CHARACTERIZING BLACK CARBON EMISSIONS FROM A PRESCRIBED BURN USING PORTABLE SENSORS

by

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(Under the Direction of Christina H. Fuller)

ABSTRACT

Prescribed burning is a key tool for managing forests in the Southeastern US, but it releases black carbon (BC), a pollutant that deteriorates air quality. This study evaluated BC during a prescribed burn at Jones Center in Georgia, using MA-200 sensors located Upwind, Downwind, and at an Apartment, while monitoring meteorological conditions. Non-parametric tests and regression models showed that the Downwind locations recorded elevated BC levels, with statistically significant differences. The influence of meteorology on BC dispersal was location-specific: wind direction strongly affected BC levels at the Apartment location, while humidity and temperature displayed varying significance based on location and timings. Results indicate the role of local conditions in influencing pollutant behavior during burns. This study adds to the understanding of how emissions from such burns impact air quality in unmonitored rural areas and pinpoints that the meteorological context is important for exposure analysis.

INDEX WORDS: Prescribed Burns, Black Carbon (BC), Air Quality, Rural Exposure

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CHAPTER ONE: INTRODUCTION

1.1 INTRODUCTION

Wildland fires (wildfires and prescribed fires) are not a foreign concept in the land management space that exists in the US (Afrin, 2021). Such fires were once used for activities ranging from hunting to plant source generation to facilitating travel from place to place (Petralia & Potosnak, 2024). In recent decades, the areas burned from such fires have drastically increased, especially in the US, with their size and frequency being sponsored by Climate Change (Li et al.,202). The United States Environmental Protection Agency (USEPA) estimates that wildland fire emissions account for roughly 44% of all particulate matter emissions (<2.5 μm aerodynamic diameter) across the United States (Adetona et al, 2016; Ran, 2019). Particulate matter released from wildland fires contains a variety of elements, including elemental carbon (EC) or black carbon (BC), organic carbon (OC), ionic species, trace elements, water-soluble organic carbon (WSOC), water-soluble iron (Fe (II)), and particle number concentration (Carrico & Karacaoglu, 2023; Balachandran et al., 2013; Jaffe et al., 2020; Karanasiou et al., 2021).

The impacts of wildland fires (wildfires and prescribed burns) have a substantial influence on ambient PM2.5, particularly in the Southeastern United States, which contains roughly 70% of the prescribed burns within the United States (Afrin et al, 2021). Several factors influence the emission of pollutants, such as PM2.5, some of which include fuel type, fuel moisture, fire conditions, amount of fuel consumed, temperature, weather, fire stages, etc. (Jaffe et al., 2020; Balachandran et al., 2013). More than 2 million hectares of land are managed with prescribed fire in the Southeastern United States, with Georgia being among the top states with an estimated 550,000 hectares burned annually (Odman et al., 2018). Prescribed burns are most prevalent in the winter and spring seasons. They also restore ecosystems such as longleaf pine and wiregrass, reduce wildfire risk, and manage invasive species (Tian et al., 2008; Petralia & Potosnak, 2024). Although prescribed fires emit fewer pollutants than wildfires, they can still significantly affect air quality, particularly for nearby and Downwind communities (Gaither et al., 2019). Several epidemiological studies have linked these exposures, including pollutants such as PM2.5, to serious health challenges, including cardiovascular, neurological, and respiratory disease, and increased risks of adverse birth outcomes and premature death (El Asmar et al., 2024; Huang et al., 2021).

Black carbon, a key component of particulate matter, has been proposed as a useful indicator in air quality management, given its strong association with a variety of adverse health effects (Wu et al., 2021). A study showed that prescribed fires were expected to cause health effects across a variety of endpoints: an additional 280 to 700 deaths, 4,400 lower respiratory outcomes, 7,300 upper respiratory symptoms, nearly 400 episodes of acute bronchitis, and several thousand missed workdays, among other consequences (Reisen, Meyer, et al., 2011; Adetona et al., 2016). Such findings highlight the need for more attention to the health consequences of prescribed fires as their prevalence increases in fire-dependent landscapes such as the Southeastern U.S.

To estimate the impacts of pollutant emissions, especially particulate matter (PM2.5) from activities such as prescribed fires, many tools and systems are often used: satellite-based products, permit records, aircraft and drones, statistical modelling tools, stationary monitors, and so on. Unfortunately, these tools have countless issues that prevent them from accurately capturing emissions from prescribed burns. Such issues include the inability of such products to detect the location, size and the timing of such fires, the struggle of such products to distinguish between a prescribed burn and other wildland fires, over-estimation and underestimation of some statistical models, non-uniform distribution of stationary monitors, and so on (Huff et al., 2021; Sadia Afrin & Garcia–Menendez, 2020; El Asmar et al., 2024). With all this in perspective, it is paramount that another means of collecting data be explored. Portable and low-cost air monitors seem to fill the gaps highlighted by the other tools. Examples of such include the MA-series aethalometers: MA200, MA350, MA300; and the AE-series aethalometers: AE33, AE21, AE31, etc. (El Asmar et al., 2024).

These sensors are portable, low-cost, simple to operate, and can be installed rapidly while providing high-resolution data on ambient concentrations almost in real-time (Huang et al., 2021). They are also capable of identifying changes in air quality and can even investigate, to a limited extent, the spatial variability of some elements of smoke plumes (El Asmar et al., 2024). Acknowledging that meteorological parameters, including wind speed, wind direction, temperature, and relative humidity, have a significant influence on the variations in surface level concentrations, portable monitors with internal sensors or used in conjunction with local weather stations can test if there is a relationship between BC concentrations and meteorological data (Reisen, Meyer, et al., 2011; Liu, 2014; Odman et al., 2018; Miller et al., 2019).

The MA-200 is a relatively new instrument, but has already been compared to a lot of reference-grade instruments. Although the MA-200 has many strengths, it still has limitations, some of which include its high sensitivity to a change in environment, leading to errors that should be corrected, the need for regular maintenance and complex corrections, and its potential for sampling bias. Generally, collocating sensors helps to capture smoke events across various locations. It also minimizes issues related to predicting Downwind pollutant concentrations and is not affected by the uncertainty of planned burning locations and times (El Asmar et al., 2024).

This study was located at the Jones Center in Ichauway, an 18,000-plus hectare reserve located within the Lower Coastal Plains and Flatwoods areas in southern Georgia. The Jones Center at Ichuaway, via its conservation initiative, highlights long-leaf pine restoration, prescribed burns, and conservation-based forestry. With over 60% of the forested land burned on an annual basis and a fire-return interval of two years or less, prescribed burns are the bedrock of forest and wildlife management at the Jones Center. With such a rich ecological heritage, regular fire routine, and strong conservation framework, the Jones Center is the perfect location to study black carbon emissions and the influence of meteorological conditions during prescribed fires.

A significant portion of current research uses PM2.5 data or aerosol optical depth (AOD) data, which, naturally, are several steps away from combustion sources. This research also taps into such opportunities by collecting BC data from three points: Upwind, Downwind, and in an Apartment, during a prescribed fire at the Jones Center. It combines BC data with meteorological data to study BC concentration at multiple locations and how atmospheric conditions affect pollutant dispersion across different locations. The outcomes from this research will provide data that will work toward identifying more localized ways to monitor specifically for communities near prescribed burning in the Southeastern U.S.

1.2 PROBLEM STATEMENT

Prescribed fires in the Southeastern part of the US are necessary for natural forest management, but they release black carbon (BC), a pollutant that is detrimental to ambient air quality and well-being. The sparse monitoring in rural burn regions and inadequate understanding of how weather affects the dispersal of black carbon limit precise exposure evaluation. This research endeavor seeks to enhance prior research by utilizing portable, low-cost sensors to quantify black carbon during prescribed fires and examine the influence of meteorological conditions on its dispersion.

1.3 PURPOSE OF THE STUDY

Ichauway is an ecologically diverse environment in the Southwestern part of Georgia, with longleaf pine forests, streams, wetlands, and farmlands. The Jones Center at Ichuaway, via its conservation initiative, highlights long-leaf pine restoration, prescribed burns, and conservation-based forestry. This center had almost 18,000 acres of land reserved for the longleaf pine forest, and a large portion of its undisturbed habitats. Ichuaway gives an uncommon opportunity to study and effectively control the environment. With over 60% of the forested land burned on an annual basis and a fire-return interval of two years or less, prescribed burns are the bedrock of forest and wildlife management at the Jones Center.

With such a rich ecological heritage, regular fire routine, and strong conservation framework, the Jones Center is the perfect location to study black carbon emissions and the influence of meteorological conditions during prescribed fires. This work stems from opportunities identified in the literature by evaluating black carbon concentrations resulting from a prescribed burn at the Jones Center. BC measurements were taken across various locations to assess spatial variation by collecting data concurrently. This study also evaluates how key meteorological conditions such as wind speed, temperature, wind direction, and relative humidity influence black carbon concentrations across various locations. This study employed the use of an observational research design to address the research questions and hypotheses, infusing approaches such as comparative, descriptive, and correlational designs.

- Descriptive design: used to summarize and report the BC concentrations at the various locations (Upwind, Downwind, and Apartment) relative to the prescribed burn. Descriptive statistics tools, such as summary statistics, box plots, and line charts, were used to observe the general behavior of black carbon and meteorological data (Petralia & Potosnak, 2024).
- Comparative design: used to see how BC levels differ across different locations, relative to the burn. Sensors were allowed to run in the three locations, after which statistical tools were used to compare differences between them. Tests such as Kruskal-Wallis were used in this regard, especially as they relate to statistically significant differences.
- Correlational design: used to check for relationships between the meteorological variables (wind speed, humidity, and temperature) and BC concentrations. To ensure data uniformity, the timing and date of the BC concentrations and the meteorological data were matched. Scatter plots were used to visualize relationships between BC concentration and meteorological data (Balachandran et al., 2013).

Tools such as Google Earth, WRPLOT View, and ArcGIS were used to create visualizations that helped to make sense of the results from a spatial point of view (Carrico & Karacaoglu, 2023; Petralia & Potosnak, 2024).

1.4 RESEARCH QUESTIONS AND HYPOTHESES

Building on identified opportunities in literature and the dataset structure, this study is guided by the following research questions and corresponding hypotheses:

Research Question 1:

How do black carbon (BC) concentrations differ between Upwind, Downwind, and Apartment locations during a prescribed burn?

H1: BC concentrations will be significantly higher at Downwind locations compared to Upwind and Apartment sites during the prescribed burn.

Research Question 2:

What effects do meteorological conditions have on the levels of BC at these locations?

H2: Meteorological conditions, specifically wind speed, wind direction, temperature, and relative humidity, will influence concentrations of BC.

To further examine these relationships, we introduce the following sub-hypotheses:

- **H2.1**: Higher wind speeds will be associated with higher concentrations of BC.
- **H2.2:** Higher levels of relative humidity will be associated with higher BC concentrations.
- **H2.3:** BC concentrations at the sensor locations will increase when winds are originating from the burning location of the prescribed fire.
- **H2.4**: Higher temperatures will be associated with elevated concentrations of BC.

These research questions and hypotheses have been built to assist with the opportunities identified in the problem statement. This research is intended to provide significant contributions to the environmental engineering field and policymakers. This information can assist in the development of processes to reduce and manage black carbon emissions to protect communities impacted by prescribed fires and mitigate broader environmental effects.

1.5 SIGNIFICANCE OF THE STUDY

Countless environmental studies tend to focus on pollutants such as PM2.5 and organic carbon when it comes to prescribed burn activities. Not often do we see them focus on black carbon (BC), a pollutant that is likely to be associated with combustion processes across different locations, such as the Upwind, Downwind, and Apartment locations. Research studies such as that conducted by Pearce et.al (2012) prove this, as the study focuses on PM2.5 burn gradients near burn sites as opposed to BC in such contexts. Recently, assessments of portable BC sensors such as the microAeth® series (e.g., MA-200, MA-300, MA-350) have showcased their capacity to capture spatial and temporal variations in fire emissions with finesse (Liu et al., 2021). This research adds to the body of knowledge by presenting local and fire-specific BC data that better classify exposure gradients (Pearce et al., 2012; Petralia & Potosnak, 2024). Such insights underpin the budding need for community-scale monitoring approaches, specifically in areas around such burn sites where their vulnerable members may face bigger health risks.

There are quite a few studies that explore the influence of weather conditions such as wind speed, mixing height, temperature, and the like on the dispersion of smoke, but only a few combine such with fine-scale BC data. In most cases, research studies tend to rely on particulate matter (PM2.5) or satellite-derived aerosol optical depth (AOD), which are not specific to sources of fire. The dispersal of prescribed fire smoke is influenced by meteorology, topography, and fire patterns; surface-level BC dispersion stays unclear (Kondo et al., 2022; Achtemeier, 2009). This work speaks to these opportunities identified in literature by merging local and site-specific black carbon concentrations with meteorological data, giving a burn-sensitive understanding of the behavior of pollutants. This study gains valuable insights from research done in Oregon and New Mexico, which pinpointed the influence of meteorological data on PM2.5 data (Miller et al., 2019; Maji, Ford, et al., 2024). Infusing BC data gives a more selected approach to examining exposure, fire management practices, and guiding air quality policy.

1.6 SCOPE OF STUDY

This study is intended to estimate black carbon (BC) concentrations measured in several locations (Upwind, Downwind, and in the Apartment) during a prescribed burn at the Jones Center at Ichauway, Georgia, and to examine the immediate influence of meteorological attributes: wind speed; wind direction; temperature; and relative humidity on BC concentrations. The data for this study were collected over a very short time. BC measurements were taken with an Aethlabs MA-200, and meteorological data were collected at a weather station on the Jones Center property. High-resolution BC data were collected at one-minute intervals, and meteorological data were collected at 15-minute intervals. The study used statistical descriptive statistics, non-parametric tests, and simple univariate linear and multiple linear regression models to evaluate relationships, trends, and predictions across several variables.

