \\ & \hline \end{aligned}$ | $\begin{aligned} & \text { y } \\ & \ddagger \end{aligned}$ | $\left\|\begin{array}{c} y \\ f \end{array}\right\|$ | $\vec{\infty}$ | $\vec{\infty}$ | $\hat{O}$ | M |
| $\begin{aligned} & \text { 菎O } \\ & 0 \end{aligned}$ | $\left\lvert\, \begin{aligned} & \underset{i}{2} \\ & \text { d } \end{aligned}\right.$ | $\left\lvert\, \begin{gathered} \underset{N}{\mathrm{~N}} \end{gathered}\right.$ | $\left\lvert\, \begin{gathered} \underset{子}{n} \\ \end{gathered}\right.$ | $\left\lvert\, \begin{gathered} \text { In } \\ \underset{N}{2} \end{gathered}\right.$ | $\left\|\begin{array}{l} \infty \\ \underset{\sim}{\mathrm{N}} \end{array}\right\|$ | $\left\|\begin{array}{l} \infty \\ \underset{\sim}{\mathrm{N}} \end{array}\right\|$ | $\left\|\begin{array}{l} 0 \\ \end{array}\right\|$ | $\stackrel{0}{0}$ | $\cdots$ | $\cdots$ | $\cdots$ | $\cdots$ | $\overrightarrow{\mathrm{a}}$ | ご | $\stackrel{m}{\mathrm{e}}$ | $\underset{\sim}{\tilde{a}}$ | $\left.\frac{n}{\lambda} \right\rvert\,$ | $\left.\frac{n}{n} \right\rvert\,$ | $\left\|\frac{y}{4}\right\|$ | $\frac{\mathrm{y}}{\mathrm{~N}}$ | $\stackrel{T}{\square}$ | $\stackrel{\rightharpoonup}{\square}$ | $\begin{aligned} & \mathrm{N} \\ & \text { ì } \end{aligned}$ | $\begin{aligned} & \mathrm{y} \\ & \stackrel{y}{\mathrm{~N}} \end{aligned}$ | $\begin{aligned} & \mathrm{C} \\ & \underset{\sim}{n} \end{aligned}$ | $\left.\begin{array}{\|l} \mathrm{N} \\ \mathrm{~N} \end{array} \right\rvert\,$ | $\begin{aligned} & 9 \\ & \vdots \\ & \vdots \end{aligned}$ | $\left\|\begin{array}{l} \text { a } \\ \text { Ni } \end{array}\right\|$ | $\begin{aligned} & \mathrm{y} \\ & \end{aligned}$ | $\stackrel{\mathrm{N}}{\mathrm{~N}}$ | $\begin{aligned} & n \\ & 0 \\ & 0 \end{aligned}$ | ～ |
| $\underset{\sim}{\stackrel{N}{2}}$ | 品 | 䧕 | $\left\|\begin{array}{c} \text { 总 } \end{array}\right\|$ | 吾 | $\left\|\frac{0}{2}\right\|$ | $\begin{array}{\|c} 0 \\ \text { 足 } \end{array}$ |  |  | $\begin{aligned} & \text { 部 } \\ & 0 \\ & \text { ad } \\ & \text { n } \end{aligned}$ | $\begin{aligned} & \text { 弨 } \\ & \text { oud } \\ & \text { w } \\ & \vdots \end{aligned}$ |  | $\begin{aligned} & \text { च्व } \\ & \text { g } \\ & \text { g } \\ & \vdots \end{aligned}$ |  |  | $\begin{aligned} & \text { 무 } \\ & \text { odu } \\ & \text { W } \\ & \vdots \end{aligned}$ |  | 品 | 豆 | 豆 | $\frac{\ddot{0}}{\frac{0}{4}}$ | 品 | 号 |  | $\left\|\begin{array}{l} \overrightarrow{0} \\ 0 \\ 0 \\ 0 \\ \vdots \\ \vdots \end{array}\right\|$ |  |  | $\left\|\begin{array}{c} 0 \\ 0 \\ 0 \end{array}\right\|$ | 吾 | 要 | 霛 | 芸 | 㤩 |
| 菬 | तन | 筬 | त | ल | त | ल | \％ | $\overrightarrow{\mathrm{c}}$ | ल | त | \％ | ल | ก | त | ल | $\bar{\square}$ | 筬 | $\overrightarrow{\mathrm{c}}$ | त | ल | N10 | ल | ल | त | 袻 | N | － | ल | 凩 | N | ल | N |
|  | $\overrightarrow{\mathrm{N}}$ | 9 | $\left\|\begin{array}{c} n \\ n \\ \sim \end{array}\right\|$ | $\left\lvert\, \begin{aligned} & \hat{0} \\ & \mathbf{0} \end{aligned}\right.$ | $\left\|\begin{array}{c} \underset{\sim}{c} \\ \end{array}\right\|$ | $\left\|\begin{array}{l} \infty \\ 0 \\ - \end{array}\right\|$ | $\left\lvert\, \begin{gathered} \dot{\sigma} \\ \hline \end{gathered}\right.$ | 응 | $0$ | $\underset{\sim}{\underset{\sim}{n}}$ | $\hat{\mathrm{a}}$ | $\stackrel{\infty}{\infty}$ | $\left\|\begin{array}{l} \circ \\ \mathrm{C} \end{array}\right\|$ | $\left\lvert\, \begin{gathered} 0 \\ \mathrm{C} \end{gathered}\right.$ | m | in | $\pm$ | － | $\left\|\begin{array}{l} \infty \\ \underset{\sim}{\infty} \end{array}\right\|$ | $\overrightarrow{~ \overrightarrow{~ m}} \mid$ | $\stackrel{\infty}{\infty}$ | n | $\hat{0}$ | $\stackrel{\sim}{n}$ | $\infty$ | $\left\|\begin{array}{c} n \\ \infty \\ - \end{array}\right\|$ | $9$ | 0 |  | $\xrightarrow{\text { N }}$ | $\cdots$ | 0 |
| $\begin{aligned} & \text { 䔍 } \\ & \text { 留 } \\ & \text { H } \end{aligned}$ | $\left\|\begin{array}{c} \ddot{\sim} \\ \stackrel{y}{*} \end{array}\right\|$ | 志 | $\left\lvert\, \begin{gathered} \stackrel{\sim}{\mathrm{N}} \\ \hline \end{gathered}\right.$ | $\begin{aligned} & \text { 品 } \\ & 0 \end{aligned}$ | $\left\|\right\|$ | $\left\|\begin{array}{c} 5 \\ 0 \\ 0 \end{array}\right\|$ | $\left\|\begin{array}{c}  \pm \\ \sim \end{array}\right\|$ | $\begin{aligned} & \text { I } \\ & 0 \\ & 0 \end{aligned}$ | $\underset{H}{ \pm}$ | 落 | $\left\lvert\,\right.$ | 吉 | $\underset{H}{ \pm}$ | $\left.\begin{array}{\|l\|} \hline \\ 0 \\ 0 \end{array} \right\rvert\,$ | $\pm$ | $\left\|\begin{array}{l} \text { E } \\ 0 \\ 0 \end{array}\right\|$ | $\stackrel{\sim}{\sim}$ | \％ | $\stackrel{ \pm}{\mathrm{L}}$ | $\left\|\begin{array}{l} 7 \\ 0 \\ 0 \end{array}\right\|$ | $\underset{\sim}{\mathcal{L}}$ | $\begin{aligned} & \text { 5 } \\ & \text { 5 } \end{aligned}$ | $\left\lvert\, \begin{aligned} & \pm \\ & \stackrel{\rightharpoonup}{\omega} \\ & \hline \end{aligned}\right.$ | $\begin{array}{\|c} 5 \\ 0 \\ 0 \end{array}$ | $\begin{aligned} & \mathbb{む} \\ & \stackrel{y y}{*} \end{aligned}$ | $\begin{array}{\|c} \text { E } \\ 0 \\ \hline \end{array}$ | $\begin{aligned} & \mathbb{Z} \\ & \underset{y y}{*} \end{aligned}$ | $\left\lvert\, \begin{gathered} \text { ㅁ } \\ \text { O } \end{gathered}\right.$ | $\underset{H}{ \pm}$ | 品 | $\underset{H}{ \pm}$ | \＃ |
| $\begin{aligned} & \text {. } \\ & \text { त్ర } \\ & \text { O } \\ & \text { H } \end{aligned}$ | $\left\|\begin{array}{c} - \\ 0 \\ 0 \\ i \end{array}\right\|$ | $\left\|\begin{array}{c} \overrightarrow{\mathrm{g}} \\ 0 \\ -1 \end{array}\right\|$ | $\left\|\begin{array}{c} \overrightarrow{\mathrm{g}} \\ 0 \\ -1 \end{array}\right\|$ | $\left.\begin{aligned} & \vec{u} \\ & 0 \\ & i \end{aligned} \right\rvert\,$ | $\left\|\begin{array}{c} y \\ 0 \\ 0 \\ 1 \\ -1 \end{array}\right\|$ | $\left\|\begin{array}{c} 1 \\ 0 \\ 0 \\ -1 \end{array}\right\|$ | $\left\|\begin{array}{c} -3 \\ \mathrm{O} \\ \mathrm{H} \end{array}\right\|$ | $\left\|\begin{array}{c} -\vec{y} \\ 0 \\ H \end{array}\right\|$ | $\left\lvert\, \begin{gathered} 1 \\ 0 \\ 0 \\ H \end{gathered}\right.$ | $\left\|\begin{array}{c} 1 \\ 0 \\ 0 \\ n \end{array}\right\|$ | $\left\|\begin{array}{c} n \\ 0 \\ 0 \\ -1 \end{array}\right\|$ | $\begin{aligned} & \mathrm{m} \\ & \mathrm{O} \\ & \mathbf{y} \end{aligned}$ | $\left.\begin{aligned} & -\overrightarrow{0} \\ & 0 \\ & 0 \end{aligned} \right\rvert\,$ | $\begin{gathered} \overrightarrow{\mathrm{g}} \\ 0 \\ -1 \end{gathered}$ | $\begin{aligned} & \text { N } \\ & \text { O } \\ & \text { Hin } \end{aligned}$ | $\left\|\begin{array}{c} N \\ 0 \\ 0 \\ 0 \end{array}\right\|$ | $\left\|\begin{array}{c} \overrightarrow{\mathrm{g}} \\ 0 \\ -1 \end{array}\right\|$ | $\begin{aligned} & \overrightarrow{\mathrm{g}} \\ & 0 \\ & -i \end{aligned}$ | $\left\|\begin{array}{c} \vec{y} \\ 0 \\ 0 \end{array}\right\|$ | $\left.\begin{gathered} \overrightarrow{\mathrm{g}} \\ 0 \\ -1 \end{gathered} \right\rvert\,$ | $\left.\begin{gathered} \overrightarrow{0} \\ 0 \\ i \end{gathered} \right\rvert\,$ | $\underset{i}{0}$ | $\left.\begin{array}{\|c} -1 \\ 0 \\ -1 \end{array} \right\rvert\,$ | $\left\|\begin{array}{c} \overrightarrow{\mathrm{g}} \\ 0 \\ \mathrm{H} \end{array}\right\|$ | $\begin{aligned} & \text { O } \\ & \mathbf{H} \end{aligned}$ | $\left.\begin{gathered} n \\ 0 \\ 0 \\ 1 \end{gathered} \right\rvert\,$ | $\overrightarrow{\mathrm{O}}$ | $\left\|\begin{array}{c} \overrightarrow{\mathrm{g}} \\ \mathrm{~B} \end{array}\right\|$ | $\left\lvert\, \begin{gathered} 0 \\ 0 \\ i \end{gathered}\right.$ | $\stackrel{\rightharpoonup}{\mathrm{O}}$ | $\left\lvert\, \begin{gathered} 1 \\ 0 \\ 0 \\ H \end{gathered}\right.$ | N |
| $\begin{aligned} & \text { む } \\ & \text { 品 } \\ & \text { む } \\ & \text { ※゙ } \end{aligned}$ |  |  | $\begin{aligned} & 0 \\ & 0 \\ & 0 \end{aligned}$ | $0$ | $0$ | $0$ |  |  | $\begin{gathered} \text { M } \\ \text { y } \\ \text { n } \\ \text { n } \\ \text { y } \\ \text { y } \\ \hline \end{gathered}$ |  | Bike Park E |  |  |  |  |  |  |  |  |  |  |  | 惑 |  |  | 复 | 鿊 | $\begin{array}{\|l\|} \text { n } \\ \text { e } \\ 0 \\ 0 \\ \text { mu } \\ \hline \end{array}$ | 会 | 答 | $\begin{aligned} & 3 \\ & \text { B } \\ & \text { 気 } \\ & \text { n- } \end{aligned}$ | － |
| 登 | $\begin{array}{\|c} \hline 8 \\ \hline- \\ -1 \end{array}$ | $\begin{array}{\|l\|} \hline 8 \\ \hline 6 \\ \hline-1 \end{array}$ | $\begin{array}{\|l\|} \hline 8 \\ \hline 8 \\ \hline-7 \\ \hline \end{array}$ | $\begin{aligned} & \mathrm{O} \\ & \stackrel{y}{-1} \end{aligned}$ | $\begin{array}{\|l\|} \hline 8 \\ \hline-9 \\ \hline \end{array}$ | $\begin{array}{\|c\|} \hline 8 \\ \hline- \\ -1 \end{array}$ | $\begin{array}{\|c\|} \hline 8 \\ \hline-1 \\ \hline \end{array}$ | $\begin{aligned} & 8 \\ & \hline 0 \\ & \hline \end{aligned}$ | $\begin{aligned} & 8 \\ & 6 \\ & -1 \end{aligned}$ | $\begin{aligned} & 8 \\ & 0 \\ & 0 \end{aligned}$ | $\begin{array}{\|c} \hline \stackrel{8}{9} \\ \stackrel{-1}{ } \end{array}$ | $\begin{array}{\|c} \hline 8 \\ \underset{9}{9} \end{array}$ | $8$ | $\stackrel{8}{0}$ | $\stackrel{\stackrel{8}{9}}{-1}$ | $\begin{aligned} & \mathrm{O} \\ & \stackrel{y}{4} \end{aligned}$ | $\begin{array}{\|c} \hline 8 \\ \hline-0 \\ \hline \end{array}$ | $\begin{aligned} & 9 \\ & 0 \\ & 0 \end{aligned}$ | $\stackrel{8}{9}$ | $\begin{array}{\|c} \hline 8 \\ \stackrel{-}{9} \end{array}$ | $\begin{array}{\|c} \hline 8 \\ \underset{-1}{2} \end{array}$ | ¢ | $\stackrel{8}{\mathbf{8}}$ | $\begin{array}{\|c\|} \hline 8 \\ \hline-1 \\ 9 \end{array}$ | － | $\begin{array}{\|c} 8 \\ 0 \\ -1 \end{array}$ | $\begin{aligned} & 8 \\ & \stackrel{3}{n} \end{aligned}$ | ¢ | 8 | $\stackrel{\bigcirc}{\text { ¢ }}$ | \％ | － |
| $\stackrel{\text { N}}{\substack{0}}$ |  | $\left\lvert\, \begin{gathered} \stackrel{\rightharpoonup}{2} \\ \text { d } \\ - \\ \hline \end{gathered}\right.$ | $\left\|\begin{array}{l} \mathrm{N} \\ \mathrm{C} \\ \mathrm{~N} \\ \mathrm{~N} \end{array}\right\|$ | $\left\|\begin{array}{l} \hat{\rightharpoonup} \\ \underset{N}{N} \\ \underset{N}{2} \end{array}\right\|$ | $\left\|\begin{array}{l} \mathrm{N} \\ \mathrm{~N} \\ \mathrm{~N} \end{array}\right\|$ | $\begin{aligned} & \mathrm{N} \\ & \mathrm{~N} \\ & \mathrm{~N} \\ & \mathrm{~N} \end{aligned}$ | $\left\|\begin{array}{c} \hat{c} \\ \underset{y}{n} \\ \underset{\sim}{n} \end{array}\right\|$ | $\left\|\begin{array}{l} \hat{3} \\ \mathbf{N} \\ \mathrm{~N} \end{array}\right\|$ | $\begin{aligned} & \vec{c} \\ & ल \\ & ल \\ & \end{aligned}$ | $\left\lvert\, \begin{gathered} \tilde{c} \\ \underset{N}{N} \\ \text { ले } \end{gathered}\right.$ | $\left\|\begin{array}{l} \hat{c} \\ \underset{N}{c} \\ ल \\ ल \end{array}\right\|$ | $\begin{array}{\|c} { }_{n}^{2} \\ \mathrm{~N} \\ \mathrm{~m} \\ \mathrm{~N} \end{array}$ | $\left\|\begin{array}{c} \underset{O}{2} \\ \text { N} \\ \text { N} \end{array}\right\|$ |  | $\begin{aligned} & \underset{\sim}{c} \\ & \frac{N}{\alpha} \\ & \text { N } \end{aligned}$ |  | $\begin{aligned} & \stackrel{\rightharpoonup}{0} \\ & \text { त्र } \\ & 0 \\ & \vec{N} \end{aligned}$ | $\begin{aligned} & \stackrel{\rightharpoonup}{\mathbf{O}} \\ & \mathbf{N} \\ & \stackrel{3}{\mathrm{~N}} \end{aligned}$ | $\begin{array}{\|c} \stackrel{\rightharpoonup}{0} \\ \underset{M}{n} \\ \stackrel{n}{n} \end{array}$ | $\left.\begin{array}{\|l} \stackrel{\rightharpoonup}{0} \\ \mathrm{~N} \\ \mathrm{~N} \\ \mathrm{~N} \end{array} \right\rvert\,$ | $\left\|\begin{array}{l} \hat{\sim} \\ \underset{\sim}{n} \\ \underset{\sim}{4} \end{array}\right\|$ |  | $\begin{aligned} & \stackrel{\rightharpoonup}{O} \\ & \text { N} \\ & \underset{N}{n} \end{aligned}$ | $\begin{array}{\|c} \stackrel{\rightharpoonup}{0} \\ \stackrel{N}{3} \\ \stackrel{\rightharpoonup}{n} \end{array}$ | त | $\begin{aligned} & \mathrm{N} \\ & \stackrel{\rightharpoonup}{\mathrm{~N}} \\ & \stackrel{\rightharpoonup}{\mathrm{~N}} \end{aligned}$ | $\begin{gathered} \stackrel{\rightharpoonup}{\circ} \\ \text { N} \\ \text { N } \end{gathered}$ | $\begin{array}{\|c} \stackrel{\rightharpoonup}{\mathrm{o}} \\ \frac{\mathrm{~N}}{\mathrm{~N}} \end{array}$ | त | $\begin{gathered} \stackrel{\rightharpoonup}{O} \\ \text { Ǹ } \\ \text { N- } \end{gathered}$ | $\begin{aligned} & \mathrm{N} \\ & \underset{\mathrm{~N}}{\mathrm{~N}} \\ & \underset{\mathrm{~N}}{ } \end{aligned}$ | － |