In addition to being an original research study, it is also exploratory and offers perspectives important for understanding the mechanics of pollution dispersion associated with prescribed fire management in the Southeastern US. The conclusions produced from this research are context and location-specific, case-dependent upon the fire event and study site, but can be built upon for future prescribed burns research.

1.7 SUMMARY AND ORGANIZATION OF REMAINDER OF STUDY

The remainder of this study is organized as follows: Chapter 2 provides an overview of the various studies that were reviewed and applied in support of the research; Chapter 3 details the procedures and data analysis methods used in this study to address the questions; Chapter 4 presents the results of the research by addressing the research questions and evaluating the hypothesis statements; Chapter 5 includes the conclusions derived from the research and recommendations derived from the lessons learned in the study.

CHAPTER TWO: LITERATURE REVIEW

2.1.1 Brief Overview of Wildland and Prescribed Fires in the US

Wildland fires (wildfires and prescribed fires) are not a foreign concept in the land management space that exists in the US. Such fires were once used for activities ranging from hunting to plant source generation to facilitating travel from place to place (Petralia & Potosnak, 2024). In recent decades, the burned areas from such fires have drastically increased, especially in the US, with their size and frequency being sponsored by Climate Change (Li et al.,2023). In fact, from 2008 to 2019, an average of 6,846,857 acres of land was burned on an annual basis by a corresponding average of 64,072 wildfires in the United States. Also, estimates from the United States Environmental Protection Agency (USEPA) show that wildland fires contributed approximately 44% of the total emissions of particulate matter with an aerodynamic diameter less than 2.5 µm in the US (Adetona et al., 2016; Ran, 2019). Interestingly, 32% of such fires were attributed to prescribed burns, reinforcing the fact that several burns carried out in the US are prescribed burns (Maji, Li, et al., 2024; Sadia Afrin & Garcia–Menendez, 2020). The particulate matter emitted contains constituents such as organic and elemental carbon (Carrico & Karacaoglu, 2023).

Ironically, prescribed burns have been recommended as a great tool that can be used to douse the effect of climate-induced wildfires, reverse past fire suppression policies, and help manage the growth of the wildland urban interface (Wu et al., 2021). This is so because, unlike uncontrolled wildfires, prescribed fires are carried out under strict, controlled, and in some cases, regulated conditions that are enforced by land managers and the likes. Despite such stringent operational clauses, prescribed burns still offer immense benefits, making the entire practice worthwhile (Schollaert et al., 2024; Carrico & Karacaoglu, 2023).

2.1.2 Importance of Prescribed Fires in the Southeastern US (Georgia)

The Southeastern United States is a region vulnerable to wildfires from a combination of its landscape, climatic characteristics, and its long history of prescribed fire (Petralia & Potosnak, 2024). A major cause of this is that forests in this region are fire-dependent and thus need such fires to survive and thrive (Odman et al., 2018). Examples of these forests include longleaf forests, slash and loblolly pine forests with palmetto-galberry understories in Florida, Georgia, and South Carolina, with pine and mixed hardwood forests in the upper coastal plain of South Carolina, as well as shortleaf pine-grass assemblages in Arkansas (Maji, Li, et al., 2024). The states in the Southeastern US utilize prescribed fire for different reasons, including changing natural fuel loads that may become wildfires, regenerating nutrients in the soil, managing insects and diseases, improving wildlife habitat, and so on. In the Southeastern US, over 2 million hectares are treated by prescribed fires, and Georgia is among these states with approximately 550,000 hectares treated through prescribed fire each year (Odman et al., 2018).

Throughout much of the 20th century, large plantations in Southern Georgia were developed to manage wild game for hunting (deer, quail, turkey), requiring burning practices undertaken at prescribed intervals (Gaither et al., 2019). Another motivation for the state of Georgia aligned with prescribed burning is for restoration activities of longleaf pine (Pinus palustris) and wiregrass ecosystems in the coastal plains of Georgia (Jang & Jung, 2023). Prescribed burns are generally understood to produce lower emissions than wildfires, making them a good land management tool (Maji, Li, et al., 2024; Jang & Jung, 2023).

2.1.3 Correlation between Prescribed Fire Emissions, Public Health, and Air Quality

In 2017, the Southeast burned approximately 7.6 million acres (3 million hectares) of the total 11.3 million acres (4.6 million hectares) that burned nationally (El Asmar et al., 2024). Among the Southeast states, Florida and Georgia burned over 1 million acres (0.4 million hectares) of land on an annual basis (El Asmar et al., 2024). With an average of 0.15 million acres of burn area expanding annually and solid controls on other pollution sources in the Southeastern US, it is no wonder that prescribed fires are thought to contribute up to approximately 27% of total emissions. Such emissions therefore depress air quality, diminish visibility, and generally negatively impact public health (Maji, Li, et al., 2024; Liu, 2014; Ravi et al., 2018; Odman et al., 2018).

Even with prescribed burns being conducted in suitable weather conditions, they still produce localized and regional air pollution (El Asmar et al., 2024). Such burns were shown to account for 10-15% of the annual average ambient levels, which may increase to 20-30% during the burning season (January to April) when burning is most extensive (Maji, Li, Vaidyanathan, et al., 2024). The particle pollution contributions could absorb a portion of the ambient air quality improvements obtained in the United States over the years (Maji, Li, et al., 2024). A recent study by Liu (2014) documented that smoke plumes from two prescribed fires in Central Georgia raised PM2.5 concentrations above the daily limit established by US National Ambient Air Quality Standards with the probable result of degrading air quality and comfort for residents in the vicinity, especially vulnerable populations, including elderly individuals, children, and people with respiratory issues.

It should also be mentioned that emissions from prescribed fires typically settle around the burn sites and even endanger the health of those living close by (Gaither et al., 2019). Many epidemiological studies have linked exposure to these emissions, particularly to toxic pollutants such as PM2.5, with serious adverse human health outcomes, including cardiovascular, neurological, and respiratory diseases, increased risk of adverse birth outcomes, and premature mortality (El Asmar et al., 2024; Huang et al., 2021). Another study showed that because of increased wildland fire occurrences in the two Southeastern states of Florida and Georgia, premature deaths and respiratory-related hospitalizations increased substantially (Gaither et al., 2019). Also, a health impact assessment in the Southeastern US estimated increased hospitalization for asthma and increased all-cause mortality related to the exposure to prescribed burns (Schollaert et al., 2024). These studies recognize that prescribed burns can be used to mitigate some of the impacts of wildfires, but that they still have some impacts on both people and the environments that surround those burns.

2.1.4 Assessing Fine-Scale Spatial and Meteorological Variability of Pollutant Concentrations using Direct Measurement Tools

To estimate the impacts of pollutant emissions, especially particulate matter (PM2.5) from activities such as prescribed fires, many tools and systems are often used. Countless studies use permit records, as they provide precise measurements of these burns; unfortunately, the southeastern states of the US lack a complete record of such burns (Maji, Li, et al., 2024). Other studies rely on satellite-based products to identify and provide information regarding prescribed burns. Quite a few limitations exist with this method and they include the inability of satellites to detect such low-intensity and short-lived burns, obstruction by cloud cover, the inability of such products to detect the location, size and the timing of such fires, the struggle of such products to distinguish between a prescribed burn and other wildland fires, the complex nature of fire emissions (Sadia Afrin & Garcia–Menendez, 2020; El Asmar et al., 2024). Aircraft and drones have also been deployed for a couple of prescribed fire studies, and although they provide high resolutions that are useful for monitoring the evolution of smoke particles Downwind, such measures are not continuous and could miss various aspects of the smoke, e.g., at night (El Asmar et al., 2024).

Statistical Modelling tools such as CMAQ, HYSPLIT, and Blue Sky are also used in many studies, but the downside to them is that their quality depends on the quality of their inputs (Carrico & Karacaoglu, 2023; Miller et al., 2019; Odman et al., 2018). Stationary monitors such as SLAMS consider surface concentrations, but they are mostly deployed by the authorities based on the needs of the state and local air pollution management agencies, making such distribution non-uniform. As a result, those who live in rural areas lack the necessary infrastructure to monitor the impacts from sole plumes from prescribed fires (Huff et al., 2021). With all this in perspective, it is paramount that another means of collecting data be explored. Portable, low-cost air monitors seem to fill the gaps highlighted by the other tools.

One study that made use of a combination of some of the methods listed above highlighted the fact that a method that can get more accurate ground-based data, especially in rural areas, should be explored (Sadia Afrin & Garcia–Menendez, 2020). Another study highlighted their reliance on satellite data and the Bluesky model but did not give them reliable data due to cloud cover obstructions and how the blue-sky model underestimated and overestimated the emissions (Maji, Li, et al., 2024).

Portable sensors are easy to use and deploy whilst collecting ambient concentrations with high-resolution data in almost real time (Huang et al., 2021). They could also be used to monitor air quality patterns and, to some extent, investigate the spatial variability of species in smoke plumes (El Asmar et al., 2024). Since meteorological variables such as wind speed, wind direction, temperature, relative humidity play a huge role in the variations exhibited by surface level concentrations, portable monitors furnished with internal sensors or used alongside nearby weather stations can be used to see if there is any relationship between such BC concentrations and the meteorological data around them (Reisen, Meyer, et al., 2011; Liu, 2014; Odman et al., 2018; Miller et al., 2019).

2.2 PRESCRIBED FIRE ACTIVITY IN SOUTHEASTERN US

2.2.1 Geographic Distribution and Timing of Prescribed Burning

Prescribed burns occur in many locations across the U.S. but ultimately are shaped by demographics and politics (Petralia & Potosnak, 2024; Kondo et al., 2022). Their occurrence is complex as it relates to considerations of human use of the forest, seasonal ecology, ecosystem needs, diverse management goals, and burn duration (Tian et al., 2008). Prescribed burns are implemented in the Southeast (64%) and the West (33%), utilized less frequently in the Northeast (3%), based on factors such as land use and ease of dispersion of the emissions from smoke (Wu et al., 2021). Compared with seasonal prescribed burns in Kentucky and Virginia in the north and Texas and Oklahoma in the west the credit for increased activity of prescribed burns goes to the extensive acreage of longleaf pine (Pinus palustris) and its forest savanna ecosystems of the southeastern US south (Petralia & Potosnak, 2024; Balachandran et al., 2013). Prescribed burns in the southeastern U.S. were also reported by Jaffe et al. (2020) as occurring primarily in the winter season, often aimed at maintaining multiple upland longleaf and forest savanna ecosystems. However, as spring arrived, such burns were shifted to the central region and grazing lands, highlighting the importance of the 4% of burns attributed to the Southeastern parts of the US (Jaffe et al., 2020; Petralia & Potosnak, 2024).

A recent assessment of prescribed burns estimated that 70% of the prescribed burns conducted in the U.S. occur in the Southeastern U.S. and represent around 25% of total primary PM2.5 emissions (Sadia Afrin & Garcia–Menendez, 2020). The southeast states of Georgia, Florida, Alabama, and South Carolina burned approximately 3-4 million hectares each annually (Gaither et al, 2019). In the state of Georgia, such burns typically happen in the Winter and Spring, because the weather conditions allow for it, compared to the conditions that come with the Summer and Fall, which are many at times intense and in some cases, erratic. Historical burns conducted from 1994-2005 showed that 87% of all prescribed burns were conducted from December to April, with 37% of the total number done in March alone (Tian et al., 2008)

2.2.2 Rationale for Prescribed Burning: Ecosystem Management and Wildfire Risk Reduction

Wildland fires are a traditional tool useful for shaping most North American Systems. Native Americans used such fires as an agricultural tool to manage wildlife habitats and hunting grounds. With time, such fires were suppressed. However, that shift led to the buildup of fuels, which, in addition to climate change, has increased the occurrence and impacts of wildfires. Consequently, forest managers readopted the discarded practice of prescribed burns (Jaffe et al., 202; Petralia & Potosnak, 2024). The impacts of climate change and human-induced ignitions have made it more important to tackle the wildfire beast before it gets out of hand. A recent review affirmed this, highlighting that wildfire activity in the US is on the rise, along with the corresponding fire suppression costs. Costs associated with federal wildfire suppression hit an all-time high in 2018 of $3 billion (Jaffe et al., 2020). Wildfires in November of 2016 in Tennessee, North Carolina, and Georgia produced PM2.5 concentrations greater than 100 $\mu g/m^3$ in many cities, suggesting a need for a better fire management strategy (Jaffe et al. 2020). Information provided from the National Interagency Fire Center over the period 2014-2023 shows that 6.5 million acres were burned, demonstrating an increase in the number of large wildfire events. There is increasing consensus that the re-establishment of natural fire regimes is necessary for sustainable health in forests (Schollaert et al., 2024). Prescribed burns can help fulfill this need since they are set for moving the fire at a lower intensity to burn the understory while protecting trees (Jang & Jung, 2023; Odman et al., 2018; Petralia & Potosnak, 2024).

Controlled burns are carried out for various reasons, such as primary fuel management, ecological restoration, and support for agricultural goals (Petralia & Potosnak, 2024). In the southeastern U.S., they are used to manage forest ecosystems and slow the growth and infestations of endangered species, all to reduce larger, intense forest fires (Balachandran et al., 2013).

2.2.3 Fuel Types and Combustion Phases (Flaming vs Smoldering)

Several factors influence the emission of pollutants, such as PM2.5. Some of which include fuel type, fuel moisture, fire conditions, amount of fuel consumed, temperature, weather, fire stages, etc. (Jaffe et al., 2020; Balachandran et al., 2013). Many tree species in the forests of the Southeastern United States are fire-adapted and need fire (Odman et al., 2018). Yet, there are some recognized fire-adapted forests, including longleaf pine forests, slash and loblolly pine forests with palmetto-galberry understories that are located across Florida, Georgia, and South Carolina, as well as pine and mixed hardwood forests in the upper coastal plain of South Carolina and shortleaf pine-grass assemblages in Arkansas (Maji, Li, et al., 2024). In Georgia, various stakeholders, including private and public agencies, have committed considerable resources to conserve longleaf pine (Pinus Palustris) and wiregrass ecosystems in the coastal plain by implementing carefully orchestrated fire regimes (Gaither et al., 2019).

There are two combustion phases during the process of forest fires, including flaming and smoldering (Ran, 2019). The flaming phase refers to the period of active burning, while the smoldering phase is noted for long-period, low-intensity burning after flames have been extinguished. Since the smoldering phase has a cooler temperature range, smoldering combustion typically produces larger emissions per unit of fuel consumed; however, Janhall, Andreae, and Poschl indicated that particulate matter (PM) emissions from the flaming phase exceeded those of the smoldering phase. Emissions from the flaming and smoldering phases behave differently during the atmospheric dispersion processes, due to differences in release rates and timing (Tian et al., 2008).

Biel et al. (2020) recognized that prescribed burns in the southeastern United States tend to have more occurrences of smoldering combustion than prescribed burns in the rest of the nation (Jaffe et al., 2020). However, results show that in the case of prescribed burns in Georgia, the occurrence of smoldering combustion usually consumes surface fuels, whereas large woody and below-ground fuels are not counted as active across the smoldering phase (Tian et al. 2008). Emissions produced from low-intensity burning with the high humidity characteristic of the Southeastern United States can lead to dense fogs, sometimes with virtually no visibility, and magnified risk of catastrophic vehicle accidents, mostly in areas characterized by fine-scale topographic depressions (Jaffe et al., 2020).

2.3 AIR QUALITY IMPACTS OF PRESCRIBED FIRES

2.3.1 PM2.5 as a Primary Emission from Prescribed Burns

Biomass burning emits a range of air contaminants, including gases and particulates. Gases include carbon dioxide, carbon monoxide, hydrocarbons, and trace gases. PM2.5 is a major component of biomass smoke; the negative effects of this fine particle contamination on air quality have become a greater focus of concern locally and globally over the past two decades, as the adverse health implications become better understood. As far as air pollution in rural areas goes, the types of land management practices that result in air pollution are smoke from wildfires, smoke from burning agricultural residuals, fire from prescribed burns in forests and vegetation, burning biomass, etc. (Reisen, Meyer, et al. 2011; Schollaert et al., 2024). In 2017, wildland fires accounted for 44% of the US' primary emissions of fine particulate matter (PM2.5), 32% of which were attributed to prescribed burns (Huff et al., 2021; Maji, Li, et al., 2024). In the Southeastern part of the US, wildland fires contributed to 31% of the primary PM2.5, 81% of which came from prescribed burns (Maji, Li, et al., 2024; El Asmar et al., 2024).

The various particles ejected as a result of such fires are comprised of elemental carbon (EC) or black carbon (BC), organic carbon (OC), ionic species, trace elements, water-soluble organic carbon (WSOC), soluble iron (Fe (II)), and total particle number concentration (Carrico & Karacaoglu, 2023; Balachandran et al., 2013; Jaffe et al., 2020; Karanasiou et al., 2021). BC, formed from flaming (as opposed to smoldering) combustion, are graphitic-like particles (20-30 nm) that form larger particles (200 nm), are hydrophobic (Jaffe et al., 2020). Fires in the southeastern and Midwestern regions of the US contribute minor, but significant, quantities to particulate organic carbon; Spring is the peak fire season, and prescribed burns are the majority type of fire that occurs (Jaffe et al., 2020). Several studies affirmed the fact that the BC level was 5-fold during the flaming stage compared to the smoldering stage, emphasizing the significance of the burning stage in determining the chemical makeup of particulate matter (Wu et al., 2021).

2.3.2 Health Consequences of Prescribed Fires

Concerns regarding the health impacts of smoke related to fire are relevant, especially for communities that are Downwind (Jaffe et al. 2020). A health risk assessment of the continental

U.S. revealed that from 2008 to 2012, there were between 3,900 and 6,300 hospital admissions for respiratory cases and 1,700 and 2,800 for cardiovascular cases due to short-term smoke exposures. Since then, smoke levels in the U.S. have increased (and likely now exceed) levels from previous years, which will likely lead to increased health impacts (Jaffe et al. 2020). There has been some recent scientific literature about health impacts from wildfires; however, there is less literature on exposure to prescribed fires (Jaffe et al. 2020).

It is generally accepted that exposure to ambient PM2.5 from biomass burning is associated with increased morbidity and mortality, and the body of evidence is quite large (Karanasiou et al. 2021). A study in Georgia found that air pollution due to prescribed burns can have substantial health effects, potentially leading to hundreds of morbidity and mortality cases (Afrin and Garcia-Menendez 2021). Another study found that firefighters who performed prescribed burns had increased levels of pollutants at exposure levels that exceeded occupational exposure limits (Barbosa et al. 2024). Prescribed burns are low-intensity burns; however, exposure to these burns can result in increased health issues, including a decrease in respiratory health (Barbosa et al. 2024).

According to Wu et al. (2021), black carbon is one of the components of particulate matter and a good indicator for the management of air quality due to its strong relationship with adverse health outcomes. In another study, the authors found that prescribed burns would result in health impacts for various endpoints: 280-700 deaths, 4400 lower respiratory illnesses, 7300 upper respiratory symptoms, just about 400 acute bronchitis cases, and lost workdays in the thousands among other endpoints (Reisen, Meyer, et al. 2011). Prescribed burns also contributed to degraded visibility in specific Class 1 areas protected by law in parts of the Pacific Northwest of the U.S. (Ravi et al. 2018). Overall, the evidence suggests that it is important to apply greater attention to health impacts from prescribed burns, given that their application will likely be increasingly used in fire-prone landscapes such as the Southeastern U.S.

2.3.3 Timeframe and Longevity of Prescribed Burn Effects

Sadia Afrin and Garcia-Menendez (2020) showed that for more than 60 % of study sites, the predictive capability of nearby permitted fires was stronger than meteorological conditions, suggesting greater impacts on PM2.5 levels for prescribed burns. In particular, the Georgia sites in the study had a large effect, with an average variance in 24 hr. PM2.5 concentrations attributable to burning were more than four times that explained by meteorological variables (Afrin, 2021). Moreover, the effects of prescribed burning on air quality returned to pre-burn conditions in 1-2 days after the burn (Afrin, 2021).

2.3.4 Brief Discussion about Community Level Impacts

Wildland fires, both wildfires and prescribed burns, have important implications on ambient PM2.5 concentrations in the Southeastern region of the United States, which is home to nearly 70% of prescribed burns conducted (Afrin, 2021). Many prescribed burns are conducted near communities that fall along the wildland-urban interface (WUI), affecting millions of people (Afrin, 2021). The literature focused on wildland fire smoke suggests that those most impacted are from socioeconomically disadvantaged backgrounds, specifically the elderly (Afrin, 2021). Furthermore, prescribed fires can increase PM2.5 in rural areas where air quality monitoring and management have few resources (Afrin, 2021). Characteristics of communities with repeated burns differ from the general population, increasing their vulnerability to smoke (Afrin, 2021). A recent study collectively showed higher PM2.5 concentrations from prescribed burns, non-discriminately impacting areas that have higher levels of African American populations (Afrin, 2021).

A study conducted in Georgia showed that for prescribed burns, the areas impacted most disproportionately include populations in areas of lower socioeconomic status, larger elderly population, higher number of disabled persons, and accessibility to housing and transportation (Afrin & Garcia-Menendez, 2021). In 2018, another study found that prescribed burn smoke was positively associated with African Americans and mobile home housing at the Census tract level in Georgia (Kondo et al., 2022). In summary, these results suggest that prescribed burns might have an environmental justice undertone to them, because such burns have constantly been situated close to those who lack the resources to avoid such exposures.

2.4 CHALLENGES IN EXPOSURE ASSESSMENT

2.4.1 Sparse Distribution of Regulatory Monitoring Stations

Regulatory monitoring stations are essential in assessing the effects of smoke locally and regionally over both short and long-time scales (El Asmar et al., 2024). These stations are typically operated by a federal, state, or tribal agency (Jaffe et al., 2020). For example, the State and Local Air Monitoring Stations (SLAMS) network measures surface PM2.5 concentrations for compliance with the National Ambient Air Quality Standards (NAAQS) (Huff et al., 2021). In many environmental health studies, regulatory monitoring data have been combined with model simulations to create estimates of pollution with spatial detail to determine health impacts. This will help establish the link between air pollution exhibited at the time of a prescribed burn to the relevant health impacts. In many cases, though, the distance between regulatory monitors prohibits the quality and resolution of that data (Huang et al., 2021; Jaffe et al, 2020; Schollaert et al, 2024; Childs et al, 2022).

This defect is caused primarily by the locations of monitors being driven by state and local air pollution management agencies through their State Implementation Plans (SIPs), which do not seek uniform coverage (Huff et al., 2021). As a result, there are several rural communities that are regularly subjected to prescribed burning but lack enough monitoring capability, which limits both public awareness and research capabilities in those communities.

2.4.2 Under-detection by Satellite Remote Sensing

Accurately determining the impacts of wildland fires requires proper identification and characterization of a fire. One of the typical methods for accomplishing this is with satellite remote sensing, which generally detects thermal anomalies or changes in vegetation cover. While making positive contributions in many cases, the satellite remote sensing route has some disadvantages, especially regarding prescribed burns. Factors including cloud cover, limited spatial resolution, and the complexities of fire emissions can significantly interfere with objectively detecting and examining low-intensity burns, such as prescribed fire (El Asmar et al., 2024). Satellites are ill-equipped to easily identify small, low-temperature fires that typically occur when combusting below the forest canopy, i.e., understory burns (Liu, 2014; Jaffe et al., 2020; Sadia Afrin & Garcia-Menendez, 2020).

These limitations underscore the need to develop further ground-based monitoring possibilities. Portable, low-cost air quality monitors are a feasible possibility as these monitors provide immediate, localized information on pollutant concentrations. This would be particularly useful in areas with small, controlled burns that are difficult to see via satellite, increasing public awareness and informing air quality regulators (Sadia Afrin & Garcia–Menendez, 2020).

2.4.3 Episodic Nature of Smoke Events

Prescribed burns are fires intentionally set as part of active management efforts during a specific "window" with conditions such as wind, temperature, humidity, and other parameters as approved in a simple burn plan (Liu, 2014). There are major challenges associated with the collection of data during sporadic smoke events, including the uncertain timing of a smoke event, the duration of the smoke episode, and the wind patterns that can, at a fundamental level, determine the impact of the area (Wheeler et al., 2023). The unpredictability of these factors leads to satellite instruments not being able to fully capture prescribed burns. Satellite sensors cannot take the same path every time because of their orbital tracks; they also make such movements at specific times and locations, meaning that many prescribed burns, which often last a brief time, have several sensor misses (Liu, 2014). In the Southeastern United States, there are considerable uncertainties in remote sensing fire data techniques about the location, size, and timing of fires (Sadia Afrin & Garcia–Menendez, 2020).

2.5 USE OF MA-200 FOR SMOKE AND PM2.5 MONITORING

2.5.1 Overview of MA-200 Sensor Performance

Black Carbon (BC) is a pollutant comprised of a variety of carbon-based materials formed from the incomplete combustion of carbon-containing fossil fuels and biomass (Liu et al., 2021; Chakraborty et al., 2023). Black Carbon is suspected to be very harmful to human health (Liu et al., 2021; Chakraborty et al., 2023). The International Agency for Research on Cancer designates this pollutant as a 2B Carcinogen, and studies show that there is a correlation between exposure to black carbon and cardiovascular, neurological, and respiratory diseases (Liu et al, 2021). Evaluating black carbon is complicated because of the ambiguity in its chemical definition. The black carbon particles themselves are very resistant to degradation and are very effective at absorbing short- and long-wave light radiation (Liu et al., 2021; Chakraborty et al., 2023).

Most of the direct measurement approaches to quantifying BC utilize an aerosol light absorption on a filter measurement technique which is the preferred method, for example, when using an aethalometer or multi-angle absorption photometer, because you can gain real-time air quality measurements and understand better, your local air quality and pollutant exposures (Liu et al., 2021; Chakraborty et al., 2023). The MA-200 is specifically designed to measure black carbon concentrations for different exposure scenarios, including personal exposure measurements, ambient and vertical profile measurements, and indoor emission concentration measurements (Liu et al., 2021; Chakraborty et al., 2023).

2.5.2 Case Studies Validating Sensor Accuracy vs. Regulatory Monitors

The MA-200 is a relatively new instrument but has already been compared to a lot of reference-grade instruments. In one study, BC concentrations were taken from different locations, post-processed using methods (ONA, CMA, LPR), and compared with a stationary monitor- AE33. When comparing the two instruments, there was a strong correlation (Pearson's $R = 0.933$) in the time interval of about 30 to 60 minutes between walks (Liu et al., 2021; Chakraborty et al., 2023). In the end, there was no wavelength dependence between the monitoring device's stationary vs. portable position (Liu et al., 2021).

Another study conducted by Blanco-Donado et. al only found a 9% difference between the MA-200 and AE33 eBC concentrations. These results suggest that the MA-200 monitor’s BC results can be trusted.