|  | $\cdots$ | 告 | $\sim$ | $\sim$ | n | $\cdots$ | $\underset{\sim}{\infty}$ | $\stackrel{\sim}{\sim}$ | － | － | तి | त | $\xrightarrow{2}$ | ก | へ | ก | 응 | 응 | $\bigcirc$ | 으－ | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 |
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|  | 윽 | $\stackrel{\rightharpoonup}{\mathrm{N}} \mid$ | ～ | 守 | 8 | $8$ | 8 | 8 | 8 | 8 | そ | $\cdots$ | $\stackrel{\square}{\square}$ | 윽 | 으－ | $9$ | n | n | 8 | 8 | － | － | ヶ | そ | $\underset{ }{2}$ | べ | 안 | ㅇ |
|  | $\left\lvert\, \begin{aligned} & \mathrm{Z} \\ & \text { I } \end{aligned}\right.$ | $\stackrel{m}{o}$ | $\cdots$ | $\stackrel{\infty}{\sim}$ | $\left\lvert\, \begin{aligned} & 0 \\ & 9 \end{aligned}\right.$ | $\underset{n}{n}$ | $\left\lvert\, \begin{gathered} \mathrm{J} \\ \text { an } \end{gathered}\right.$ | $\stackrel{n}{0}$ | $\stackrel{T}{\mathrm{a}}$ | $\underset{O}{\mathrm{O}}$ | $\vec{a}$ | $0$ | － | $\vec{\Omega}$ | $\stackrel{\infty}{-}$ | $\stackrel{9}{=}$ | － | $\stackrel{\text { Y }}{-}$ | － | $\stackrel{\mathrm{N}}{-}$ | －7 | $\underset{O}{\mathrm{~N}}$ | $\stackrel{9}{\square}$ | $\infty$ | $\left\|\begin{array}{l} n \\ a \end{array}\right\|$ | $\stackrel{0}{\square}$ | $\stackrel{0}{-}$ | \％ |
|  | － | H | －1 | －1 | 出 | 垵 | －1 | －1 | H | H | －1 | H | 穴 | 出 | H | －1 | －1 | －1 | －1 | －1 | － | － | H | － | H | H | H | H |
| $\text { 家 } \sum_{n}^{n} \frac{\pi}{n} \frac{6}{3}$ | N | त | N | N | － | N | $\xrightarrow{\text { C }}$ | ＋ | $\xrightarrow{\text { Y }}$ | $\stackrel{\text { Y }}{+}$ | $\underset{\sim}{y}$ | $\left\lvert\, \begin{gathered} \mathrm{y} \\ 7 \end{gathered}\right.$ | $\cdots$ | $\stackrel{\sim}{-}$ | $\infty$ | $\left\|\begin{array}{c} \infty \\ -1 \end{array}\right\|$ | $\vec{F}$ | $\overrightarrow{7}$ | 7 | $\vec{\square}$ | $\left\lvert\, \begin{gathered} \mathrm{a} \\ \hline \end{gathered}\right.$ | $\left\lvert\, \begin{gathered} \mathrm{m} \\ \hline \end{gathered}\right.$ | M | m | $\cdots$ | $\left\|\begin{array}{l} m \\ a \end{array}\right\|$ | ă | n |
|  | Z | 又 | Z | z | Z | \％ | Z | 乙 | z | 乙 | \％ | 又 | z | z | z | Z | i | － | ； | $\cdots$ | Z | z | 乙 | \％ | z | \％ | 二 | Z |
| $\begin{aligned} & \text { च्म 合 } \\ & 0 \\ & \text { in } \end{aligned}$ | $\because$ | $\cdots$ | $\infty$ | $\infty$ | 9 | 9 | $\underset{\sim}{7}$ | $\cdots$ | त̇ | $\mathrm{y}$ | $\infty$ | $\infty$ | $\cdots$ | m | $\pm .$ | $\left\|\begin{array}{c}  \pm \\ 0 \end{array}\right\|$ | $\left\lvert\, \begin{gathered} \mathrm{J} \\ \mathrm{~N} \end{gathered}\right.$ | $\stackrel{\text { d }}{\sim}$ | $\stackrel{-}{0}$ | $\bigcirc$ | $\cdots$ | $\stackrel{9}{\square}$ | － | － | $\begin{aligned} & 9 \\ & 0 \end{aligned}$ | $9$ | － | － |
|  | $-$ | $-$ | － | － | － | － | 8 | 8 | 8 | 8 | (i) | $\stackrel{\sim}{\mathrm{N}}$ | 亿 | 亿 | in | n | ल | m | ल | ल | － | － | － | － | － | － | － | － |
| $\begin{aligned} & \text { Ca } \\ & \text { ᄋ } \end{aligned}$ | $\left\|\begin{array}{c} G \\ \dot{G} \end{array}\right\|$ | $\begin{gathered} \dot{G} \\ \underset{y}{2} \end{gathered}$ | 筞 | \％ | $\left\lvert\, \begin{gathered} \infty \\ \underset{寸}{ } \end{gathered}\right.$ | $\begin{gathered} \infty \\ \underset{子}{n} \end{gathered}$ | $\left\|\begin{array}{c} 9 \\ i \\ \infty \\ \infty \end{array}\right\|$ | $\left\|\begin{array}{c} 9 \\ \infty \\ \infty \end{array}\right\|$ | $\left\|\begin{array}{c} 0 \\ \infty \\ \infty \end{array}\right\|$ | $\begin{aligned} & 0 \\ & \infty \\ & \infty \end{aligned}$ | $\frac{\vec{\infty}}{\vec{\infty}}$ | $\frac{-1}{-\infty}$ | 午 | 午 | $\stackrel{T}{8}$ | $\left\|\begin{array}{c} T \\ 0 \\ i \end{array}\right\|$ | $\overrightarrow{\dot{q}} \mid$ | $\vec{m}$ | $\begin{aligned} & a \\ & \end{aligned}$ | $\underset{\sim}{a}$ | $\left\lvert\, \begin{aligned} & \infty \\ & \underset{\sim}{\infty} \\ & \underset{\sim}{2} \end{aligned}\right.$ | $\left\lvert\, \begin{aligned} & \infty \\ & \infty \\ & + \end{aligned}\right.$ | $\begin{aligned} & 2 \\ & 2 \\ & 2 \end{aligned}$ | $\stackrel{N}{\circ}$ | $\infty$ | $\mathfrak{m}$ | $\because$ | ก |
| $\begin{gathered} \text { 윱O } \\ H \\ H \end{gathered}$ | $\begin{aligned} & \mathrm{m} \\ & \mathrm{C} \end{aligned}$ | $\begin{gathered} n \\ \underset{\sim}{n} \end{gathered}$ | $\overrightarrow{~ \vec{~}} \mid$ | $\overrightarrow{~ I}$ | $\left\|\begin{array}{l} \underset{~ n}{n} \\ \hline \end{array}\right\|$ | $\begin{aligned} & \text { à } \\ & \text { ñ } \end{aligned}$ | $\stackrel{n}{\leftrightharpoons}$ | $\stackrel{?}{\leftrightharpoons}$ | $\underset{\sim}{\text { I }}$ | $\stackrel{ \pm}{ \pm}$ | $\stackrel{n}{\approx}$ | $\underset{\sim}{\approx}$ | $\begin{aligned} & \infty \\ & \underset{\sim}{2} \end{aligned}$ | $\begin{aligned} & \infty \\ & + \\ & + \end{aligned}$ | $\underset{\sim}{4}$ | $\stackrel{\underset{N}{\mathrm{~N}}}{\substack{2}}$ | $\underset{\sim}{\infty}$ | $\begin{gathered} 1 \\ \substack{2 \\ N} \end{gathered}$ | $\begin{aligned} & 0 \\ & 0 \\ & \sim \end{aligned}$ | $\begin{aligned} & 0 \\ & 0 \\ & c \end{aligned}$ | $\overrightarrow{\text { à }}$ | $\overrightarrow{\mathrm{N}}$ | $\stackrel{\rightharpoonup}{4}$ | $\left\lvert\, \begin{aligned} & \sim \\ & \text { N } \end{aligned}\right.$ | 示 | N | $\cdots$ | $\cdots$ |
| $\stackrel{\otimes}{\stackrel{\sim}{\sim}}$ |  | $\begin{gathered} 0 \\ 0 \\ 0 \\ \vdots \\ \vdots \\ \rho \end{gathered}$ | $\begin{array}{\|c} \text { 気 } \\ 0 \\ \text { n } \\ \vdots \\ \vdots \end{array}$ | $\begin{gathered} \text { व } \\ 0 \\ 0 \\ \text { n } \\ \vdots \\ p \end{gathered}$ |  | $\begin{aligned} & \sqrt{2} \\ & 0 \\ & 0 \\ & \text { on } \\ & \text { n } \\ & \vdots \end{aligned}$ | 嵒 | 品 | 怘 | 嵒 | 品 | \|⿹ㅕㅂ | 品 | 品 | 品 | 品 | 嵒 | 品 | 嵒 | 灵 | $\begin{aligned} & \text { 䨗 } \\ & \hline \end{aligned}$ |  | 部 | $\left\lvert\, \begin{aligned} & \frac{0}{2} \\ & \frac{2}{4} \\ & \hline \end{aligned}\right.$ | 票 | 变 | $\frac{0}{2}$ | 或 |
| 费 | $\cdots$ | 入入 | $\cdots$ | ल | त | N | तु | त | N | तु | $\cdots$ | ल | त | ก | त | ก | N | N | N | ก | त | ल | त | m | N | ल | N | M |
|  | $\stackrel{?}{\approx}$ | $0$ | $\hat{0}$ | $\overrightarrow{=}$ | $\|\overrightarrow{\mathrm{a}}\|$ | $\frac{9}{2}$ | $\stackrel{\dot{a}}{\dot{a}} \mid$ | $\vec{y}$ | $\begin{aligned} & n \\ & \underset{\sim}{2} \end{aligned}$ | $\stackrel{n}{\square}$ | $\underset{\sim}{n}$ | $\underset{=}{\infty}$ | $\underset{-1}{-1}$ | त | $\left\lvert\, \begin{array}{l\|} 0 \\ \infty \end{array}\right.$ | $\left\|\begin{array}{c} n \\ \infty \end{array}\right\|$ | $\stackrel{N}{\mathrm{O}}$ | $=$ | $\left\lvert\, \begin{aligned} & 0 \\ & \underset{\sim}{2} \end{aligned}\right.$ | $\underset{\sim}{2}$ | $\vec{o}$ | $\left\|\begin{array}{c} \underset{\sim}{u} \\ \stackrel{n}{2} \end{array}\right\|$ | 0 | $\vec{\sim}$ | $\begin{aligned} & 0 \\ & \vdots \\ & \hdashline \end{aligned}$ | $\underset{n}{n}$ | $\stackrel{\square}{\square}$ | $\cdots$ |
| 䔍 悲 n | $\mid \underset{H}{\sim}$ | $\begin{gathered} \text { I } \\ 0 \\ 0 \end{gathered}$ | $\underset{\sim}{\sim}$ | $\begin{aligned} & \text { 뭉 } \\ & \text { 号 } \end{aligned}$ | $\begin{gathered} \underset{\sim}{\sim} \\ \underset{H}{*} \end{gathered}$ | $\begin{aligned} & \text { I } \\ & 0 \\ & 0 \end{aligned}$ | $\left\lvert\,\right.$ | 高 | $\begin{gathered} \infty \\ \\ \end{gathered}$ | 吉 | $\begin{aligned} & \mathbb{N} \\ & \underset{H}{4} \end{aligned}$ | 딩 | $\underset{\sim}{\underset{\sim}{w}}$ | $\begin{aligned} & \text { 밍 } \end{aligned}$ | $\|\underset{H}{\sim}\|$ | $\left\lvert\, \begin{gathered} \text { 品 } \\ 0 \end{gathered}\right.$ | $\underset{H}{ \pm}$ | $\begin{aligned} & \text { F } \\ & \text { 号 } \end{aligned}$ | $\stackrel{\otimes}{\omega}$ | 高 | $\left\lvert\,\right.$ | 高 | 䖪 | 吉 | $\left\lvert\, \begin{gathered} \underset{H}{\sim} \\ \hline \end{gathered}\right.$ | $\begin{aligned} & \text { 밍 } \end{aligned}$ |  | 젱 |
| 등 | $\left\|\begin{array}{r} -1 \\ 0 \\ 0 \\ -1 \end{array}\right\|$ | $\begin{gathered} -1 \\ 0 \\ 0 \\ H \end{gathered}$ | $\left\|\begin{array}{c} 1 \\ 0 \\ 0 \\ 0 \end{array}\right\|$ | $\left\lvert\, \begin{gathered} 1 \\ 0 \\ 0 \\ H \end{gathered}\right.$ | $\left\|\begin{array}{c} n \\ 0 \\ 0 \\ -i \end{array}\right\|$ | $\begin{aligned} & n \\ & 0 \\ & 0 \\ & n \end{aligned}$ | $\left.\begin{gathered} -\overrightarrow{3} \\ 0 \\ 0 \end{gathered} \right\rvert\,$ | $\left\|\begin{array}{l} -\overrightarrow{0} \\ 0 \\ H \end{array}\right\|$ | $\left(\begin{array}{c} c \\ 0 \\ 0 \\ n \end{array}\right.$ | $\begin{aligned} & \text { O} \\ & \text { O } \\ & \text { Hin } \end{aligned}$ | $\left\|\begin{array}{r} -\overrightarrow{3} \\ 0 \\ H \end{array}\right\|$ | $0$ | $\left\|\begin{array}{c} -\vec{y} \\ 0 \\ -i \end{array}\right\|$ | $\begin{gathered} -7 \\ 0 \\ \vdots \end{gathered}$ | $\left\|\begin{array}{c} 1 \\ 0 \\ 0 \\ H \end{array}\right\|$ | $\left\|\begin{array}{c} c \\ 0 \\ 0 \\ -1 \end{array}\right\|$ | $\left.\begin{aligned} & \overrightarrow{0} \\ & 0 \\ & i \end{aligned} \right\rvert\,$ | $\left\|\begin{array}{c} -\overrightarrow{3} \\ 0 \\ -\quad \end{array}\right\|$ | $\left(\begin{array}{c} 1 \\ y \\ 0 \\ \vdots \end{array}\right.$ | $\left\|\begin{array}{c} N \\ 0 \\ 0 \\ i \end{array}\right\|$ | $\left\|\begin{array}{l} -\overrightarrow{3} \\ 0 \\ -H \end{array}\right\|$ | $\left.\begin{aligned} & \overrightarrow{0} \\ & 0 \\ & i \end{aligned} \right\rvert\,$ | $\left\lvert\, \begin{gathered} 1 \\ 0 \\ 0 \\ H \end{gathered}\right.$ | $\left\|\begin{array}{c} 1 \\ 0 \\ 0 \\ 0 \end{array}\right\|$ | $\overrightarrow{\mathrm{O}}$ | $\begin{aligned} & -3 \\ & 0 \\ & H \end{aligned}$ | $\begin{aligned} & 1 \\ & y \\ & 0 \\ & y \end{aligned}$ | N |
|  |  | $\begin{gathered} \text { y } \\ \text { n } \\ \text { n } \\ 2 \\ 0 \\ 0 \\ 0 \\ 0 \end{gathered}$ | $\begin{gathered} \text { y } \\ \text { un } \\ \text { m } \\ \text { a } \\ 0 \\ 0.0 \\ 0 \end{gathered}$ |  |  |  |  |  |  | $\begin{aligned} & \text { B } \\ & \text { In } \\ & \text { Un } \\ & \text { Un } \\ & \text { Un } \\ & 0 \\ & 0 \\ & 0 \end{aligned}$ |  | Cascade Church E | n 0 0 0 0 0 0 0 0 | $\begin{gathered} \text { a } \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{gathered}$ | $\begin{aligned} & \text { n } \\ & 0 \\ & 0 \\ & 0 \\ & 0 \\ & 0 \\ & 0 \\ & 0 \\ & 0 \end{aligned}$ | $\begin{array}{\|l\|} \hline 1 \\ \hline 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \hline \end{array}$ |  |  |  |  |  |  |  |  |  |  |  |  |
| 買 | $\begin{gathered} 8 \\ \stackrel{0}{-1} \end{gathered}$ | $8$ | $\stackrel{8}{9}$ | $8$ | $\begin{gathered} \hline 8 \\ \stackrel{9}{-1} \end{gathered}$ | $8$ | $\left\|\begin{array}{c} 8 \\ \dot{\infty} \end{array}\right\|$ | $\left\|\begin{array}{\|c} \hline 0 \\ \dot{\infty} \end{array}\right\|$ | $\begin{aligned} & 8 \\ & \dot{s} \end{aligned}$ | o | $\begin{aligned} & 8 \\ & \dot{c} \\ & \hline \end{aligned}$ | $\begin{array}{\|c\|} \hline \stackrel{\circ}{\infty} \\ \hline \end{array}$ | $\begin{aligned} & 8 \\ & 0.0 \\ & -1 \end{aligned}$ | $\begin{aligned} & 8 \\ & 0 \\ & -6 \end{aligned}$ | $\begin{aligned} & 8 \\ & \hline-2 \\ & -1 \end{aligned}$ | $\begin{aligned} & 8 \\ & \hline 0 \\ & \hline \end{aligned}$ | $\begin{aligned} & 8 \\ & \hline 0 \\ & \hline 1 \end{aligned}$ | $\begin{aligned} & \hline 8 \\ & 0.0 \end{aligned}$ | $\begin{aligned} & 8 \\ & 0 \\ & -1 \end{aligned}$ | $\begin{aligned} & \hline \mathbf{o} \\ & \hline-1 \end{aligned}$ | $\begin{aligned} & 8 \\ & \hline 0 \\ & \hline \end{aligned}$ | $\begin{aligned} & 8 \\ & 0.0 \\ & 0 \end{aligned}$ | $\begin{aligned} & 8 \\ & 6 \\ & \hline-1 \end{aligned}$ | $\begin{aligned} & \hline 8 \\ & 0 \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 8 \\ & \mathbf{0} \end{aligned}$ | \％ | － | \％ |
| No N | $\begin{array}{\|c} 2 \\ 0 \\ \text { ते } \\ \text { ते } \end{array}$ | $\begin{aligned} & \mathrm{N} \\ & \underset{\sim}{2} \\ & \mathbf{N}_{1} \end{aligned}$ | $\begin{array}{\|c} \hat{3} \\ \text { N} \\ 0 \\ \text { N} \end{array}$ | $\begin{array}{\|c} \text { n } \\ \text { N } \\ \text { त } \\ \text { तin } \end{array}$ | $\begin{aligned} & \hat{Z} \\ & \text { in } \\ & \text { N } \\ & \text { N } \end{aligned}$ |  | $\begin{array}{\|c} \hat{N} \\ \text { N} \\ \text { N} \\ \text { N } \end{array}$ | $\begin{aligned} & \text { n} \\ & \text { N} \\ & \text { Ǹ } \\ & \text { Nin } \end{aligned}$ | $\begin{aligned} & n \\ & \text { n } \\ & \text { n} \\ & \text { n} \end{aligned}$ | $\begin{aligned} & \underset{\sim}{n} \\ & \text { N} \\ & \text { N} \end{aligned}$ | $\begin{array}{\|c} n \\ \text { N} \\ \text { n } \\ \text { n } \end{array}$ |  | $\begin{array}{\|c} \hat{n} \\ \text { N} \\ \text { ñ } \\ \text { N } \end{array}$ | $\begin{aligned} & \text { n } \\ & \text { N} \\ & \text { n} \\ & \text { n} \end{aligned}$ | $\begin{aligned} & n \\ & ⿳ 亠 口 子 \\ & \text { N} \\ & \text { n} \end{aligned}$ |  |  | $\begin{aligned} & \text { n } \\ & \text { in } \\ & \text { N } \\ & \text { N } \end{aligned}$ |  | $\begin{array}{\|c} \substack{2 \\ \text { N } \\ \text { N } \\ \text { N }} \end{array}$ |  | $\begin{array}{\|c} \hat{3} \\ \hat{N} \\ 0 \\ \text { N} \end{array}$ | $\begin{gathered} n \\ \hat{c} \\ \text { N } \\ \text { N } \end{gathered}$ |  | $\begin{aligned} & \mathrm{A} \\ & \mathbf{0} \\ & \text { N } \\ & \text { N } \end{aligned}$ | $\begin{array}{\|c} \left.\begin{array}{c} y \\ 0 \\ \text { y } \\ \text { N} \end{array}\right) \end{array}$ |  | － |