2.5.3 Advantages of the MA-200

The MA-200 monitor is beneficial for a myriad of reasons, some of which include spatial coverage, rapid deployment, real-time surface air monitoring, and so on. The portability of the MA-200 device allows it to be easily transported from place to place, including rural areas. This also means that it can be deployed to as many regions as possible, as soon as the need for it arises. The MA-200 sensors are also able to detect low-intensity burns such as prescribed burns and can either be used as stand-alone data or serve as inputs for satellite or statistical models such as Blue Sky (Sablan et al., 2024; Sadia Afrin & Garcia–Menendez, 2020). A benefit of sampling at ground level is the certainty of identifying the emission source and combustion condition, which permits a focused examination of the smoldering element (Reisen et al., 2018). Therein, it also allows for a strong observational dataset of the many fires and atmospheric parameters key to the complex processes of plumes (Jaffe et al., 2020).

2.5.4 Limitations of the MA-200 Sensor

Although the MA-200 has many strengths, some of the limitations are highlighted in this subsection. The Ma-200 is a mobile instrument, and so when it experiences a change in locations, i.e., from a highly polluted one to a less polluted one, noise is introduced into its data. Also, if the sensor runs on a very high frequency (e.g., 1 Hz) or there is an unstable flow during data collection, errors displayed as negative values would be introduced into the data. Such errors must be corrected without eliminating them, as such values are useful for explaining environmental fluctuations. Such data can be corrected using post-processing algorithms made available by the AethLabs team on their website. These algorithms cancel out the noise without eradicating the negative values, giving researchers quality data to work with. Holder et al. found that noise estimates from the MA-series aethalometers can be up to five times higher than those of the reference instrument for one-minute averaged data (Liu et al., 2021; Chakraborty et al., 2023). In addition, the MA-200 sensor needs regular maintenance. In the event of issues with the MA-200 sensors, this may necessitate a return to the manufacturers, adding time delays to research timelines (Liu et al., 2021).

In conclusion, the raw black carbon (BC) concentrations provided by the Aethalometer require complex corrections for measurement artifacts related to both filter loading and the multiple scattering effect (Liu et al., 2021; Chakraborty et al., 2023). High concentrations of equivalent BC (eBC) can produce substantial error or potential bias that needs to be corrected for filter loading, e.g., (Chakraborty et al., 2023; Liu et al., 2021). Lastly, and still in line with other ground sampling techniques, the MA-200 collects only a small percentage of the total smoke produced by the fire (e.g., Reisen et al., 2018). Thus, when assessing point-source measurements, it is critical to consider the possibility of sampling bias given the environmental conditions of the fire.

2.6 INFLUENCE OF METEOROLOGICAL CONDITIONS ON POLLUTANT DISPERSION

2.6.1 Wind Speed and Direction: Key Factors in Smoke Transport

Fire emissions can vary based on the type and condition of fuel, weather, and burning conditions. Therefore, understanding how fuels, vegetation, fire, topography, and wind tend to interact in a location may improve understanding of smoke spread (Maji, Li, et al., 2024). Research indicates that meteorological events, such as wind and precipitation, are strong correlates with prescribed burning events (Odman et al., 2018). For example, PM2.5 concentrations have been known to be influenced by weather characteristics such as wind speed and mixing height (Reisen, Meyer, et al., 2011). In addition, the interaction of wind, fire behavior, vegetation, and dispersion into the atmosphere is even more complicated in hilly, uneven terrain (Miller et al., 2019). The topography of an area dictates the flow of wind in that region, and it does this by channeling flow along valleys. On the other hand, vegetation cover and moisture tend to influence wind turbulence and fine time scales. For example, when the Earth's surface cools at night, such cooling leads to the downslope winds from sunset to sunrise, but the heating of the Earth by daytime leads to up-valley winds. Such mechanisms transport smoke (or overnight smoldering emissions) into valley settlements where people live. Willamette Valley residents in Oregon experienced this in 2017 when stagnant air and low wind speeds created a situation of smoke buildup near the ground and magnified concentrations of PM (Jaffe et al., 2020).

Studies show that wind conditions conducive to optimal air quality are more likely to occur in the Spring (13%) than in the Fall during prescribed burns (5%) (Miller et al., 2019). In situations of high wind speed, the atmosphere stabilizes, vertical mixing is reduced, and more smoke remains near the ground (Liu, 2014; Jaffe et al., 2020). Generally, prescribed burns are used to reduce wildfire risk, whilst enhancing the dispersion of smoke, before affecting Downwind communities (Maji, Li, et al., 2024). The impact of wind on smoke behavior was further illustrated in one study, as it was discovered that transport winds had a low correlation with smoke plume rise (Liu, 2014).

2.6.2 Relative Humidity and Temperature: Influence on Combustion Efficiency and Plume Rise

Smoke has a strong connection with the physical atmosphere (Jaffe et al., 2020). As smoke modifies the radiative properties of the atmosphere by blocking solar radiation and re-radiating heat into the surrounding air, it can increase atmospheric stability in the mixed layer, reduce surface temperature, and limit the height of mixed-layer wind speeds (Jaffe et al., 2020). Smoke plume rise indicates the potential maximum height a smoke plume derived from a prescribed fire can rise into the atmosphere (Urbanski, 2014). Particles from prescribed fires that rise higher in smoke plumes are likely to disperse from rural burn sites and may impact air quality in the more populated areas downrange of those sites (Liu, 2014). Generally, fire plumes rise during the afternoon, as humidity decreases, temperatures increase, and atmospheric boundary layers reach full development (Jaffe et al., 2020).

A regression model investigation examining smoke plume rise found relative humidity to have a weak relationship with it. Surface air temperature and atmospheric stability both revealed a similarly associated relationship with smoke plume rise, much like the relationships noted with fuel temperature and atmospheric boundary layer height, and plume rise (Liu, 2014). This investigation also emphasized that fire behavior is most influenced by relative humidity and temperature. At the same time, the relative humidity and air temperature must not be too dry and warm, either, as that could result in uncontrollable burns, like the 2000 Cerro Grande Fire at the Los Alamos National Lab in New Mexico (Miller et al., 2019).

2.6.3 Timing of Burns to Minimize Smoke Exposure: Before Rains, Stable Winds, Cool/Dry Weather

Prescribed burns in the US take place in specific regions and at specific times of the year. These burns typically occur in the spring and fall, when the risk of prescribed fires escalating to wildfires is low, compared to the summertime (Sablan et al., 2024). Weather plays an important role in the chance of a burn happening. In general, burns are avoided on rainy days, following heavy rain, or during long dry periods (Jang & Jung, 2023; Odman et al., 2018; Petralia & Potosnak, 2024). In a study using the GFC burn permit database for 2010-2014, it showed that weather conditions along with seasonal conditions play a role in the decision-making for land managers (Odman et al, 2018). This is quite realistic, as weather conditions could either douse or exacerbate the impacts of burns. Warm and dry conditions fostered the burning process of biomass fuel in the Huff et al. (2021) study, agreeing with existing literature in that space. But too hot or too dry conditions could worsen the situation. Over the past two decades, climate change has contributed to larger burned areas in the US. Between 2001 and 2019, fires burned at least 1.5 million hectares nationally in 17 different years, and at least 4 million hectares burned between 2015 and 2017 (Jaffe et al., 2020; Iyaz, 2022).

2.6.4 Fog Formation from Moist Smoke in Winter/Spring

Research has shown that the smoke released from the prescribed burns carried out between January and April can contain sufficient moisture capable of promoting the formation of a polluted dense fog at night (Huff et al., 2021). In the humid southeastern United States, smoldering phase emissions, along with the high moisture in the atmosphere (from the fire as well as the environment), can create dense fog that results in near-zero visibility conditions (Jaffe et al., 2020).

2.7 GROUND-BASED MEASUREMENTS AND DIRECT OBSERVATION APPROACHES

2.7.1 Importance of Collocating Sensors Upwind/Downwind for Gradient Analysis

In almost all cases, sensor placement would allow for monitoring of smoke events in different locations nearby, and it would help alleviate challenges with predicting pollutants traveling Downwind, while also being unaffected by uncertainty in intended burning locations or schedules (El Asmar et al., 2024). Collocating these sensors would provide more spatial resolution to account for smoke from the same flames at multiple locations, which could help to investigate shifts in smoke chemistry with more confidence.

One study carried out in Augsburg, Germany, demonstrated this concept, as they co-located MA-200 devices and stationary regulatory monitors to demonstrate the unit-to-unit comparability of black carbon concentrations recorded from the units (Liu et al., 2021). Another study used sensors such as AE33, AE22, and AE31 to conduct side-by-side and background comparisons, along with TEOM-based PM2.5 concentrations in comparison to the state monitoring stations. Such comparisons enhanced confidence in the particulate mass measurements that could not be calibrated easily, like gas monitors (El Asmar et al., 2024).

2.7.2 The Use of Instruments like MA-200 for Black Carbon Detection

Black carbon consists mainly of sp2-bonded carbon in a graphene-like structure, which is highly stable and has a large absorbance range across many short and long wavelengths of light (Liu et al., 2021; Chakraborty et al., 2023). Many measurement techniques based on the properties of BC have been developed, and how BC is defined differs based on which measurement technique is used. Typically, there are three kinds of assessments to determine the mass concentration of BC:

(1) The mass concentration of elemental carbon (EC) is determined through thermal optical analysis of aerosol collected onto filters, for example, using a thermal-optical OC-EC (organic carbon - elemental carbon) analyzer developed by the Sunset Lab, logs onto data sets, and is part of the total measurement.

(2) An approximate equivalent black carbon (eBC) can be determined by light absorption of aerosols collected onto filters, as noted by Hansen et al. (1984), which can be from aethalometers, multi-angle absorption photometry, and a photo-acoustic device such as a photo-acoustic soot spectrometer.

(3) The amounts of refractory BC (rBC) can also be determined using laser-induced incandescence (LII), a technique that was developed after the single particle photometer (SP2) technology.

Of the range of commercially available instruments, aethalometers are in popular use by many scientific agencies and regulatory bodies for real-time assessment of black carbon (BC) or equivalent black carbon (eBC) (Chakraborty et al., 2023). Some common examples include the MA-series, such as the MA200, MA350, and MA300; and AE-series instruments like AE33, AE21, AE31, amongst others (El Asmar et al. 2024).

2.7.3 Case Examples of Sensor Networks Deployed During Prescribed Fires

In a research project conducted in Eastern Kansas during the spring of 2021, 39 Purple Air sensors were combined with satellite data to examine exposures from prescribed burns. The sensors were able to detect fire locations, confirm smoke in the atmosphere, and detect higher concentrations of aerosols. In addition to distinguishing PM2.5 smoke-related levels, the research brought awareness to the importance of portable low-cost sensors in rural areas to better understand local impacts from smoke. The study showed that prescribed burns produced a significant increase in surface PM2.5 concentrations (Sablan et al., 2024). In another study conducted in southwestern Georgia, four low-cost PM sensors (Plantower PMS 3003) were used with a reference monitor (BAM) and were incorporated with a chemical transport model (CMAQ) along with data fusion techniques. The sensors were able to capture the relative differences in PM2.5 concentrations, and the temporal trends at the sites were strongly correlated, which provided an extra benefit of low-cost sensors to exposure assessments. These sensors helped to distinguish impacts from prescribed burning, in conjunction with additional temporal and spatial information that is often overlooked when using models or traditional monitoring networks.

Additionally, low-cost sensors are invaluable alternatives when regulatory monitors are either unavailable or not functioning properly. Nevertheless, the study underscored the importance of more research focused on sensor calibration and data correction, particularly concerning the best practices for reconciling low-cost sensor data with reference-grade instruments (Huang et al., 2021).

2.7.4 Benefits of Combining Ground Data with Meteorological Observations

Control burns are usually executed when the fire behavior/ dynamics (e.g., fuel types) and weather/burning conditions (e.g., Burning Index, spot weather forecasts) are favorable (Maji, Li et al., 2024). Fire emissions data can be collected from ground datasets or via remote sensing techniques (Li et al., 2023). Understandably, smaller fires, such as prescribed burns, are not perceived by remote sensing products; therefore, there are considerable uncertainties in satellite-based estimates, even more so with the absence of surface-level fire data (Huang et al., 2018; Nowell et al., 2018). This pointed to the necessity for ground-fire data in regions of interest for assessing air quality impacts (Sadia Afrin & Garcia–Menendez, 2020). Additionally, meteorological conditions can be used to predict the occurrence of a wildland burn, and such information can be used to train data-driven models (Li et al., 2023).

An analysis done by the Georgia Forestry Commission (GFC) of burns permit data taken from 2010 to 2014 hugely confirmed that the season and weather hugely influenced the decisions taken by the land manager (Odman et al., 2018). This is logical, because weather can either douse or aggravate the environmental, health, and overall air quality impact that such burns have over a region. Infusing meteorological data into ground data analysis improves our understanding of the environmental and health impacts of such burns.

2.8 OPPORTUNITIES IN LITERATURE

2.8.1 Limited Studies Synthesizing Meteorological Conditions, Smoke Dispersion, and Sensor Data

Most environmental studies tend to make use of satellite products or chemical transport models to predict pollutant concentrations from wildland fires. In some cases, they compare the data obtained from such sources with stationary, regulatory, or portable monitors, burn permits, and burning emissions inventories to know which technique yields the best estimates (Huang et al., 2021; Sablan et al., 2024; Miller et al., 2019; Schollaert et al., 2024). Other studies infuse meteorological data into models such as blue-sky or novel regression models, which are used to predict or estimate pollutant concentrations (Liu, 2014). Some research uses some of the tools: satellite detectors, regulatory monitors, and portable sensors to compare pollutant concentrations across locations, which are quite beneficial (Liu et al., 2021). Interestingly, not many studies integrate meteorological data with real-time BC data.

This research will attempt to fill this gap by correlating meteorological factors (temperature, relative humidity, wind speed, and direction) with MA-200 data to analyze BC concentrations throughout different locations and the influence of those meteorological factors. One study took a similar approach through a combination of meteorological conditions, smoke dispersion modeling, and ground acquired data (Miller et al., 2019), which corresponds to the air quality issues related to prescribed burns in the complex terrain of a bend in Oregon (Miller et al., 2019).

2.8.2 Need for Better Fire Records: Exact Burn Time, Duration, and Fuel Details

Fire records are critical for researchers as well as the public because they provide critical inputs for several statistical and chemical transport models. Unfortunately, these permits often lack post-burn data, and the records often have uncertainties associated with them stemming from incompleteness, inconsistent or varied recordkeeping standards, and varied reporting requirements from different agencies. In recent years, however, the availability of digital prescribed fire records has substantially increased in several states (Afrin, 2021). Some studies in the Southeastern US focus on Georgia and Florida specifically because these states contain robust digital permits inventories due in part to the hard work of the Georgia Forestry Commission (GFC) and the Florida Forest Service (Jang & Jung, 2023; Odman et al., 2018;

Petralia & Potosnak, 2024). The situation is not uniform in other states, with digital records, when available, lacking or not containing enough data fields (Sadia Afrin & Garcia–Menendez, 2020).

Having more information than was provided in permits, such as exact coordinates, start times, durations, fuel types burned, and atmospheric conditions, would certainly improve the value of bottom-up fire records for air quality assessment (Sadia Afrin & Garcia–Menendez, 2020). Remarkably, there would also be significant value in obtaining post-burn occurrence or treated area data because these permits do not account for this information (Sadia Afrin & Garcia–Menendez, 2020). Addressing these opportunities in the research would further efforts to develop a complete assessment of prescribed fires' impact on air quality across the region. Even though prescribed fires are noted as the primary source of PM2.5 emissions in the Southeast, emissions inventories and observational networks do not come close to capturing the full extent of prescribed fires' impacts (Afrin, 2021; El Asmar et al., 2024). In general, the permit records are often better at measuring actual areas burned than satellite data and vast records of prescribed fires (though there is a dearth of complete prescribed fire datasets for the southeastern states). Interestingly, the records from burn permits are always accurate; however, permit records sometimes inaccurately represent the location (though they require maps), date, and time of burns, thus potentially leading to the misidentification of the location and size of the burn area (Maji, Li, et al., 2024).

2.8.3 Future Climatic Implications: Longer Fire Season, More Frequent Burns

The burning of biomass plays a significant role in total carbon emissions on both a regional and global scale, with global estimates indicating ~2.0 Pg C/year (Reisen et al., 2018). Year-to-year variations in carbon emissions are significant on global and regional scales, as seen during the El Niño years of 1997 and 1998, as well as during the more recent widespread fires, including forest and peatland fires in Southeast Asia in 2015 (Reisen et al., 2018). In Australia, estimated net carbon fluxes because of fire emissions are around 26 Tg C/year (Reisen et al., 2018). Most carbon emissions estimated (~95%) consist of carbon dioxide (CO2), carbon monoxide (CO), and methane (CH4). Furthermore, the fine particulate matter (PM2.5) that is converted to carbon is less than ~5% of the overall carbon emissions (Reisen et al., 2018). While PM2.5 is a very small portion of carbon emissions, it is an important contributor of bushfire smoke and is consistently above air quality standards and causing the greatest risk of adverse health effects associated with biomass burning (Reisen et al., 2018).

Smoke particles also contribute to regional climate (Liu et al, 2014). As climate continues to change, it is predicted that in some areas of the world, large fire events are likely to be more frequent, particularly the western United States, Canada, Australia, and Russia, which will alter air quality and health impacts (Reisen et al., 2018). In the U.S.A., there has been evidence that the frequency and intensity of wildfires have increased over time, which leads to a longer fire weather season defined by more pronounced high temperatures and low humidity. This trend, driven by climate change, has resulted in larger burns (Maji, Li, et al., 2024).

2.9 RELEVANCE TO PRESENT STUDY

2.9.1 Justification for the study at the Jones Center, GA

Ichauway has a range of landscapes including longleaf pine forests, wetlands, river & streams, agricultural fields, and more. The focus is to manage and protect all the various facets of land and facilities. The essential land management practices include an extensive prescribed fire program, ecologically based forest management, and a longleaf pine ecosystem restoration on the Ichauway land (The Jones Center at Ichauway, 2024). Longleaf pine ecosystems were one of the most abundant and widespread forest types in North America, covering over 92 million acres in the Southeast. They have now been reduced to less than 5% of the original range, and therefore, longleaf pine and species associated with longleaf pine are conservation priorities in the region for recovery and restoration. Subsequent benefits provided from longleaf pine forests include wildlife habitat (game and non-game), biodiversity, high-quality timber products, societal benefits and services (e.g., water yield and carbon storage), recreation, and aesthetic value. Ichauway includes approximately 18,000 acres of ancient longleaf pine forests (much of which has not been disturbed and retains native groundcover), creating a rare opportunity to enhance the knowledge and understanding of these ecosystems (The Jones Center at Ichauway, 2024; The Jones Center at Ichauway, 2022).

At Ichauway, staff burn approximately sixty percent of forested acres annually, maintaining a fire-return interval of two years or less. All fire ignitions are ground ignitions via 4-wheel ATVs. Prescribed burning is done year-round, and land management resources dictate the burning, with approximately 35% of burning in the growing season. This fire management enables the integrity of the natural longleaf pine forest structure and function, and reduces fuel loads to limit damage from wildfires (The Jones Center at Ichauway, 2024). There are approximately 50 endangered, threatened, or special concern species, both plants and animals, on the Jones Center property (The Jones Center at Ichauway, 2024). These species include the red-cockaded woodpecker (RCW), gopher tortoise, fox squirrel, Florida pine snake, and gopher frog. The land management of the Jones Center supports the populations of these important species by principally maintaining a high-quality longleaf pine ecosystem, which is sustained through constant fire (The Jones Center at Ichauway, 2024; The Jones Center at Ichauway, 2022). The

Jones Center provides a unique platform for this study due to its strong natural history, integrated fire management, and impressive conservation practice.

2.9.2 Use of MA-200 at Three locations: Upwind, Downwind, and Apartment

The southeastern United States contains one of the most extensive urban-wildland interfaces in the United States, with millions of residents living in areas adjacent to and/or intermixed with fire-prone lands (Afrin, 2021). This, along with regulating prescribed burns when conditions should result in incomplete combustion, has the potential to cause concerns over air quality and public health in surrounding communities (Sadia Afrin & Garcia–Menendez, 2020). Prior research shows that using portable low-cost sensors, which can be deployed in different locations, increases the identification of the smoke events while also increasing the spatial resolution of black carbon concentrations related to the location of the prescribed burns (Liu et al., 2021; Chakraborty et al., 2023; Huang et al., 2021; El Asmar et al., 2024).

This study aimed to apply the same principle by collocating MA-200 sensors at three locations: Downwind, Upwind, and Apartment locations. These locations were selected to see how the BC concentrations varied across those places, relative to the burn location. Regarding the Apartment location, it was chosen because it was a bit far from the burn location, unlike the other locations, presenting an opportunity to explore smoke dispersion at a far distance.

2.9.3 Goals of the Study: Access Spatial Differences in BC Exposure and the Impact of Meteorological Conditions

This study will measure the concentration of black carbon released during a prescribed fire at the Jones Center, based on the previously stated opportunities in literature. The black carbon was measured in several locations to explore variation in spatial context. This study will also examine how weather factors such as wind direction, wind speed, temperature, and relative humidity influence black carbon concentrations at various sites.

2.10 CONCLUSION

2.10.1 Summary of Relevant Findings from the Literature

Prescribed burning (PB) is the controlled ignition of both dead and live vegetation for resource management such as agriculture, land-clearing, silviculture, or simply limiting the scope of the wildfire risk (Jang & Jung, 2023; Odman et al., 2018; Petralia & Potosnak, 2024). Many species of trees survive fire as part of their life cycle in the Southeastern USA forests (Jang & Jung, 2023; Odman et al., 2018; Petralia & Potosnak, 2024). Each year, there are more than 2 million hectares of land undergoing prescribed burning in the Southeastern USA, with Georgia alone treating almost 550,000 hectares each year (Odman et al., 2018; Petralia & Potosnak, 2024). Prescribed fire combined with other sources of air pollution leads to the release of PM2.5 being the predominant contributor in the Southeastern USA where it contributes around 250 Gg from prescribed burning (27% of total emissions), though it remains uncertain just how much prescribed fire contributes to area air pollution (Sadia Afrin & Garcia--Menendez, 2020; Jang & Jung, 2023; Odman et al., 2018).

PM2.5 from prescribed fires is complex and consists of many things: elemental carbon (EC), or black carbon (BC), organic carbon (OC), ionic compounds, trace metals, water-soluble organic carbon (WSOC), water-soluble iron (Fe(II)), particle number concentrations (Carrico & Karacaoglu, 2023; Balachandran et al., 2013; Jaffe et al., 2020; Karanasiou et al., 2021). Black carbon is an essential component of PM2.5 that has been put forth as a critical metric for air quality management due to consistent associations with a variety of negative health effects (Wu et al., 2021). The prescribed burning activity is very dependent on weather, especially precipitation and wind. If a forecast is available, then it can help predict the immediate future of the demand for burning (Jang & Jung, 2023; Odman et al., 2018). Likewise, air quality predictions can rely on forecasts. Given the number of permitting systems already established (across several southeastern states), prescribed burns can be suspended on days of forecasted poor air quality and permitted when their weather conditions are acceptable.

2.10.2 How Does This Study Build On Existing Knowledge

As many studies have examined the PM2.5 and organic carbon levels that arise from prescribed burns, there have been few studies specifically detailing black carbon (BC) concentrations across different micro-locations (site of burn, site immediately Downwind of burn, residential neighborhoods). Pearce et al. (2012) measured PM2.5 concentrations Downwind of burn locations, but did not thoroughly investigate black carbon, which will provide a more specific measure of combustion. Previous studies of the microAeth® series (MA200, MA300, MA350) have highlighted the capacity of mobile BC sensors to determine BC concentrations and capture, with improved spatial and temporal reliability, concentration gradients in these conditions (Liu et al., 2021). This study's data set on BC, as mentioned in Pearce et al. (2012) and the Chicagoland study (2024), which focused on pollutants concentrated Downwind, will provide specific combustion-related insights from the data. It also reinforces the need for localized monitoring methods for burns, particularly for those communities that are more at risk.

Many studies have noted the role of atmospheric conditions such as mixing height, wind speed, and relative humidity, but few studies have analyzed high-resolution black carbon measurements along with meteorological conditions to investigate their effects on micro-scale pollutant dispersion. New data demonstrated that smoke from prescribed fires dispersed significantly differently based on the topography, atmospheric conditions, and fire arrangement (Kondo et al., 2022; Achtemeier, 2009). Still, much of the research is dependent on PM2.5 data or satellite-measured aerosol optical depth (AOD) information; the specific dispersion of black carbon sources, particularly on the surface and in complex terrain, is not widely understood. Such a conclusion can be reached based on those studies conducted in Oregon and New Mexico, which investigated how meteorology could influence pollutant dispersion (Miller et al., 2019; Maji, Ford, et al., 2024). However, they mainly relied on PM2.5 data; this research is important since it can lead to more specific analysis on combustion sources and source sensitivity by employing black carbon measurements.

CHAPTER THREE: METHODOLOGY

3.1 INTRODUCTION

Most previous studies on smoke from prescribed burns have focused on PM2.5 and organic carbon, while there has been less attention on black carbon (BC), which is more associated with combustion as a pollutant. Furthermore, very few studies have reported BC concentrations, or from BC sources, across locations, in and Upwind, Downwind, and within communities adjacent to prescribed burns. Research by Pearce et al. (2012), for example, has illustrated a gradient of PM2.5 surrounding burn sites, but BC remains significantly less studied in this context. Recent progress with portable devices, namely microAeth devices (MA-200, MA-300, MA-350), has demonstrated the ability to take high-resolution spatial and temporal measurements of BC concentrations (Liu et al., 2021). Utilizing the findings from Pearce et al. (2012) and the Chicagoland study (2024) that determined higher pollutant levels in communities located Downwind of emissions using a localized, combustion-based model of BC exposure, data will be generated to promote a more localized monitoring approach for communities near prescribed burn sites in the southeastern US.

Furthermore, while meteorological variables, including wind speed, wind direction, temperature, and relative humidity, are acknowledged to affect the dispersion of smoke, studies that exist that incorporate these confounding variables with high-resolution measurements of black carbon (BC) are few. Much of the current studies rely on either PM2.5 data or satellite-derived aerosol optical depth (AOD), which does not relate directly to any combustion sources. As smoke dispersion is impacted by terrain, fire configuration, and atmospheric dynamics it is useful to improve our understanding of what happens with BC at ground level (Kondo et al., 2022; Achtemeier, 2009). This research effort aims to address these missing factors with BC measurements taken during the prescribed fire at three sites: Upwind, Downwind, and distant that took place at the Jones Center. The purpose was to correlate these measurements to the meteorological data and determine how the concentrations of BC varied spatially, while also assessing how the weather conditions alter pollution dispersion across the different locations.

3.1.1 Flow of the Methodology Chapter

This chapter begins by giving an overview of the methods used, after which it references the research questions and hypothesis statements that would be tested. It then goes ahead to highlight the research designs used in the study. Afterwards, details of the data collection process, sampling, instrumentation, and data analysis methods were explained. Other methodological sub-sections, such as the assumptions, ethical assurances, and quality assurance, would also be looked at before concluding with the summary chapter.

3.1.2 Overview of Methods Used

To address the research questions, black carbon (BC) concentrations were measured during a prescribed burn at the Jones Center in Southwest Georgia using three MA-200 sensors located Upwind (to the Southeast), Downwind (to the Northwest), and on the screened porch of an apartment situated to the Northeast. At the same time, meteorological information (wind speed, wind direction, temperature, and relative humidity) was recorded from a weather station on Jones Center grounds. The BC observations were recorded every minute, while the meteorological observations were made every 15 minutes. R Studio was used to preprocess and integrate meteorological and BC data, as well as perform all analyses.