Figure 3. A) Variation in average particulate concentrations by sample location. B) Zoomed view to highlight locations closely clustered.

Field Sites AirBeam Tests Metadata
The following figures and metadata provide details on each study site. Figures highlight test
locations, tree and open field, with white markers (numbers indicate which AirBeam unit was
used at that place, i.e. \#1, 2 or 3). The start and end location, equivalency check, of all AirBeams
is represented with a yellow marker.
$4^{\text {th }}$ Street River Walk Access Parking Lot 2-1-17
When: 2-1-17 16:00-17:15 EDT
Who: K. Youngquist and Care Bacon
Where: $\quad 4$ th Street River walk access parking lot
What: $\quad 4$ th street has a thin line of trees near highway 280 . Test in tree line compared to open grass near parking lot. Units 1 and 3 used based on equivalency tests.
How: Unit 1 placed in treeline and unit 3 in field next to parking lot.
Notes: $\quad 26$ trees bigger than 3 inch diameter and less than 5 inch diamter in line of sight. Road is higher elevation than trees and field.
Hypothesis: Thin tree line will not create enough of a fence to reduce particulate matter farther from the road as compared with open parking lot without trees.

Particulate Notes

| Time | Note |
| :---: | :---: |
| 16:25-16:37 | 2 cars idle in parking lot |
| 16:54-17:01 | Smell of smoke. Fort Benning perscribed burn earlier (around noon). Wind shifted from <br> out of SW. |

Car Data:

| Time | Cars | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: |
| $16: 30$ | 45 | 1 | 45 |
| $16: 40$ | 47 | 1 | 47 |
| $16: 45$ | 127 | 2 | 63.5 |
| $16: 56$ | 90 | 2 | 45 |
| $17: 03$ | 101 | 2 | 50.5 |

Area PM2. 5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $15: 00$ | 0.1 |
| $16: 00$ | 1.1 |
| $17: 00$ | 1.7 |
| $18: 00$ | 2.8 |

Weather
Weather.com:

| Time | Wind Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{F}\right)$ | \% Humidity | Dew Point $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $17: 15$ | SW | 9 | 73 | 36 | 44 | 30.10 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind Direction | Wind Direction <br> $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 18 \mathrm{pm}$ | W | 270 | 4.7 | 22.8 | 38.8 |  |  | 29.75 |
| $16: 28 \mathrm{pm}$ | W | 270 | 3.7 | 21.7 | 34.9 | 7.3 | 13.8 | 29.75 |
| $16: 33 \mathrm{pm}$ | NW | 315 | 6.2 | 22.2 | 39.7 | 7.6 | 13.7 | 29.76 |
| $16: 38 \mathrm{pm}$ | NW | 315 | 8.1 | 22.1 | 41.3 | 8.2 | 140 |  |
| $16: 43 \mathrm{pm}$ | NW | 315 | 3.1 | 22.4 | 40.5 | 8.8 | 14.6 | 29.9 |
| $16: 49 \mathrm{pm}$ | W | 270 | 1.3 | 22.4 | 39.6 | 8.0 | 14.1 | 29.76 |
| $16: 51 \mathrm{pm}$ |  |  | 0 |  |  |  | 136 |  |
| $16: 53 \mathrm{pm}$ |  |  | 0 | 22.4 | 41.0 | 8.6 | 14.4 | 29.75 |
| $16: 54 \mathrm{pm}$ | SW | 225 | 4 |  |  |  | 145 |  |
| $16: 58 \mathrm{pm}$ | NW | 315 | 5.4 | 22.6 | 40.8 | 8.8 | 14.6 | 29.74 |
| $17: 03 \mathrm{pm}$ | NW | 315 | 1.8 | 22.7 | 40.8 | 9.1 | 158 |  |
| $17: 08 \mathrm{pm}$ | NW | 315 | 2.9 | 22.8 | 40.8 | 8.4 | 14.9 | 29.75 |
| Average | WNW | 292.5 | 3.4 | 22.4 | 39.8 | 8.3 | 145 |  |

Airbeam Location Data:

| Time | Lat A1 | Long A1 | Lat A3 | Long A3 | Device Facing <br> Direction ( $)$ | Elevation A1 <br> $(\mathrm{ft})$ | Elevation A3 <br> $(\mathrm{ft})$ | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 07-17: 08$ | $32.4529361^{\circ}$ | $-84.9926944^{\circ}$ | $32.4529389^{\circ}$ | $-084.9935917^{\circ}$ | $330^{\circ} \mathrm{NW}$ | 310 | 230 | 1 |



Figure 5. The River Walk parking lot has a thin tree buffer adjacent to highway 280.

Columbus State University ROTC 2-217

When: 2-2-17 15:30-17:52 EDT
Who: K. Youngquist and Care Bacon
Where: CSU Lindsey Creek Road/ROTC Field
What: CSU has dense line of trees near I-185. Test in tree line compared to open area near sign. Units 1 and 3 used based on equivalency tests.
How: Unit 1 placed in treeline and unit 3 in open.
Notes: $\quad$ Road is 10 feet lower elevation than trees and field.
Hypothesis:
In the winter, dense tree line will have higher particulate matter level as compared with open area without trees.

Particulate Notes

| Time | Note |
| :---: | :--- |
| $17: 02$ | Campus police smoking near bridge. Smelled worse in trees. |
| 17:03 | Staff leaving campus |
| 17:42-17:43 | ROTC ran by devices and through the trees |

Car Data:

| Time | Cars | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: |
| $16: 57$ | 242 | 2 | 121 |
| $17: 19$ | 254 | 2 | 127 |
| $17: 29$ | 250 | 2 | 125 |
| $17: 38$ | 237 | 2 | 119 |
| $17: 48$ | 282 | 2 | 141 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $14: 00$ | 7.1 |
| $15: 00$ | 7.9 |
| $16: 00$ | 9.7 |
| $17: 00$ | 11.9 |
| $18: 00$ | 11.1 |

## Weather

Weather.com:

| Time | Wind Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp ( $\left.{ }^{\circ} \mathrm{F}\right)$ | \% Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $17: 00$ | W | 9 | 73 | 51 | 53 | 30.13 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind Direction | Wind Direction <br> $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 56$ | W | 270 | 0.9 | 23.9 | 51.6 | 13.4 | 17.3 | 29.73 |
| $17: 01$ | W | 270 | 1.0 | 23.4 | 55.0 | 14.0 | 17.5 | 29.74 |
| $17: 06$ | W | 270 | 1.5 | 23.3 | 52.6 | 13.0 | 16.8 | 29.73 |
| $17: 11$ |  |  | 0 | 22.9 | 56.1 | 13.5 | 166 |  |
| $17: 17$ |  |  | 0 | 22.9 | 55.1 | 13.5 | 16.9 | 29.73 |
| $17: 22$ |  |  | 0 | 22.8 | 55.7 | 13.2 | 16.6 | 29.73 |
| 17.26 | SW | 225 | 1.3 | 22.8 | 54.4 | 13.1 | 165 |  |
| $17: 31$ |  |  | 0 | 24.2 | 51.7 | 13.9 | 17.5 | 29.73 |
| $17: 36$ | SW | 225 | 1.4 | 23.1 | 53.2 | 13.3 | 16.9 | 29.73 |
| $17: 41$ | SW | 225 | 1.7 | 22.6 | 55.5 | 13.3 | 16.7 | 29.73 |
| $17: 46$ | W | 270 | 2.7 | 22.0 | 56.5 | 16.7 |  |  |
| $17: 51$ | W | 270 | 1.6 | 21.9 | 56.4 | 12.8 | 165 |  |

Airbeam Location Data:

| Time | Lat A1 | Long A1 | Lat A3 | Long A3 | Device Facing <br> Direction ( $\left.{ }^{\circ}\right)$ | Elevation (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 48-17: 15$ | 32.502139 | -84.946553 | 32.501955 | -84.94642 | $231^{\circ}$ SW | 314 | 1 |
| $17: 16-17: 52$ | 32.502222 | -84.946608 | 32.501955 | -84.94642 | $231^{\circ} \mathrm{SW}$ | 314 | 2 |



Figure 5. Columbus State College has a big field of trees adjacent to an open space.

Manchester Expressway Park and Ride Bike Park 2-3-17

When: $\quad 2 / 3 / 2017$ 16:30-17:18 EDT
Who: K. Youngquist and Trevor Gundberg
Where: Manchester Expressway Park and Ride Bike Park, 3690 Manchester Expy, Columbus, GA 31909
What: The bike park has a dense patch of trees surrounding the parking lot and playground on all sides except the north entrance to parking lot. Test beyond tree line compared to parking lot.
How: Unit \#1 in open and \#3 in tree line. Moved two airbeams at similar distances from road, behind trees and the other in parking lot.
Notes: Broke pencils and pens, cut session short. Only one other car in parking lot due to cold windy weather.
Hypothesis: In the winter, the dense tree line will create a fence, reducing particulate matter farther from the road as compared with open parking lot without trees.

## Particulate Notes

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $16: 00$ | 8.8 |
| $17: 00$ | 5.5 |
| $18: 00$ | 6.1 |

## Weather

Weather.com: Cloudy the whole time

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp ( $\left.{ }^{\circ} \mathrm{F}\right)$ | \% Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure <br> $($ in $)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 30$ | NNW | 11 | 55 | 68 | 45 | 30.21 |
| $17: 18$ | NNW | 11 | 55 | 66 | 44 | 30.20 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind Direction <br> $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 35$ | NNW | 337.5 | 3.1 | 13.8 | 66.2 | 8.2 | 11 | 29.8 | 113 |
| $16: 40$ | NNW | 337.5 | 6.4 | 13.4 | 69.2 | 7.9 | 10.4 | 29.79 | 110 |
| $16: 45$ | NNW | 337.5 | 7.5 | 13.5 | 68.3 | 7.6 | 10.2 | 29.79 | 106 |
| 16.50 | NNW | 337.5 | 5.1 | 13 | 68.5 | 7.4 | 9.9 | 29.8 | 105 |
| $16: 55$ | NNW | 337.5 | 5.6 | 13 | 69.4 | 7.5 | 10.1 | 29.71 | 105 |
| $17: 00$ | NNW | 337.5 | 3.4 | 13 | 68.6 | 7.3 | 9.8 | 29.8 | 101 |
| $17: 05$ | NNW | 337.5 | 4.1 | 13.2 | 67.4 | 7.3 | 10.0 | 29.8 | 96 |
| $17: 10$ | NNW | 337.5 | 9.8 | 12.7 | 69.2 | 7.3 | 9.9 | 29.8 | 96 |
| $17: 15$ | NW | 315 | 7.2 | 13.1 | 68.3 | 7.3 | 9.9 | 29.8 | 93 |

Airbeam Location:

| Time | Lat A1 | Long A1 | Lat A3 | Long A3 | Device <br> Facing <br> Direction $\left({ }^{\circ}\right)$ | Elevation <br> $(\mathrm{ft})$ | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 34-16: 46$ | $32.508447^{\circ}$ | $-84.935431^{\circ}$ | $32.508608^{\circ}$ | $-84.934950^{\circ}$ | $\mathrm{N} 338^{\circ}$ | 340 | 1 |
| $16: 49-17: 01$ | $32.508347^{\circ}$ | $-84.935400^{\circ}$ | $32.508525^{\circ}$ | $-84.934833^{\circ}$ | $\mathrm{N} 338^{\circ}$ | 340 | 2 |
| $17: 06-17: 18$ | $32.508233^{\circ}$ | $-84.935347^{\circ}$ | $32.508444^{\circ}$ | $-84.934811^{\circ}$ | $\mathrm{N} 338^{\circ}$ | 340 | 3 |



Figure 6. The Bike Park has U-shaped tree canopy with an open area in the center adjacent to Manchester Expressway.