3.2 RESEARCH QUESTIONS AND HYPOTHESES

The research questions and hypotheses guiding this study have already been presented in Section 1.4 of the introductory chapter.

3.3 STATISTICAL ANALYSIS PLAN

This study utilized an observational design for the exploration of research questions and hypotheses. Data-wise, the descriptive design was used to summarize and report the BC concentrations at the various locations (Upwind, Downwind, and Apartment) relative to the prescribed burn. Descriptive statistics tools, such as summary statistics, box plots, and line charts, were used to observe the general behavior of black carbon and meteorological data (Petralia & Potosnak, 2024). The comparative design was used to see how BC levels differed across different locations, relative to the burn. To obtain BC data, the sensors were allowed to run in three locations, after which statistical tools were used to compare differences between them. Tests such as Kruskal-Wallis were used in this regard, especially as they relate to statistically significant differences.

The correlational design was used to check for relationships between the meteorological variables (wind speed, humidity, and temperature) and BC concentrations. To ensure data uniformity, the timing and date of the BC concentrations and the meteorological data were matched. Scatter plots were used to visualize relationships between BC concentration and meteorological data (Balachandran et al., 2013). Univariate Linear and multiple linear regression models were used to estimate these relationships whilst explaining the differences across the locations (Sadia Afrin & Garcia–Menendez, 2020). Tools such as Google Earth, WRPLOT View, and ArcGIS were used to create visualizations that helped to make sense of the results from a spatial point of view (Carrico & Karacaoglu, 2023; Petralia & Potosnak, 2024).

3.4 DATA COLLECTION DETAILS

3.4.1 Study Location and Population Characteristics

The Jones Center in Ichauway, a large reserve of greater than 18,000 hectares in the lower coastal plains and flatwoods of southern Georgia, is depicted in Figure 1 (DEIMS-SDR, 2023; NSF, 2025). Ichauway is in the Dougherty Plain and is defined by a topography with local elevations above mean sea level of 90 to 200 feet, surficial material made up primarily of sandy soils with poorly drained clays in varying classifications of drainage (excessively drained sands to very poorly drained clays) (The Jones Center at Ichauway, 2024). The terrestrial research areas are mostly located in the southern area of the Jones Center (DEIMS-SDR, 2023). Latitude and longitude coordinates for the Jones Center are approximately 31.19484° N, -84.46861° W (DEIMS-SDR, 2023). The longleaf forests at Ichauway have been actively managed for more than eighty years with ecologically based management strategies frequent prescribed fire and selective cutting of trees. Upland longleaf pine forests make up the largest land cover type at Ichauway, covering approximately 18,000 acres (Jones Center, 2025; The Jones Center at Ichauway, 2024). Apart from the spring prescribed burns held at the Jones Center, which many times start from the month of April, the Jones Center sometimes runs short fire campaigns to see how well the fires burn before the extended fire season. In this study, BC concentration data were obtained from three locations subject to fire (Upwind, Downwind, and Apartment), as seen in Figure 2.

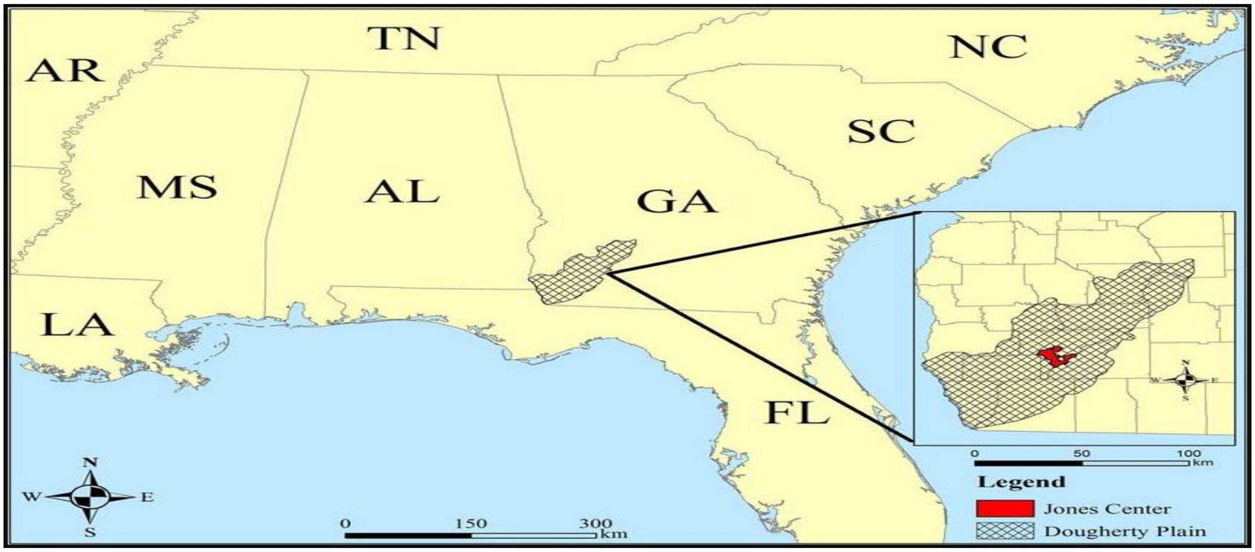


Figure 1: The Joseph W. Jones Ecological Research Center at Ichauway located on the Dougherty Plain in Southwest Georgia (Deemy & Rasmussen, 2017).

Figure 2: MA-200 and prescribed burn locations. Yellow dot: Downwind; Blue dot: Upwind; Orange dot: Apartment; Teal dot: Burn location.

3.4.2 Instrumentation

The MA200 measures optical absorption by black carbon on a filter at five optical wavelengths: infrared, red, green, blue, and ultraviolet (880, 625, 528, 470, and 375nm, respectively). The MA200 uses a commonly accepted measure of black carbon called "equivalent black carbon" (eBC) from the 880nm channel, specifically the IR BCc channel. The

MA200 has a limit of detection of 30 μg/m³ for eBC using a 5-minute time base at a sampling rate of 150mL/min (SingleSpot™ mode) with a resolution of 1ng/m3. For mobile monitoring applications, the MA200 can be used to estimate a person's exposure and measure eBC mass concentrations in different locations (Liu et al., 2021).

In this study, three aethalometers, MA200-0427, MA200-0422, and MA200-0428, were used to measure black carbon concentrations from different locations relative to the prescribed burn. Before deployment, the sensors were prepared and adjusted in the lab, undergoing zero calibration checks and a thorough examination to ensure they were in good condition. In general, the MA200 instrument can monitor black carbon at timescales of 1, 5, 10, 30, 60, and 300 seconds. This study collected black carbon concentrations at a time interval of 1minute.

3.4.3 Data Collection Procedures

Two days before the burn (19th of April 2023), the MA-200-0428 at the Apartment location started recording background concentrations of black carbon. This kicked off from 7:49 pm and ended at 9:43 pm. The next day, the same background concentrations were taken throughout the day from 7:12 am to 9:43 pm. On the day of the burn (21st of April 2023), MA 200-0428 started taking readings from 7:19 am. The other sensors at the Upwind (MA 200-0427) and Downwind (MA 200-0422) locations started collecting their data at 8:56 am. It is noteworthy to mention that the three sensors were collocated side by side, before (9:11 am to 9:34 am) and after the burn (1:00 pm to 1:30 pm), to ensure that they were running as they should and that the readings recorded were consistent.

The sampling time was from 9:45 am to 12:55 pm, and during this time, the three monitors were placed at different locations: MA-200 0428 was placed on the screen porch at the Apartment, MA200-0422 was placed at the Downwind location, and MA200-0427 was placed at the Upwind location. Although some post- and pre-sampling data were available for use, only sampling time data were used for analysis. After data collection, the MA200 sensor's data was downloaded and extracted using the Aethlabs dashboard. Additionally, the meteorological data used in this study were obtained from an on-site weather station located at the Jones Center. The meteorological data spanned from 11:55 pm on April 18 to 11:30 pm on April 21, 2023.

3.5 DATA ANALYSIS METHODS

In this section, the analytical skeleton used to answer research questions and test the hypothesis statements is explored. The tools and techniques used were because of the data structure, variable type, and the aim of the study. Such analytical tools include descriptive statistics, Kruskal-Wallis tests, Dunn's post hoc test, and the univariate linear and multiple linear regression models. Together, these tools ensured that the BC concentrations across the locations were evaluated, while considering the influence of the meteorological conditions.

3.5.1 Research Questions and Hypotheses

The research questions and hypotheses statements directing this study have already been presented in Section 1.4 of the introductory chapter.

3.5.2 Data Types and Sensor Configuration

The data used in this study, black carbon concentration data and meteorological data, were a perfect fit both to answer the research questions and test the hypothesis statements. To ensure uniformity across all sensors, this study made use of the black carbon concentration data run on the single spot mode. Also, it is noteworthy to mention that only the MA-200, located at the Upwind and the Downwind locations, were run in Dual spot mode. This allowed them to use their in-built correction system to correct errors due to high attenuation values.

3.5.3 Data Preparation and Preprocessing

1. Preprocessing Raw BC Data: After extracting the BC data from the MA-200, they were renamed according to their location (A: Apartment, D: Downwind, and U: Upwind) and narrowed down to columns relevant to this study: Date local, Time local, and IR BC 1. The IR BC 1 data was taken at 1-minute intervals and trimmed to the sampling time: 9:45 am to 12:55 pm.
2. Splitting Date and Time**:** The Date local and Time local columns were then split into Year, Month, Day, Hour, Minute columns to aid the merging and further analysis in R Studio. The split operation was carried out using the Microsoft Excel software.
3. Meteorological Data Processing: Meteorological data, recorded at 15-minute intervals, also had irrelevant variables (e.g., soil temperature, pressure) present in its original dataset. To prepare it for merging in R, the original dataset was cleaned to contain only necessary data: Date, Temperature, Wind Speed, Wind Direction, and matched to the same sampling time interval.
4. Data Integration in R Studio:

- Codes were run in R to merge the one-minute BC data from each location.
- The merged one-minute BC dataset was matched to the 15-minute meteorological data using replication logic.

3.5.4 Descriptive Statistics and Visualization

Descriptive statistical tools such as the mean, median, mode, interquartile range, box plots, and line charts were used to explore the variable of interest: black carbon and meteorological data. These tools gave insight into how the variables behave over time across the three locations. Wind Roses were also used to give spatial and directional insight into the wind speed and prevailing wind direction variables across the various locations (El Asmar et al., 2024). Lastly, the ArcGIS software was used to geolocate the sensors and the burn location using coordinates obtained from the MA-200 and one of the burn managers.

3.5.5 Test for Normality

- Histograms were used to visually evaluate distribution symmetry for black carbon and the meteorological data.
- A Shapiro-Wilk Test was completed on the black carbon data to determine if the data were normally distributed. A p-value of 0.05 or lower was considered a rejection of the null hypothesis that the data were normally distributed. Since the source BC data was not normally distributed, all additional analyses were done with non-parametric tests.

3.5.6 Inferential Statistical Tests

- A Kruskal-Wallis Test was used to determine if there was a statistically significant difference between each of the three locations (A, D, and U) regarding the variable of interest (IR BC 1). A p-value lower than 0.05 means that there is statistically significant difference in IR BC 1 pollution between the three sites. A p-value of 0.05 or greater means that there is no statistically significant difference. The Kruskal-Wallis test shows that a difference exists; it does not indicate which specific groups are different from each other (Geeks for Geeks, 2020).
- Then, if the p-value from the Kruskal-Wallis test shows significance, Dunn's Post-Hoc Test (with Bonferroni Correction) is run to figure out which locations differ from one another. Dunn’s Test will indicate the pairs of locations that have statistically significant differences in IR BC 1 pollution levels, respectively.

3.5.7 Modeling Procedures

Data Transformations

- Before running the regression models, the black carbon concentration data were log-transformed to normalize the data and stabilize variance.
- Also, two rows of data were removed from the BC dataset, reducing the 1-minute dataset from 191 to 189 rows of data. NANs and negative values were also removed from the dataset before modelling.

Interpretation of Log-Transformed Coefficients

Since the Black Carbon (BC) concentration data were log-transformed, the coefficients from the regression results mean the following:

- A positive β means that the dependent variable (BC) increases by $(e^{\beta} - 1) \times 100\%$ per unit increase in the predictor variable (wind speed, wind direction, relative humidity).
- A negative β indicates that the dependent variable (BC) decreases by $(1 - e^{\beta}) \times 100\%$.
- To assess smaller unit changes in the predictor variable (e.g., 0.1 or 0.05), the effect on the outcome can be computed by $e^{\beta * 0.1}$ or $e^{\beta * 0.05}$ to provide some further insights into the impact of the variable on the outcome at a finer level.

Visual Adjustments

- The scatterplots in this study showed "stacked vertical" lines, and this was due to the repeated values exhibited by the one-minute meteorological dataset.

Univariate Linear Regression (1-min and 15-min models)

Prior to carrying out the univariate linear regression modeling, the wind direction variable was categorized into eight categories. Also, since the wind direction was a circular variable, histograms were used to visualize it.