## All Saints Presbyterian Church 2-9-17

When: 2-9-17 16:30-17:30
Who: K. Youngquist (Alone)
Where: All Saints Presbyterian Church, 7170 Beaver Run Rd, Midland, GA 31820
What: All Saints has a dense patch of trees surrounding the parking lot. Test in trees and beyond tree line compared to parking lot.
How: Start/end three airbeams at distance from road. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road, one in trees and the other in parking lot.

Hypothesis: In the winter, trees will create a fence, reducing particulate matter farther from the road in trees as compared with open parking lot without trees.

Particulate Notes
Particulate Notes

| Time |  |
| :---: | :--- |
| $16: 39$ | Truck idling and all airbeams particulate count increased. |

Car Data:

| Time | Cars | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: |
| $16: 36$ | 45 | 2 | 22.5 |
| $16: 53$ | 66 | 2 | 33 |
| $17: 10$ | 91 | 2 | 45.5 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $15: 00$ | 0.4 |
| $16: 00$ | 2.1 |
| $17: 00$ | 2.9 |
| $18: 00$ | 1.1 |

Weather
Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp ( $\left.{ }^{\mathrm{F}} \mathrm{F}\right)$ | \% Humidity | Dew Point ( ${ }^{(\mathrm{F})}$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 34$ | NNW | 14 | 55 | 32 | 26 | 30.24 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction( $)$ | Wind Speed <br> (mph) | Temp ( $\left.{ }^{\circ} \mathrm{C}\right)$ | \% Humidity | Dew Point ( $\left.{ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure (Hg) | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 24$ | N | 360 | 16 | 12.2 | 35.3 | -2.7 | 5.7 | 29.72 | 173 |
| $16: 35$ | N | 360 | 8.2 | 12.6 | 38.5 | -1.2 | 6.3 | 29.73 | 178 |
| $16: 40$ | NNW | 337.5 | 5.6 | 12.9 | 37.5 | -1.0 | 6.5 | 29.72 | 178 |
| $16: 45$ | NNW | 337.5 | 7.2 | 12.1 | 38.8 | -1.2 | 6.2 | 29.74 | 157 |
| $16: 50$ | NNW | 337.5 | 6.4 | 12.6 | 39.3 | -0.8 | 6.5 | 29.73 | 165 |
| $16: 55$ | N | 360 | 13.4 | 12.1 | 38.3 | -1.6 | 6 | 29.73 | 165 |
| $17: 05$ | N | 360 | 2.9 | 12.6 | 36.1 | -2.0 | 6.1 | 29.77 | 136 |
| $17: 10$ | N | 360 | 11 | 11.9 | 37.3 | -1.9 | 5.9 | 29.75 | 148 |
| $17: 18$ | N | 360 | 14.6 | 11.5 | 37.7 | -2.5 | 5.4 | 29.76 | 140 |
| $17: 24$ | N | 360 | 8.9 | 11.9 | 37.7 | -2.5 | 5.5 | 29.75 | 153 |

Airbeam Location Data:

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Facing <br> Direction <br> $\left({ }^{\circ}\right)$ | Elevation <br> (ft) | Location | Notes |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 31-16: 46$ | $32.537679^{\circ}$ | $-84.867638^{\circ}$ | $32.537679^{\circ}$ | $-84.867639^{\circ}$ | $32.537679^{\circ}$ | $-84.867637^{\circ}$ | $360^{\circ} \mathrm{N}$ | 410 | Start | In front of cross at entrance |
| $16: 49-16: 59$ | $32.537368^{\circ}$ | $-84.867639^{\circ}$ | $32.537679^{\circ}$ | $-84.867639^{\circ}$ | $32.537362^{\circ}$ | $-84.867162^{\circ}$ | $360^{\circ} \mathrm{N}$ | 410 | 1 |  |
| $17: 04-17: 13$ | $32.537183^{\circ}$ | $-84.867636^{\circ}$ | $32.537679^{\circ}$ | $-84.867639^{\circ}$ | $32.537126^{\circ}$ | $-84.867166^{\circ}$ | $360^{\circ} \mathrm{N}$ | 410 | 2 |  |
| $17: 17-17.20$ | $32.537368^{\circ}$ | $-84.867639^{\circ}$ | $32.537679^{\circ}$ | $-84.867639^{\circ}$ | $32.537362^{\circ}$ | $-84.867162^{\circ}$ | $360^{\circ} \mathrm{N}$ | 410 | 1 | \#1 fell at 5:20 due to wind |
| $17 \cdot 23-17.25$ | $32.537679^{\circ}$ | $-84.867638^{\circ}$ | $32.537679^{\circ}$ | $-84.867639^{\circ}$ | $32.537679^{\circ}$ | $-84.867637^{\circ}$ | $360^{\circ} \mathrm{N}$ | 410 | End | \#3 fell at $5: 25$ due to wind |



Figure 7. All Saints Presbyterian Church location represents a U-shaped tree arrangement with an open field in the center adjacent to highway 80.

Cascade Hills Church 2-10-17

When: $\quad 2 / 10 / 2017$ 16:20-17:00 EDT
Who: K. Youngquist and Trevor Gundberg
Where: Cascade Hills Church, 54th Street, Columbus, GA 31904
What: Cascade has a thin line of trees east of the church building. Test beyond thin tree line compared to parking lot.
How: Start/end three airbeams at fence boarder facing highway. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at same distances from road, behind trees and the other in parking lot.
Notes: Started second location, but church event caused early end. End equivalency test not performed due to manager informing us it was time to leave.
Hypothesis: In the winter, trees will create a fence, reducing particulate matter farther from the road as compared with open parking lot without trees.

Particulate Notes
Car Data:

| Time | Cars (Trevor <br> Count) | Cars (Kristin <br> Count) | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $16: 27$ | 179 | 183 | 2 | 91 |
| $16: 41$ | 219 | 212 | 2 | 108 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $16: 00$ | 0.7 |
| $17: 00$ | 1.1 |
| $18: 00$ | 3.3 |

## Weather

Weather.com:

| Time | Wind Direction | Wind Speed <br> $(\mathrm{mph})$ | $\operatorname{Temp({}^{\circ }\mathrm {F})}$ | \% Humidity | Dew Point ( $\left.{ }^{\circ} \mathrm{F}\right)$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 14$ | SSE | 8 | 67 | 20 | 23 | 30.30 |
| 16.59 | S | 10 | 67 | 20 | 24 | 30.30 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 24$ | SSW | 202.5 | 1.4 | 21.5 | 19.1 | -3.5 | 9.4 | 29.83 | 166 |
| $16: 31$ | SSW | 202.5 | 1.8 | 21.1 | 19.7 | -3.3 | 9.4 | 29.74 | 158 |
| $16: 39$ | SSW | 202.5 | 3.2 | 19.7 | 19.8 | -3.4 | 9.6 | 29.75 | 140 |

Airbeam Location Data (My iphone):

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing <br> Direction ( | Elevation <br> (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 21-16: 31$ | $32.523491^{\circ}$ | $-84.982631^{\circ}$ | $32.523491^{\circ}$ | $-84.982631^{\circ}$ | $32.523491^{\circ}$ | $-84.982631^{\circ}$ | 338 NW | 420 | Start |
| $16: 35-16: 40$ | $32.523335^{\circ}$ | $-84.982998^{\circ}$ | $32.523491^{\circ}$ | $-84.982631^{\circ}$ | $32.523673^{\circ}$ | $-84.982118^{\circ}$ | 338 NW | 420 | 1 |
| $16: 43-16: 44$ | $32.523103^{\circ}$ | $-84.983225^{\circ}$ | $32.523491^{\circ}$ | $-84.982631^{\circ}$ | $32.523611^{\circ}$ | $-84.981942^{\circ}$ | 338 NW | 420 | 2 |



Figure 8. To the east of Cascade Hills Church, the tree buffer is small adjacent to highway 80.

## Manchester Expressway Park and Ride Bike Park 2-13-17

When: $\quad 2 / 13 / 201717: 00-18: 00$ ET
Who: K. Youngquist and Trevor Gundberg
Where: Manchester Expressway Park and Ride Bike Park, 3690 Manchester Expy, Columbus, GA 31909
What: The bike park has a dense patch of trees surrounding the parking lot and playground on all sides except the north entrance to parking lot. Test beyond tree line compared to parking lot.
How. Start/end three airbeams at distance 70 ft from road in grass north of parking lot. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road, behind trees and the other in parking lot.
Notes: $\quad 1$ and 2 were not set to record until $5: 21 \mathrm{pm}$ and $5: 34 \mathrm{pm}$ respectively. Closest airbeams based on averages and peaks during start will be used moving forward (as was done on west side of parking lot) and not previous equivalency tests.
Hypothesis: In the winter, the dense tree line will create a fence, reducing particulate matter farther from the road along tree line as compared with open parking lot without trees.

## Particulate Notes

Car Data:

| Time | Cars (Trevor <br> Count) | Cars (Kristin <br> Count) | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $17: 06$ | 129 | 131 | 2 | 65 |
| $17: 56$ | 122 | 122 | 2 | 61 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $16: 00$ | 6.1 |
| $17: 00$ | 8.5 |
| $18: 00$ | 23 |

## Weather

Weather.com:

| Time | Wind Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp ( $\left.{ }^{\circ} \mathrm{F}\right)$ | \% Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure (in) | Note |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $17: 00$ | N | 6 | 73 | 15 | 25 | 30.06 | Sunny |

Ambient Weather Data (Kestrel 4000):

| Time | Wind Direction | Wind <br> Direction $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | $\operatorname{Temp}\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $17: 06$ | N | 360 | 4.8 | 23.1 | 20.6 | -0.7 | 11.3 | 29.62 | 268 |
| $17: 16$ | NNW | 337.5 | 2.6 | 23.1 | 20.6 | -0.8 | 11.3 | 29.63 | 268 |
| $17: 26$ | NNW | 337.5 | 3.7 | 22.7 | 19.8 | -1.3 | 11.1 | 29.64 | 255 |
| $17: 36$ | NNW | 337.5 | 3.8 | 22.2 | 21.2 | -1.1 | 10.7 | 29.63 | 260 |
| $17: 46$ | NNW | 337.5 | 4.5 | 21.5 | 21.8 | -1.2 | 10.5 | 29.64 | 250 |
| $17: 55$ | NNW | 337.5 | 4.7 | 21.2 | 22.9 | -0.9 | 10.4 | 29.65 | 243 |

Airbeam Location:

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing Direction <br> ( ${ }^{\circ}$ ) | Elevation <br> (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 17:21-17.24 | 32.508447 | -84.935431 | 32.508535 | -84.935441 | 32.508608 | -84.934950 | NW $338^{\circ}$ | 340 | East 1 |
| 17:26-17:32 | 32.508222 | -84.935306 | 32.508535 | -84.935441 | 32.508425 | -84.934786 | NW $338^{\circ}$ | 340 | East 2 |
| 17:34-17:40 | 32.508535 | -84.935441 | 32.508535 | -84.935441 | 32.508535 | -84.935441 | NW $338^{\circ}$ | 340 | East End |
| 17:46-17:48 | 32.508092 | -84.936525 | 32.508099 | -84.936521 | 32.508092 | -84.936522 | NW $338^{\circ}$ | 340 | West Start |
| 17:50-17:53 | 32.508092 | -84.936525 | 32.507795 | -84.936710 | 32.507850 | -84.936514 | NW $338^{\circ}$ | 340 | West 1 |
| 17:56-18:00 | 32.508092 | -84.936525 | 32.508099 | -84.936521 | 32.508092 | -84.936525 | NW $338{ }^{\circ}$ | 340 | West End |



Figure 9. The Bike Park has U-shape tree canopy with an open area in the center adjacent to Manchester Expressway.

Cascade Hills Church 2-15-17
When: $\quad 2 / 15 / 20175-5: 10 \mathrm{pm}$
Who: K. Youngquist and Trevor Gundberg
Where: Cascade Hills Church, 54th Street, Columbus, GA 31904
What: East of the church building, Cascade has a newly cleared openly in tree line.
How: Started three airbeams at fence boarder facing highway. Moved all back same spot.
Notes: Only did equivalency tests as church members started arriving.
Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp <br> $\left({ }^{\circ} \mathrm{F}\right)$ | \% Humidity | Dew <br> Point $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure <br> $(\mathrm{in})$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $4: 51 \mathrm{pm}$ | NNW | 17.3 | 61 | 36 | 34 | 29.75 |
| Clear Skies |  |  |  |  |  |  |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp <br> $\left({ }^{\circ} \mathrm{C}\right)$ | \% Humidity | Dew <br> Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet <br> Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $5: 03$ | NE | 1.8 | 20.4 | 35.1 | 2.9 | 10.4 | 29.24 | 608 |
| $5: 09$ | NE | 1.1 | 20.4 | 35.1 | 2.9 | 10.4 | 29.24 | 608 |

Airbeam Location:

| Time | Lat 1 | Long 1 | Facing | Elevation (ft) | Notes |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $5: 01-5: 07 \mathrm{pm}$ | 32.524167 | 84.980556 | NW $336^{\circ}$ | 340 | All |
| $5: 08-5: 10 \mathrm{pm}$ | 32.524064 | 84.980511 | NW $336^{\circ}$ | 340 | All |



Figure 10. To the east of Cascade Hills Church, the tree buffer is small adjacent to highway 80.

Cunningham Center 2-15-17

When: $\quad 2 / 15 / 2017$ 17:30-18:15 EDT
Who: K. Youngquist and Trevor Gundberg
Where: Cunningham Center, CSU, 3100 Gentian Blvd, Columbus, GA 31907
What: The Cunningham Center has a thin patch of trees lining the street and part of the parking lot. Test tree line compared to parking lot.
How: Start/end airbeams at distance 30 ft from road in grass north of parking lot near Cunningham sign. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at same distances from road, behind trees and the other in parking lot.
Notes: $\quad 3$ was not set to record until $5: 36 \mathrm{pm} .3$ fell over at $5: 56$ while being moved.
Hypothesis: In the winter, the small tree line will not impact particulate matter as compared with open parking lot without trees.

Particulate Notes:
Car Data:

| Time | Cars (Trevor <br> Count) | Cars (Kristin <br> Count) | Minutes | Cars/Min | Note |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $18: 05$ | 62 | 67 | 2 | 32 | 5 cars in parking lot at $5: 55 \mathrm{pm}$ |

Area PM2. 5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $16: 00$ | 0.8 |
| $17: 00$ | 1 |
| $18: 00$ | -0.1 |

Weather
Weather.com:

| Time | Wind Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp ( $\left.{ }^{\circ} \mathrm{F}\right)$ | \% Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure (in) | Note |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 17.51 | NW | 10.4 | 61 | 34 | 32 | 29.77 | Clear |



Figure 11. Cunningham Center has thin tree line adjacent to open parking lot.

Manchester Expressway Park and Ride Bike Park 2-17-17

When: $\quad 2 / 17 / 2017$ 16:00-18:00 EDT
Who: K. Youngquist and Care Bacon
Where: Manchester Expressway Park and Ride Bike Park, 3690 Manchester Expy, Columbus, GA 31909
What: $\quad$ The bike park has a dense patch of trees surrounding the parking lot and playground on all sides except the north entrance to parking lot. Test beyond tree line compared to parking lot.
How: Start/end three airbeams close to road in grass at west corner of park. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road, within trees and along path.
Notes: $\quad$ Testing started at $4: 21 \mathrm{pm}$, but airbeam 3 data (in the tree line) was not saved. So analysis can not be conducted.
Hypothesis: The trees will create a fence, increasing particulate matter in the tree line as compared to open parking lot.

## Particulate Notes

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $15: 00$ | 3.2 |
| $16: 00$ | 3.6 |
| $17: 00$ | 4.4 |
| $18: 00$ | 8.5 |
| $19: 00$ | 7.7 |

## Weather

Weather.com:

| Time | Wind Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp ( $\left.{ }^{( } \mathrm{F}\right)$ | \% Humidity | Dew <br> Point $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure <br> (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 04$ | WSW | 7 | 69 | 20 | 29 | 30.01 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ <br> Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 28$ |  |  | 0 | 22.0 | 25.3 | 0.5 | 10.9 | 29.57 | 318 |
| $16: 45$ | WSW | 247.5 | 0.8 | 21.9 | 26.5 | 1.9 | 11.6 | 29.57 | 318 |
| $16: 54$ | WSW | 247.5 | 1.1 | 21.7 | 30.0 | 3.6 | 12.2 | 29.57 | 315 |

Airbeam Location:

| Time | Lat 1 | Long 1 | Lat 2 | Long 2 | Facing | Elevation <br> $(\mathrm{ft})$ | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 26-16: 37$ | $32.5080417^{\circ}$ | $-84.9366306^{\circ}$ | $32.5080417^{\circ}$ | $-84.9366250^{\circ}$ | $338^{\circ} \mathrm{NW}$ | 330 | Start |
| $16: 39-16: 46$ | $32.5080417^{\circ}$ | $-84.9366306^{\circ}$ | $32.5078417^{\circ}$ | $-84.9367417^{\circ}$ | $338^{\circ} \mathrm{NW}$ | 330 | 1 |



Figure 12. The Bike Park has U-shape tree canopy with an open area in the center adjacent to Manchester Expressway.

## Corner of University and Manchester

When: $\quad 2 / 17 / 201717: 00-18: 00$ EDT
Who: $\quad$ K. Youngquist and Care Bacon
Where: Fall Line Bike Path - Comer of University and Manchester
What: The bike path has a tunnel of trees surrounding the path. Test on path and in tree line at distance from street.
How: Start/end three airbeams $10 f \mathrm{ft}$ from road in grass at comer. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road, within trees and along path in open area.
Notes: Smoke from Burger King across the street started around 17:34 and was picked up by units 2 and 3 farther from sources as compared with unit 1 closest to source at start/end location.
Hypothesis: The trees will create a fence, reducing particulate matter in the tree line while increasing it within the tunnel created by the trees as move away from the road.

## Particulate Notes

CarData:

| Time | Cars (Care <br> Count) | Cars (Kristin <br> Count) | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $17: 15$ | 168 | 168 | 2 | 84 |

Area PM2. 5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $15: 00$ | 3.2 |
| $16: 00$ | 3.6 |
| $17: 00$ | 4.4 |
| $18: 00$ | 8.5 |
| $19: 00$ | 7.7 |

## Weather

Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | $\operatorname{Temp}\left({ }^{\circ} \mathrm{F}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 04$ | WSW | 7 | 69 | 20 | 29 | 30.01 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $17: 04$ | W | 270 | 1.4 | 20.8 | 28.8 | 1.8 | 11 | 29.57 | 321 |
| $17: 14$ | W | 270 | 2.8 | 21.1 | 25.1 | 0.4 | 10.7 | 29.57 | 313 |
| $17: 25$ | WSW | 247.5 | 2.6 | 20.2 | 27.4 | 0.8 | 10.5 | 29.58 | 306 |
| $17: 34$ | WSW | 247.5 | 5.2 | 20.2 | 26.6 | 0.4 | 10.3 | 29.59 | 301 |
| $17: 44$ | W | 270 | 1.6 | 20.5 | 26.1 | 0.3 | 10.4 | 29.59 | 298 |

Airbeam Location

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing <br> Direction <br> (\%) | Elevation <br> (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $17: 12-17 \cdot 20$ | $32.506806^{\circ}$ | $-84.939878^{\circ}$ | $32.506806^{\circ}$ | $-84.939878^{\circ}$ | $32.506806^{\circ}$ | $-84.939878^{\circ}$ | $300^{\circ} \mathrm{NW}$ | 330 | Start |
| $17 \cdot 23-17: 28$ | $32.506806^{\circ}$ | $-84.939878^{\circ}$ | $32.506806^{\circ}$ | $-84.939431^{\circ}$ | $32.506964^{\circ}$ | $-84.939455^{\circ}$ | $248^{\circ} \mathrm{SW}$ | 330 | 1 |
| $17: 30-17: 39$ | $32.506806^{\circ}$ | $-84.939878^{\circ}$ | $32.506919^{\circ}$ | $-84.939111^{\circ}$ | $32.507031^{\circ}$ | $-84.939147^{\circ}$ | $248^{\circ} \mathrm{SW}$ | 330 | 2 |
| $17: 40-17: 43$ | $32.506806^{\circ}$ | $-84.939878^{\circ}$ | $32.506806^{\circ}$ | $-84.939878^{\circ}$ | $32.506806^{\circ}$ | $-84.939878^{\circ}$ | $270^{\circ} \mathrm{W}$ | 330 | End |



Figure 13. Trees create U-shape/tunnel arrangement around bike path at corner of University and Manchester.

Colony Bank 2-19-17

When: $\quad 2 / 19 / 2017$ 12:30-13:30 EDT
Who: K. Youngquist
Where: Colony Bank, 1581 Bradley Park Dr, Columbus, GA 31904
What: The bank has $U$ - shape arrangement of trees lining street at Bradley Park Drive and at the back of the bank between the parking lot and the highway 80 on ramp. Test at small opening in tree line and in tree line at distance from street.
How: Start/end three airbeams 15 ft from road in grass at SE corner of bank lot. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road, within trees and along opening in tree line.
Notes: Winds from NNW not in right direction for most traffic idling at stoplights, but only had permission for two days. So moved forward.
Hypothesis: Wind direction will have greater impact reducing tree baracade effect. The dense tree line will not reduce particulate matter farther from the road more as compared with open parking due to wind direction.

## Particulate Notes

Car Data:

| Time | Cars <br> (Kristin | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: |
| $12: 42$ | 93 | 2 | 46.5 |
| $13: 16$ | 92 | 2 | 46 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $11: 00$ | 7.4 |
| $12: 00$ | 4.5 |
| $13: 00$ | 3.3 |
| $14: 00$ | 2.6 |

## Weather

Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{F}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $12: 24$ | NNW | 7 | 67 | 60 | 53 | 30.09 |

Ambient Weather Data (Krestel 4000):

| Time | Wind <br> Direction | Wind <br> Direction $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $12: 40$ | NNW | 337.5 | 3.2 | 22.2 | 49.1 | 11.6 | 15.4 | 29.56 | 331 |
| $12: 52$ | NNW | 337.5 | 4.6 | 22.2 | 51.7 | 11.8 | 15.9 | 29.55 | 331 |
| $12: 59$ | NNW | 337.5 | 3.0 | 22.2 | 48.6 | 11.0 | 15.5 | 29.55 | 331 |
| $13: 09$ | NNW | 337.5 | 1.3 | 24.4 | 48.1 | 12.7 | 17 | 29.54 | 343 |
| $13: 13$ | NNW | 337.5 | 0.9 |  |  |  |  |  |  |
| $13: 19$ | NW | 360 | 1.9 | 23.2 | 47.4 | 12 | 16.4 | 29.51 | 369 |

Airbeam Locations:

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing <br> Direction <br> $(\circ)$ | Elevation <br> $(\mathrm{ft})$ | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 12:39-12:47 | $32.532353^{\circ}$ | $-84.970875^{\circ}$ | $32.532356^{\circ}$ | $-84.970875^{\circ}$ | $32.532350^{\circ}$ | $-84.970875^{\circ}$ | 96 E | 330 | Start |
| $12: 50-12.54$ | $32.532283^{\circ}$ | $-84.970914^{\circ}$ | $32.532356^{\circ}$ | $-84.970875^{\circ}$ | $32.532286^{\circ}$ | $-84.971067^{\circ}$ | 96 E | 330 | 1 |
| $12: 57-13: 00$ | $32.53222^{\circ}$ | $-84.971111^{\circ}$ | $32.532356^{\circ}$ | $-84.970875^{\circ}$ | $32.532222^{\circ}$ | $-84.971175^{\circ}$ | 133 SE | 330 | 2 |
| $13: 08-13: 10$ | $32.532244^{\circ}$ | $-84.971111^{\circ}$ | $32.532356^{\circ}$ | $-84.970875^{\circ}$ | $32.532233^{\circ}$ | $-84.971381^{\circ}$ | 170 SE | 330 | 3 |
| $13: 14-13: 17$ | $32.532308^{\circ}$ | $-84.971372^{\circ}$ | $32.532356^{\circ}$ | $-84.970875^{\circ}$ | $32.532319^{\circ}$ | $-84.971139^{\circ}$ | 170 SE |  | 4 |
| $13: 20-13 \cdot 22$ | $32.532353^{\circ}$ | $-84.970875^{\circ}$ | $32.532356^{\circ}$ | $-84.970875^{\circ}$ | $32.53235^{\circ}$ | $-84.970875^{\circ}$ | 96 E |  | End |



Figure 14. View of Colony Bank and surrounding shopping center area.