<u>Multiple Linear Regression (1-min and 15-min models): Encoding Wind Direction Using Sine and Cosine Components</u>

In meteorology, wind direction (a circular variable) is measured in degrees, and has both 0 and 360 degrees to mean the same thing: wind coming from the north. Since the linear regression model interprets variables linearly, the circularity of the wind direction variable may lead to wrong conclusions when used as is. To account for this, wind direction was converted to continuous components: north-south, east-west, using sine and cosine transformations, using the formula below:

$$\theta_{math} = (270 - \theta_{met}) \mod 360$$

$$\theta_{rad} = \theta_{math} \times \frac{\pi}{180}$$

$$wind_x = \cos(\theta_{rad}), \qquad wind_y = \sin(\theta_{rad}),$$

Equation 1: Transformation of Wind Direction into East–West and North–South Components

- θ_met: the actual meteorological wind direction in degrees that represents the source of the wind flow.
- θ_math: an adjusted angle that is modified to comply with the accepted mathematical standard, where 0° is East.
- θ_rad: the same angle converted from degrees to radians to allow it to be used with mathematical functions.
- cos(θ_rad): gives us the east-west wind component (wind_x).
- sin(θ_rad): gives us the north-south wind component (wind_y).

The wind_x and wind_y components were then utilized as predictor variables in the multiple linear regression model. This allows the model to pinpoint circular wind direction as opposed to using raw wind direction that could confuse the model into separating 0° and 360° as two distinct directions. A multicollinearity test was performed on the predictor variables before finalizing the results of the multiple linear regression (MLR) model to ensure reliable and clear estimated coefficient values. The Variance Inflation Factor (VIF) was computed for each predictor to fully assess multicollinearity (Khan et al., 2018). VIF values that exceed a range of 5 - 10 are typically seen as indicative of substantial multicollinearity.

3.6 ETHICAL AND QUALITY ASSURANCE

The data used in this study were environmental and did not use human subjects, and so there was no need for ethical approvals or consent from the Institutional Review Board. To guarantee the reliability and validity of the research findings, statistical measures such as standard error and standard deviation were used. This was to check for the variations and consistency of the black carbon emissions data across the different locations. Also, pre-deployment procedures such as the calibration and test run of instruments, consistent data collection intervals, and adequate documentation of all analysis steps were followed strictly. All these procedures make sure that the results of this research endeavor are replicable and trustworthy.

3.7 SUMMARY

In this chapter, the application of an observational research design included descriptive, comparative, and correlational methods to answer the research questions and test the hypotheses. The observational research design (i.e., descriptive, comparative, correlational) provided a structure that guided the data collection and analysis necessary to contribute to the existing knowledge in the air quality space. The analytical framework provided some insights that would be useful for thinking about air quality and prescribed fire scenarios. In the following chapter, the results from the analysis will be presented and discussed.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 INTRODUCTION

This chapter presents the findings of the data analysis to answer the research question and test the hypothesis statements. It starts by restating the research questions and hypothesis statements, then describes the characteristics of the sample. It then details the results from the analyses that correspond with the research questions and hypotheses, followed by discussions interpreting, contextualizing, and relating the findings to the existing literature. Finally, implications for policy, research, industry, theory, and practice will be discussed.

4.2 SAMPLE CHARACTERISTICS

This section gives a summary of the variables used in this study, including their notations and units of measurement. These variables denote the black carbon concentrations and the meteorological conditions across the different locations (A, U, and D). They are listed below:

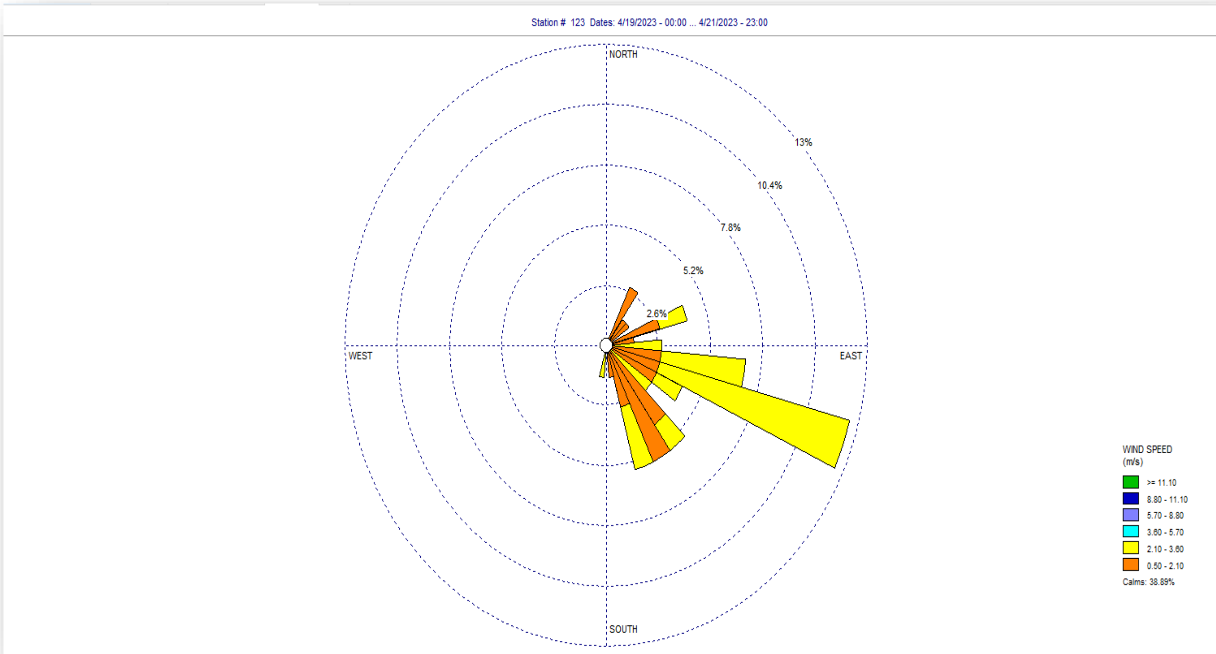
- **T** – Temperature measured in Degrees Celsius (℃). This variable represents the temperature of the surrounding environment during the sampling period.
- **WD** – Wind Direction measured in Degrees (˚). This shows the direction that the wind is blowing from.
- **WS** – Wind Speed measured in Mps (m/s). This denotes how fast the air is moving at the study location.
- **RH** – Relative humidity measured in Percentage (%). This depicts how much water vapor is in the air at a particular temperature (Cottingim, 2018).

- **A Location BC** – Black carbon data taken at the Apartment Location measured in Micrograms/Meter Cubed (μg/m3). This represents BC concentrations at the outdoor premises of the Apartment.
- **U Location BC** – Black carbon data taken at the Upwind Location measured in Micrograms/Meter Cubed (μg/m3). This depicts BC concentrations Upwind of the burn.
- **D Location BC** – Black carbon data taken at the Downwind Location measured in Micrograms/Meter Cubed (μg/m3). This depicts BC concentrations Downwind of the burn.
- **IR BC1**: Black carbon data extracted from the Infrared wavelength taken at a single spot.

Table 1: Summary Statistics of Meteorological Data Over Time (19th to 21st April 2023)

Variable	Mean	Mode	Median	Q1	Q3	IQR	Minimum	Maximum
T	20.1	28.1	21.2	13.0	26.9	13.8	7.8	29.6
WS	1.1	0	1.2	0.1	2.1	2.0	0	3.3
RH	60.9	100	56.7	36.1	89.8	53.7	22.2	100

Over the course of the three days (19^{th} to 21^{st} of April), the mean values across all the variables, RH, WS, and T, were found to be 60.9%, 1.1m/s, and 20.1°C, respectively. The minimum and maximum values across the board were T (7.8°C, 29.6°C), WS (0m/s, 3.3m/s), and RH (22.2%, 100%), respectively. Looking at the summary statistics table, it shows low temperature ranges, which are typical of the spring season, typically characterized by temperate weather. Also, the observed wind speed values are typical of prescribed burns, as it makes more sense to carry them out under not too windy conditions, so that they do not go out of control. Notably, the most prevalent wind speed was found to be 0m/s, indicative of a calm wind situation. These observations were further reinforced by the Wind class frequency distribution and the categorized wind direction figures shown in Figures 3a and b.



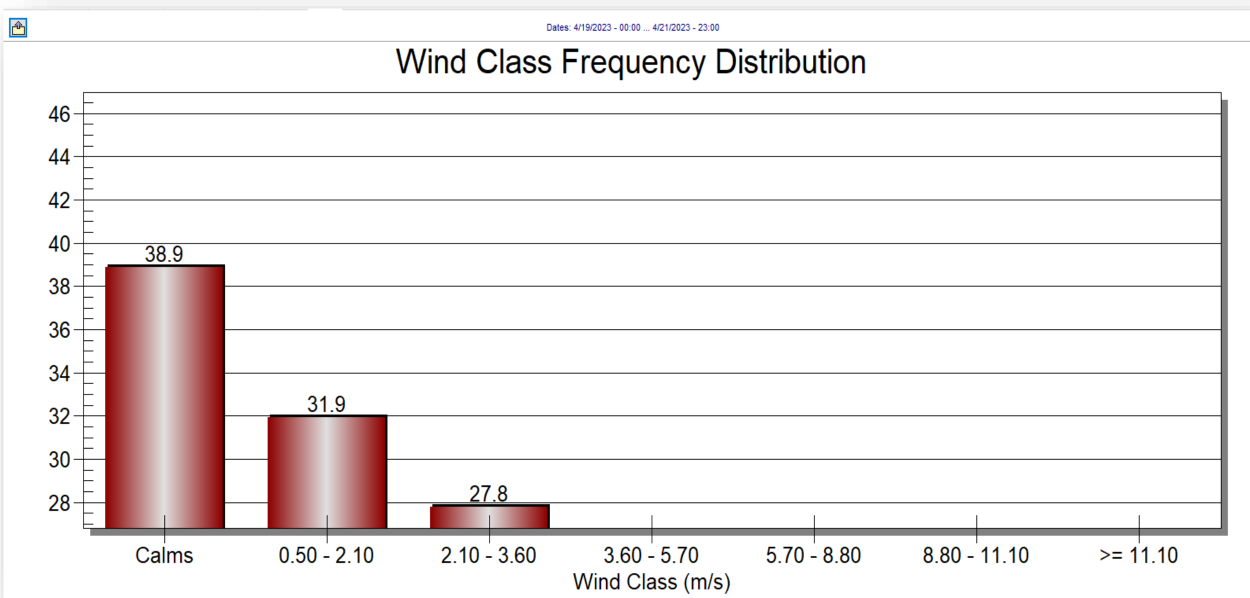


Figure 3a-b: Wind Rose and Wind Class Frequency Distribution Across All Days

Table 2: Summary Statistics of IR BC1 Over Time on April 19, 2023

Variable	Mean	Median	Mode	Q1	Q3	IQR	Minimum	Maximum
A	2,322	2,290	2,268	2,236	2,388	152	2,068	3,066

Table 3: Summary Statistics of IR BC1 Over Time on April 20, 2023

Variable	Mean	Median	Mode	Q1	Q3	IQR	Minimum	Maximum
A	994	463	422	319	841	522	30	5,059

Table 4: Summary Statistics of IR BC1 Over Time on April 21, 2023

Variable	Mean	Median	Mode	Q1	Q3	IQR	Minimum	Maximum
A	721	682	828	498	892	394	203	3,324
D	24,143	1,988	-758	-108	7,703	7,811	-8,071	383,508
U	7,323	670	608	464	922	458	-779	2,939

Tables 2 and 3 were taken from the Apartment location. The high concentrations recorded there (especially on the first day, 2,322μg/m³) had dropped to 721 μg/m³ by the third day. Also, as expected, the IR BC 1 concentrations at the Downwind location recorded the highest mean concentrations, 24,143 μg/m³, compared to the other locations, with concentrations of 734μg/m³ at the Upwind location and 721 μg/m³ at the Apartment location. The negative values that kept showing up in the Downwind location were owing to the instrument's signal noise caused by the unstable flow.

4.3 FINDINGS OF DATA ANALYSIS

4.3.1 Findings of Data Analysis Organized by Research Question

4.3.1.1 Hypothesis Statement 1

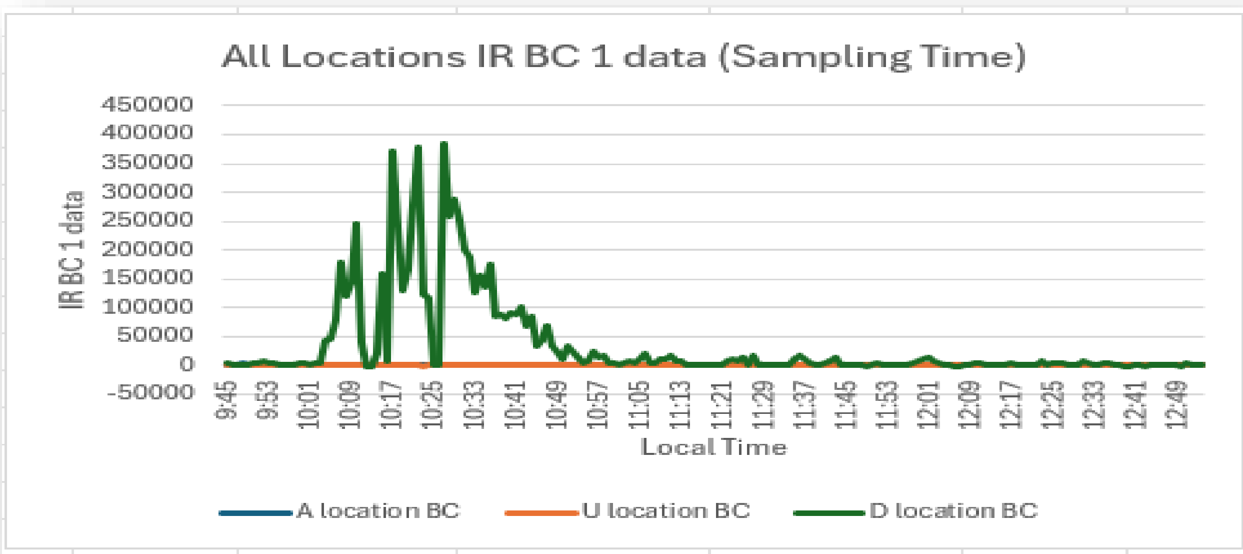
H1: BC concentrations will be significantly higher at Downwind locations compared to Upwind and Apartment sites during and after the prescribed burn.