Figure 15. Trees create U-shape tree arrangement around Colony Bank parking lot.

Haverty's and Lazyboy 2-19-17
When: $\quad 2 / 19 / 2017$ 14:57-15:55 EDT
Who: K. Youngquist and Will Kiourtsis
Where: Havertys and Lazeboy, 5555 Whittlesey Blvd \#1000, Columbus, GA 31909
What: Line of trees at fence separating back of Havertys store from exit/on ramp to highway 80 at Veterans Parkway. Traffic sits at street light waiting to turn onto Veterans. Possible PM build-up at light. Similar situation at street near Lazyboy.
How: Start/end three airbeams at opening in tree line along fence. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams one in trees and two in openings.

Hypothesis: The tree dense line will trap particulate matter increasing levels in trees as compared to open areas.

Particulate Notes
Car Data:

| Time | Cars (Will <br> Count) | Cars <br> (Kristin | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $15: 04$ | 40 | 41 | 1 | 40.5 |
| $15: 36$ | 93 | 93 | 2 | 46.5 |

Area PM2. 5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $14: 00$ | 2.6 |
| $15: 00$ | 3.8 |
| $16: 00$ | 3.5 |
| $17: 00$ | 5.7 |

Weather
Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{F}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{( } \mathrm{F}\right)$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 14.57 | NW | 3 | 73 | 43 | 49 | 30.04 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | $\operatorname{Temp}\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $15: 03$ | WNW | 292.5 | 1.6 | 24.2 | 43.9 | 11.4 | 16.3 | 29.44 | 445 |
| $15: 14$ | WNW | 292.5 | 1.6 | 24.9 | 44.2 | 12.7 | 17.7 | 29.44 | 443 |
| $15: 27$ | NW | 315 | 3.1 | 24.7 | 42.7 | 11.9 | 17 | 29.42 | 453 |
| $15: 38$ | NW | 315 | 1.3 | 27.2 | 38.1 | 11.4 | 17.5 | 29.43 | 448 |
| $15: 46$ | WNW | 292.5 | 3.5 | 26.5 | 40.3 | 12.6 | 17.9 | 29.43 | 451 |
| $15: 53$ | NW | 315 | 2.5 | 25.9 | 39.9 | 11.2 | 16.8 | 29.45 | 445 |

Airbeam Location:

| Time | Lat A1 | Long A1 | Lat A2 | Long A. | Lat A3 | Long A3 | Device <br> Facing Direction <br> ( ${ }^{\circ}$ ) | Elevation <br> (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 15:01-15:08 | $32.546186^{\circ}$ | -84.951300 ${ }^{\circ}$ | $32.546189^{\circ}$ | $-84.951300^{\circ}$ | $32.546189^{\circ}$ | $-84.951303^{\circ}$ | 15 N | 470 | Start Hav |
| 15:11-15:16 | $32.546228^{\circ}$ | -84.951422 ${ }^{\circ}$ | $32.546189^{\circ}$ | -84.951300 ${ }^{\circ}$ | $32.546178^{\circ}$ | -84.951253 ${ }^{\circ}$ | 15 N | 470 | 1 Hav |
| 15:18-15:20 | $32.546186^{\circ}$ | -84.951300 ${ }^{\circ}$ | $32.546189^{\circ}$ | -84.951300 ${ }^{\circ}$ | $32.546189^{\circ}$ | -84.951303 ${ }^{\circ}$ | 15 N | 470 | End Hav |
| 15:25-15:31 | $32.545419^{\circ}$ | -84.952392 ${ }^{\circ}$ | $32.545419^{\circ}$ | -84.952394* | $32.545422^{\circ}$ | -84.952392 ${ }^{\circ}$ | 315 NW | 485 | Start LB |
| 15:33-15:39 | $32.545419^{\circ}$ | -84.952392 ${ }^{\circ}$ | $32.545294^{\circ}$ | -84.952369 ${ }^{\circ}$ | $32.545561^{\circ}$ | -84.952222 ${ }^{\circ}$ | 315 NW | 485 | 1 LB |
| 15:42-15:48 | $32.545419^{\circ}$ | -84.952392 ${ }^{\circ}$ | $32.545292^{\circ}$ | -84.952333 ${ }^{\circ}$ | $32.545561^{\circ}$ | -84.952142 ${ }^{\circ}$ | 315 NW | 490 | 2 LB |
| 15:51-15:55 | $32.545419^{\circ}$ | -84.952392 ${ }^{\circ}$ | $32.545419^{\circ}$ | -84.952394* | $32.545422^{\circ}$ | $-84.952392^{\circ}$ | 315 NW | 490 | End LB |



Figure 16. Back side of Haverty's parking lot has a dense field of trees with little opening.


Figure 17. Back side of Lazyboy has a dense field of trees next to grass opening.

Colony Bank 2-20-19
When: 2/20/2017 17:15-18:15 EDT
Who: K. Youngquist and Trevor Gundberg
Where: Colony Bank, 1581 Bradley Park Dr, Columbus, GA 31904
What: The bank has U-shape arrangement of trees lining street at Bradley Park Drive and at the back of the bank between the parking lot and the highway 80 on ramp. Test at small opening in tree line and in tree line at distance from street.
How: Start/end three airbeams 15 ft from road in grass at SE corner of bank lot. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road, within trees and along opening in tree line.
Notes: Smoke from Burger King during testing.
Hypothesis: The dense tree line will create a fence, reducing particulate matter farther from the road more as compared with open parking lot without trees.

## Particulate Notes

Car Data:

| Time | Cars (Trevor <br> Count) | Cars <br> (Kristin | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $17: 29$ | 74 | 98 | 2 | 43 |
| $18: 01$ | 74 | 80 | 2 | 38.5 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $16: 00$ | 6.4 |
| $17: 00$ | 7.2 |
| $18: 00$ | 12.7 |

## Weather

Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{F}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure <br> $(\mathrm{in})$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $17 \cdot 20$ | SSE | 6 | 75 | 40 | 49 | 30.11 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction $\left({ }^{\circ}\right)$ | Wind <br> Speed | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 17.23 | SSE | 157.5 | 3.1 | 24.6 | 44.9 | 10.8 | 16.1 | 29.58 | 304 |
| 17.33 | SSE | 157.5 | 3.3 | 24.3 | 42.4 | 10.7 | 16 | 29.58 | 304 |
| $17: 40$ | SSE | 157.5 | 4.0 | 24.1 | 43.0 | 10.7 | 15.9 | 29.58 | 304 |
| 17.50 | SSE | 157.5 | 4.3 | 23.9 | 43.8 | 10.7 | 15.9 | 29.59 | 296 |
| $18: 00$ | SSE | 157.5 | 2.3 | 23.9 | 42.9 | 10.5 | 15.8 | 29.59 | 296 |

Airbeam Location:

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing <br> Direction <br> ० $^{\circ}$ | Elevation <br> (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $17: 19-17: 24$ | $32.532281^{\circ}$ | $-84.970919^{\circ}$ | $32.532289^{\circ}$ | $-84.970908^{\circ}$ | $32.532283^{\circ}$ | $-84.970914^{\circ}$ | $135^{\circ} \mathrm{SE}$ | 420 | Start |
| $17.27-17: 33$ | $32.532206^{\circ}$ | $-84.971275^{\circ}$ | $32.532289^{\circ}$ | $-84.970908^{\circ}$ | $32.532211^{\circ}$ | $-84.971100^{\circ}$ | $158^{\circ} \mathrm{S}$ | 420 | 1 |
| $17: 36-17: 43$ | $32.532269^{\circ}$ | $-84.971408^{\circ}$ | $32.532289^{\circ}$ | $-84.970908^{\circ}$ | $32.532297^{\circ}$ | $-84.971136^{\circ}$ | $158^{\circ} \mathrm{S}$ | 420 | 2 |
| $17: 46-17.53$ | $32.532439^{\circ}$ | $-84.971469^{\circ}$ | $32.532289^{\circ}$ | $-84.970908^{\circ}$ | $32.532472^{\circ}$ | $-84.971139^{\circ}$ | $158^{\circ} \mathrm{S}$ | 420 | 3 |
| $17: 56-18: 04$ | $32.532281^{\circ}$ | $-84.970919^{\circ}$ | $32.532289^{\circ}$ | $-84.970908^{\circ}$ | $32.532283^{\circ}$ | $-84.970914^{\circ}$ | $135^{\circ} \mathrm{SE}$ | 420 | End |



Figure 18. Trees create U-shape tree arrangement around Colony Bank parking lot.
Cascade Hills Church 2-23-17
When: $\quad$ 2/23/2017 7:55-9:05 EDT
Who: $\quad K$. Youngquist and Dalton Peters
Where: Cascade Hills Church, 54th Street, Columbus, GA 31904
What: Cascade has a line of trees near the entrance to parking lot and a second line of trees past the church building. Test in tree line compared to parking lot.
How: Start/end three airbeams at fence boarder facing highway. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road, behind trees and the other in parking lot.
Hypothesis: The highway traffic is not close enough to impact PM1 levels at the church.

## Particulate Notes

CarData:

| Time | Cars <br> (Kristin | Cars <br> (Dalton | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $8: 14$ | 190 | 179 | 2 | 92 |
| $8: 53$ | 148 | 148 | 2 | 74 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $7: 00$ | 3.9 |
| $8: 00$ | 4.2 |
| $9: 00$ | 3.5 |
| $10: 00$ | 4.8 |

## Weather

Weather.com:

| Time | Wind <br> Direction | Wind <br> Speed | $\operatorname{Temp}\left({ }^{\circ} \mathrm{F}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure <br> $(\mathrm{in})$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 7.57 | ENE | 5 | 61 | 90 | 58 | 29.86 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction( $\left.{ }^{\circ}\right)$ | Wind <br> Speed | $\operatorname{Temp}\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $8: 01$ | ENE | 67.5 | 2.3 | 16.9 | 87 | 14.8 | 15.6 | 29.36 | 510 |
| $8: 11$ | ENE | 67.5 | 2.5 | 17.3 | 85.9 | 15.0 | 15.8 | 29.37 | 506 |
| $8: 21$ | ENE | 67.5 | 4.9 | 17.4 | 85.6 | 15.0 | 15.9 | 29.35 | 505 |
| $8: 32$ | ENE | 67.5 | 7.0 | 17.2 | 86.6 | 15.0 | 15.8 | 29.37 | 501 |
| $8: 41$ | ENE | 67.5 | 3.9 | 17.3 | 86.7 | 15.2 | 16.1 | 29.38 | 496 |
| $8: 51$ | ESE | 112.5 | 6.1 | 17.5 | 87.1 | 15.4 | 16.3 | 29.37 | 498 |
| $9: 01$ | ESE | 112.5 | 4.1 | 17.3 | 85.5 | 15.1 | 16.0 | 29.37 | 501 |


| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing <br> Direction (\%) | Elevation (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 7:56-8:04 | $32.522364^{\circ}$ | -84.985139 ${ }^{\circ}$ | $32.522364^{\circ}$ | -84.985144 ${ }^{\circ}$ | $32.522361^{\circ}$ | -84.985142 ${ }^{\circ}$ | 2 N | 430 | Start W |
| 8:08-8:16 | $32.522083^{\circ}$ | -84.985014 ${ }^{\circ}$ | $32.522003^{\circ}$ | -84.985547 ${ }^{\circ}$ | $32.522361^{\circ}$ | -84.985142 ${ }^{\circ}$ | 2 N | 430 | 1 W |
| 8:28-8:33 | $32.522006^{\circ}$ | -84.984989 | $32.521889^{\circ}$ | -84.985639 | $32.522361^{\circ}$ | $-84.985142^{\circ}$ | 2 N | 430 | 2 W |
| 8:35 | $32.522364^{\circ}$ | -84.985139 | $32.522364^{\circ}$ | -84.985144* | $32.522361^{\circ}$ | -84.985142 ${ }^{\circ}$ | 2 N | 430 | End W |
| 8:40-8:46 | $32.523489{ }^{\circ}$ | $-84.982633^{\circ}$ | $32.523492^{\circ}$ | -84.982631 ${ }^{\circ}$ | $32.523486^{\circ}$ | -84.982631 ${ }^{\circ}$ | 338 NW | 420 | Start E |
| 8:48-8:57 | $32.523672^{\circ}$ | -84.982117 ${ }^{\circ}$ | $32.523333^{\circ}$ | -84.982994* | $32.523486^{\circ}$ | -84.982631 ${ }^{\circ}$ | 338 NW | 420 | 1 E |
| 8:58-9:04 | $32.523489{ }^{\circ}$ | -84.982633 ${ }^{\circ}$ | $32.523492^{\circ}$ | -84.982631 ${ }^{\circ}$ | $32.523486^{\circ}$ | -84.982631 ${ }^{\circ}$ | 338 NW | 420 | End E |



Figure 19. Cascade Hills Church the tree buffer runs parallel to highway 80.

Columbus State University Softball Field 2-23-17

When: $\quad 2 / 23 / 2017$ 16:11-17:15 EDT
Who: K. Youngquist and Kiara Mills
Where: North of CSU Softball Field, 3100 Gentian Blvd, Columbus, GA 31907
What: To the north of the CSU softball field, pine trees line the street. Test within tree line compared to open field.
How: Start/end three airbeams in grass north of parking lot near end of north Cunningham building. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road within trees and the other in parking lot.
Notes: Airbeam 2 had trouble connecting. So used 1 and 3 for test. Ended longer to record Airbeam 2 at higher PM levels.
Hypothesis: The tree tops are not full enough due to pruning to reduce particulate matter more as compared with open area without trees.

Particulate Notes
Car Data:

| Time | Cars <br> (Kristin <br> Count) | Cars (Kiara <br> Counted <br> only one <br> side) | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $16: 51$ | 58 | 38 | 2 | 24 |
| $17: 11$ | 73 | 52 | 3 | 21 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $15: 00$ | 0.4 |
| $16: 00$ | 1.8 |
| $17: 00$ | 3.1 |
| $18: 00$ | 3.8 |

## Weather

Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | $\operatorname{Temp}\left({ }^{\circ} \mathrm{F}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 14$ | E | 9 | 76 | 45 | 54 | 29.80 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 39$ | E | 90 | 3.3 | 25.3 | 47 | 13.1 | 17.5 | 29.36 | 513 |
| $16: 49$ | E | 90 | 2.9 | 24.8 | 49 | 13.4 | 17.6 | 29.36 | 510 |
| $17: 02$ | E | 90 | 1 | 24.7 | 50.4 | 13.7 | 17.6 | 29.36 | 510 |
| $17: 09$ | E | 90 | 2.1 | 24.6 | 50 | 13.4 | 17.5 | 29.36 | 510 |

Airbeam Location:

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing <br> Direction <br> $(\circ)$ | Elevation <br> (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $16: 31-16.43$ | $32.505614^{\circ}$ | $-84.941900^{\circ}$ | $32.505611^{\circ}$ | $-84.941897^{\circ}$ | $32.505608^{\circ}$ | $-84.941894^{\circ}$ | 75 E | 330 | Start |
| $16: 46-16.55$ | $32.505472^{\circ}$ | $-84.941839^{\circ}$ | $32.505611^{\circ}$ | $-84.941897^{\circ}$ | $32.505558^{\circ}$ | $-84.942050^{\circ}$ | 75 E | 330 | 1 |
| $16: 58-17.01$ | $32.505333^{\circ}$ | $-84.941942^{\circ}$ | $32.505611^{\circ}$ | $-84.941897^{\circ}$ | $32.505481^{\circ}$ | $-84.942197^{\circ}$ | 85 E | 330 | 2 |
| $17: 08-17.21$ | $32.505614^{\circ}$ | $-84.941900^{\circ}$ | $32.505611^{\circ}$ | $-84.941897^{\circ}$ | $32.505608^{\circ}$ | $-84.941894^{\circ}$ | 85 E | 340 | End |



Figure 20. North of CSU softball field is a small patch of trees.

## St. Mary's United Methodist Church 2-24-17

When: $\quad$ 2/24/2017 15:52-17:06 EDT
Who: $\quad \mathbb{K}$. Youngquist and Kiara Mills
Where: St. Mary's Road UMC, 3993 St Marys Rd, Columbus, GA 31907
What: To the west of St. Mary's Church a thin tree line exists between the church and the highway. Test within tree line compared to open.
How: Start/end three airbeams in open grass on west side of church. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road within trees and the other in open lawn.
Hypothesis: Thin tree line will not cause difference in particulate levels as compared with open areas.

## Particulate Notes

Car Data:

| Time | Cars <br> (Kristin | Cars (Kiara <br> Count) | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $15: 59$ | 119 | 120 | 2 | 60 |
| $16: 38$ | 118 | 116 | 2 | 59 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $15: 00$ | 1.6 |
| $16: 00$ | 4.1 |
| $17: 00$ | 11.1 |

## Weather

Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | $\operatorname{Temp}\left({ }^{\circ} \mathrm{F}\right)$ | \% Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{F}\right)$ | Pressure <br> (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $15: 52$ | SSW | 6 | 81 | 39 | 54 | 29.81 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction( $\left.{ }^{\circ}\right)$ | Wind <br> Speed | Temp $\left({ }^{\circ} \mathrm{C}\right)$ | $\%$ Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $15: 54$ | SSW | 202.5 | 1.8 | 27.9 | 39.7 | 12.9 | 18.0 | 29.36 | 514 |
| $16: 04$ | SW | 225 | 5.4 | 28.2 | 43.1 | 14.4 | 19.2 | 29.35 | 523 |
| $16: 17$ | SW | 225 | 3.1 | 29.1 | 39.2 | 14.0 | 19.3 | 29.35 | 514 |
| $16: 23$ | SW | 225 | 3.9 | 28.0 | 40.6 | 13.5 | 18.6 | 29.35 | 518 |
| $16: 34$ | SW | 225 | 7.6 | 27.7 | 42.1 | 13.7 | 18.7 | 29.35 | 526 |
| $16: 44$ | SSW | 202.5 | 5.8 | 27.4 | 41.1 | 13.1 | 18.2 | 29.35 | 523 |
| $16: 54$ | SW | 225 | 4.5 | 27.3 | 41.8 | 13.3 | 18.3 | 29.34 | 526 |
| $17: 04$ | SW | 225 | 3.8 | 27.1 | 40.2 | 12.4 | 17.7 | 29.35 | 523 |
| $17: 14$ | SW | 225 | 5.9 | 27.0 | 41.4 | 12.8 | 17.9 | 29.35 | 526 |

Airbeam Location:

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing <br> Direction <br> () | Elevation <br> (ft) | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $15: 54-16: 02$ | $32.446883^{\circ}$ | $-84.927222^{\circ}$ | $32.446878^{\circ}$ | $-84.927222^{\circ}$ | $32.446881^{\circ}$ | $-84.927222^{\circ}$ | 258 | 340 | Start |
| $16: 04-16: 13$ | $32.446883^{\circ}$ | $-84.927222^{\circ}$ | $32.447069^{\circ}$ | $-84.927183^{\circ}$ | $32.446772^{\circ}$ | $-84.927190^{\circ}$ | 258 | 340 | 1 |
| $16: 14-16: 24$ | $32.446883^{\circ}$ | $-84.927222^{\circ}$ | $32.447067^{\circ}$ | $-84.927139^{\circ}$ | $32.446744^{\circ}$ | $-84.927142^{\circ}$ | 258 | 340 | 2 |
| $16: 26-16: 36$ | $32.446883^{\circ}$ | $-84.927222^{\circ}$ | $32.446878^{\circ}$ | $-84.927222^{\circ}$ | $32.446881^{\circ}$ | $-84.927222^{\circ}$ | 258 | 340 | End |



Figure 21. St. Mary's UMC Church has tree buffer along I-185 with open grass area.

Williams Road 2-28-17
When: $\quad 2 / 28 / 2017$ 15:47-17:00 EDT
Who: K. Youngquist and Dalton Peters
Where: Williams Road Field across from Shell Gas Station
What: Cleared field sits beside thick field of trees across the street from gas station and off ramp of I-185. Test within tree line compared to open.
How: Start/end three airbeams in cleared field near road. Pick two with closest averages and peaks. Leave third at start location. Move two comparable airbeams at similar distances from road, within trees and the other in open field.
Notes: Calm wind might account for highest particulate at control, as it was closest to street and gas station. Yellow jackets interupted 3rd location test, 3 minutes shorter than others.
Hypothesis: Trees higher particulate matter, trapping gas station and idling car exhaust.
Particulate Notes
Car Data:

| Time | Cars <br> (Kristin | Cars (Dalton <br> Count) | Minutes | Cars/Min |
| :---: | :---: | :---: | :---: | :---: |
| $16: 02$ | 20 | 20 | 1 | 20 |
| $16: 59$ | 34 | 35 | 2 | 17 |

Area PM2.5 via GA EPD Air Branch:

| Time | PM2.5 |
| :---: | :---: |
| $15: 00$ | 6.7 |
| $16: 00$ | 9.3 |
| $17: 00$ | 10.1 |
| $18: 00$ | 9.2 |

## Weather

Weather.com:

| Time | Wind <br> Direction | Wind Speed <br> $(\mathrm{mph})$ | Temp ( $\left.{ }^{( } \mathrm{F}\right)$ | \% Humidity | Dew Point <br> $\left({ }^{( } \mathrm{F}\right)$ | Pressure (in) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $15: 47$ | WSW | 7 | 68 | 79 | 61 | 30.18 |

Ambient Weather Data (Kestrel 4000):

| Time | Wind <br> Direction | Wind <br> Direction $\left({ }^{\circ}\right)$ | Wind Speed <br> $(\mathrm{mph})$ | $\operatorname{Temp}\left({ }^{\circ} \mathrm{C}\right)$ | \% Humidity | Dew Point <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Wet Bulb <br> $\left({ }^{\circ} \mathrm{C}\right)$ | Pressure <br> $(\mathrm{Hg})$ | at ft |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $15: 57$ | SW | 225 | 3.2 | 20.9 | 78.0 | 17.2 | 18.6 | 29.56 | 326 |
| $16: 09$ | SW | 225 | 3.9 | 21.3 | 77.5 | 17.5 | 18.9 | 29.55 | 331 |
| $16: 17$ | SW | 225 | 1.8 | 22.9 | 72.2 | 17.8 | 19.6 | 29.55 | 335 |
| $16: 27$ |  |  | 0.0 | 24.5 | 70.7 | 18.8 | 20.6 | 29.54 | 345 |
| $16: 37$ |  |  | 0.0 | 25.0 | 65.5 | 17.8 | 20.0 | 29.54 | 348 |
| $16: 47$ | Cloudy |  | 0.0 | 24.0 | 68.3 | 17.7 | 19.8 | 29.53 | 356 |
| $16: 51$ | SW | 225 | 4.1 | Wind picked up but went away at 4.52 |  |  |  |  |  |
| $16: 57$ | SW | 225 | 1.2 | 22.4 | 73.4 | 16.7 | 18.3 | 29.52 | 356 |

Airbeam Location:

| Time | Lat A1 | Long A1 | Lat A2 | Long A2 | Lat A3 | Long A3 | Device <br> Facing <br> Direction <br> $\left({ }^{\circ}\right)$ | Elevation <br> $(\mathrm{ft})$ | Location |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $15: 53-16: 05$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | 225 | 520 | Start |
| $16: 09-16: 18$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | $32.569447^{\circ}$ | $-84.966069^{\circ}$ | $32.569683^{\circ}$ | $-84.966369^{\circ}$ | 225 | 520 | 1 |
| $16: 20-16.28$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | $32.569619^{\circ}$ | $-84.965933^{\circ}$ | $32.569797^{\circ}$ | $-84.966236^{\circ}$ | 225 | 520 | 2 |
| $16: 31-16: 40$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | $32.569611^{\circ}$ | $-84.966075^{\circ}$ | $32.569667^{\circ}$ | $-84.966169^{\circ}$ | 225 | 520 | 3 |
| $16: 43-16: 52$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | $32.569475^{\circ}$ | $-84.966192^{\circ}$ | $32.569544^{\circ}$ | $-84.966286^{\circ}$ | 225 | 520 | 4 |
| $16: 54-17: 03$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | $32.569536^{\circ}$ | $-84.966475^{\circ}$ | 225 | 520 | End |



Figure 22. Williams Road has dense tree field next to clear open field.

EVALUATING COLUMBUS, GEORGIA, TREE CANOPY INTERACTIONS WITH AIR POLLUTANTS USING HIGH SPECTRAL IMAGERY AND PORTABLE PM SENSORS

A thesis submitted to the College of Letters and Sciences in partial fulfillment of the requirements for the degree of MASTER OF SCIENCE

DEPARTMENT OF EARTH AND SPACE SCIENCES

## By

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2018

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Wilts Cu s
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$\frac{5 / 7 / 2018}{\text { Date }}$
$\qquad$
Dr. Samuel Abegaz


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$30=20$