4.3.1.2 Descriptive Statistics

For the first research question, the table below summarizes descriptive statistics of the BC concentration data that were collected in locations during the sampling period (prescribed burn).

Table 5: Summary Statistics of IR BC1 Over Time on April 21, 2023 (Sampling Time)

Location	Mean	Median	Mode	Q1	Q3	IQR	Minimum	Maximum	Standard Deviation
A	664	600	474	499	780	281	344	3,324	283
U	678	625	682	493	821	328	207	1,871	258
D	34,028	2,901	2,670	312	17,129	16,817	-2,095	383,508	73,882



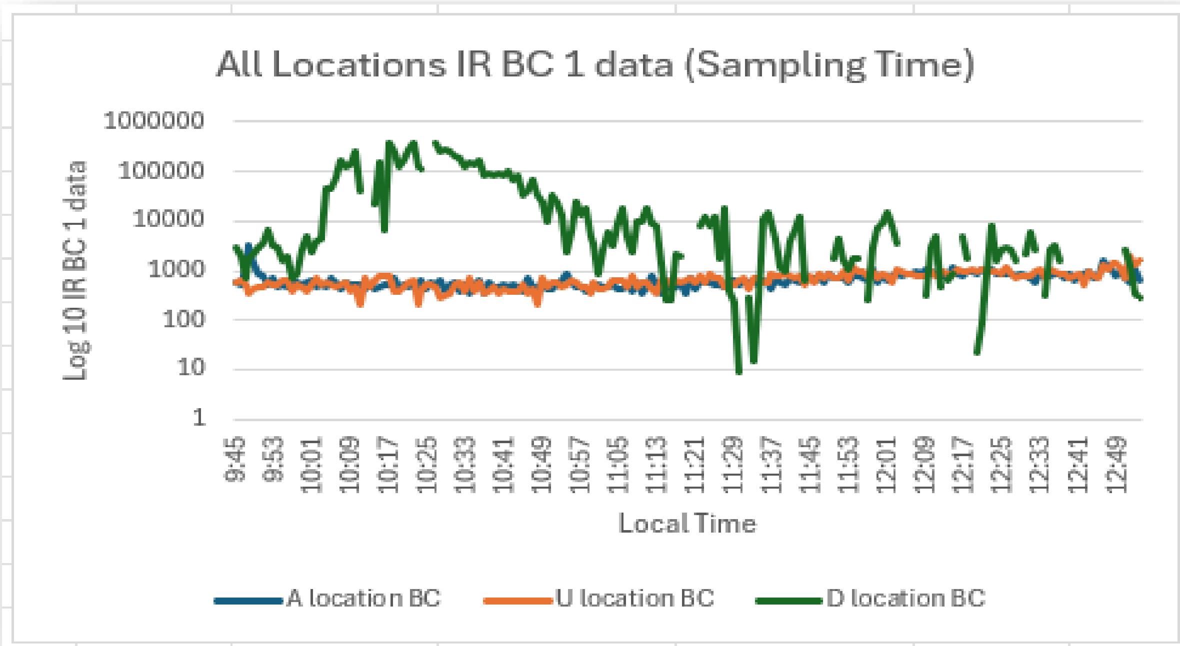


Figure 4a-b: Line charts showing IR BC1 concentrations across all locations during the sampling period. The chart on the left displays the data on a normal scale, while the chart on the right shows log-transformed values (base 10) to highlight differences between the IR BC1 concentrations at the Upwind and Apartment locations.

The values in Table 5 are consistent with Table 4, the Downwind location has the highest mean IR BC 1 concentration (34,028 µg/m³), with the Upwind and Apartment locations subsequent but not very close (678 µg/m³ and 664 µg/m³, respectively). This clearly illustrates that the Downwind sensor had the highest exposure to black carbon emissions. Also, as seen in Figures 4a and 4b, concentrations at the Downwind location began to peak at approximately 10:00 a.m., with concentrations reaching over 383,508 µg/m³ until approximately 10:49 a.m. The peak concentrations over the Downwind location are the only clear peaks, as subsequent smaller peaks occurred between 11:00 a.m. and noon, but to a much lesser extent than the first higher peak had occurred. Low dips were also observed for the Downwind location, at 11:29 a.m. and 12:17 p.m. (Figure 4b).

Although they are geographically distant from each other, the Upwind and the Apartment locations are capturing relatively similar BC concentrations (Table 5). This indicates that the plume dispersion and meteorology in those areas were similar, unlike the conditions observed Downwind. The high concentrations of black carbon observed by the Downwind location could have been attributed to the intense release of smoke when the fire was first lit and actively burning biomass. As the fire lost intensity, the smoke production was also probably diminished, resulting in decreasing concentrations of BC.

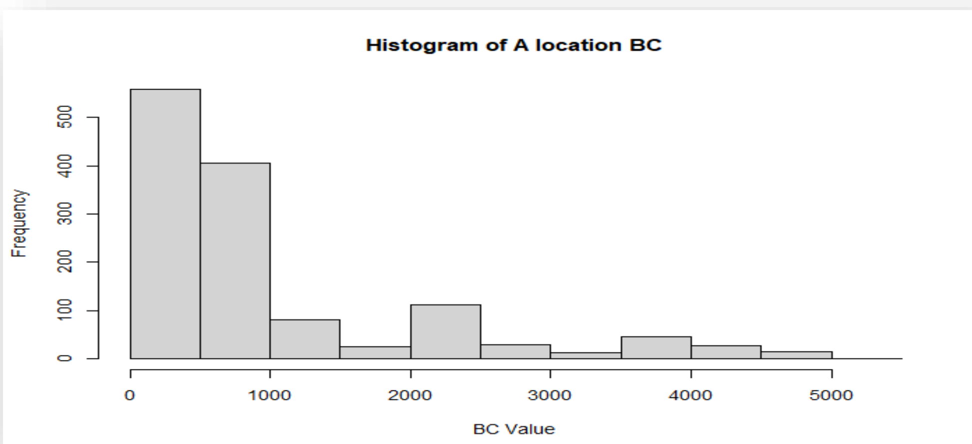
The median values show a similar trend to the means, with the Downwind location being the highest median concentration of black carbon at 2,901 $\mu g/m^3$, while the Upwind location and Apartment location recorded 625 $\mu g/m^3$ and 600 $\mu g/m^3$ of median black carbon, respectively. The relatively high amount of median black carbon at the Downwind location, in combination with its maximum value of 383,508 $\mu g/m^3$, indicates many high-concentration values. Likely, these extreme values are mostly in the right tail of the distribution; the high maximum value also shows that the distribution of values is very positively skewed, which will necessitate normalization of data before continuing with analyses.

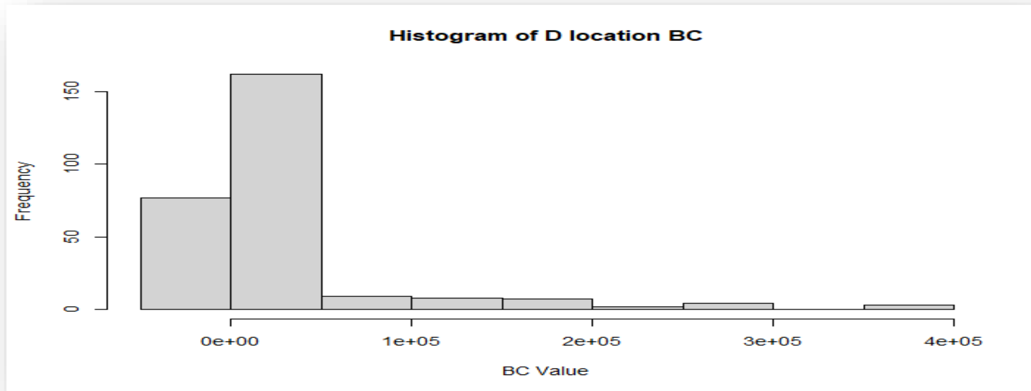
As seen in Table 5, standard deviation provides a snapshot of variation in black carbon (BC) concentrations in the three locations. Locations A and U elicited relatively low standard deviations, 283 $\mu g/m^3$ and 258 $\mu g/m^3$, respectively, suggesting that the BC concentrations at these locations were relatively consistent in their location and clustered around their respective means (664 $\mu g/m^3$ for A and 678 $\mu g/m^3$ for U). Conversely, location D exhibited an extremely large standard deviation of 73,882 $\mu g/m^3$, vastly exceeding the mean of 34,028 $\mu g/m^3$, implying a substantial variation from the mean, an exaggerated degree of variability, and outliers within the dataset. Moreover, the interquartile range of 16,817 µg/m³, the negative minimum of -2,095 µg/m³, and the marginally considerable differences between the mean and median (2,901 µg/m³) suggest an asymmetric distribution in location D.

4.3.1.3 Inferential Statistics

Tests for Normality

Before carrying out any advanced analysis, black carbon concentration data (1 minute and 15 minutes) were checked to see if they followed a normal distribution. This was an essential step that was used to determine the methods to use to run further analysis. To start with, histograms were used to visually check for normality, followed by the Shapiro-Wilk normality test, which provided a solid assessment of normality. The results from these tests (shown below) gave more direction to the type of inferential tests (parametric or non-parametric) used for further analysis.





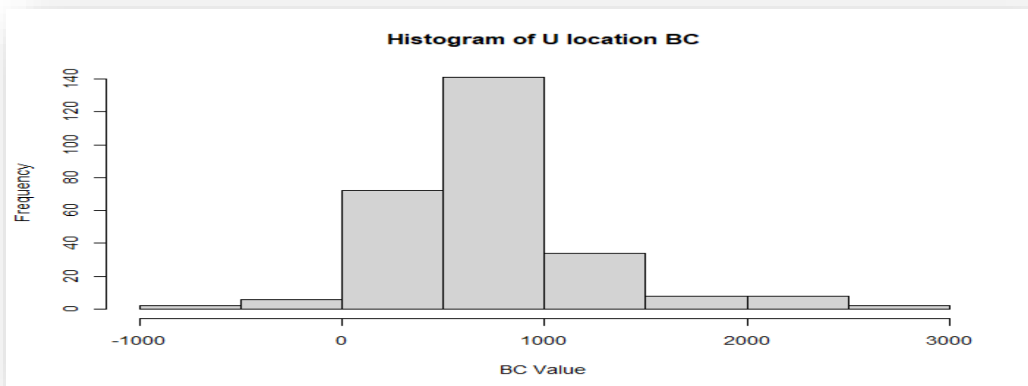
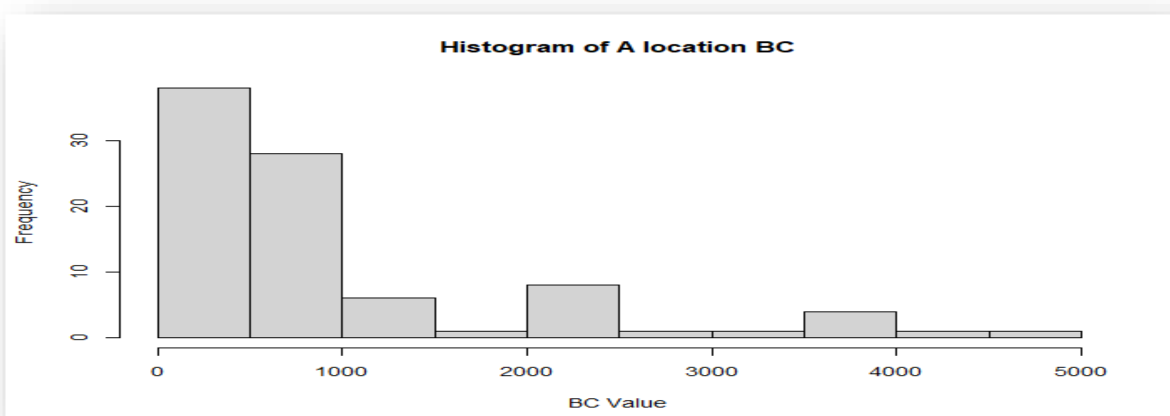
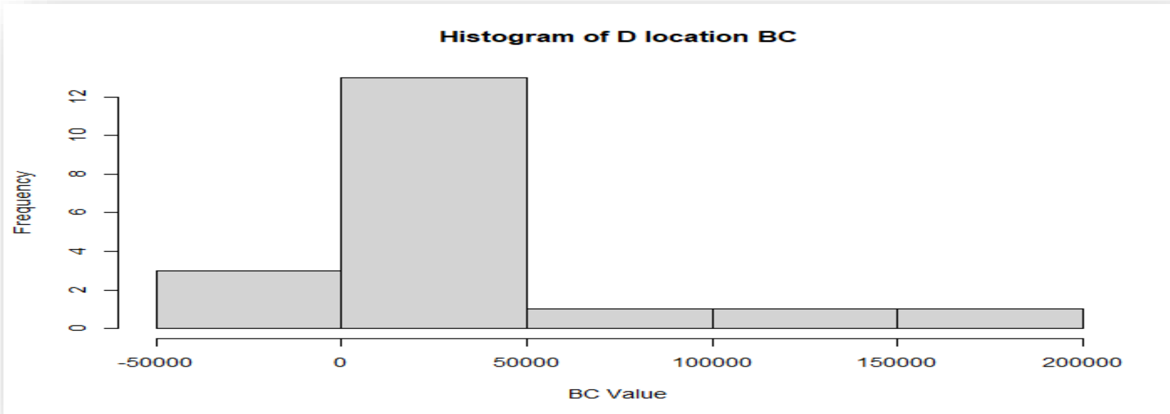


Figure 5a-c: Histograms of IR BC1 Data Recorded at One-Minute Intervals





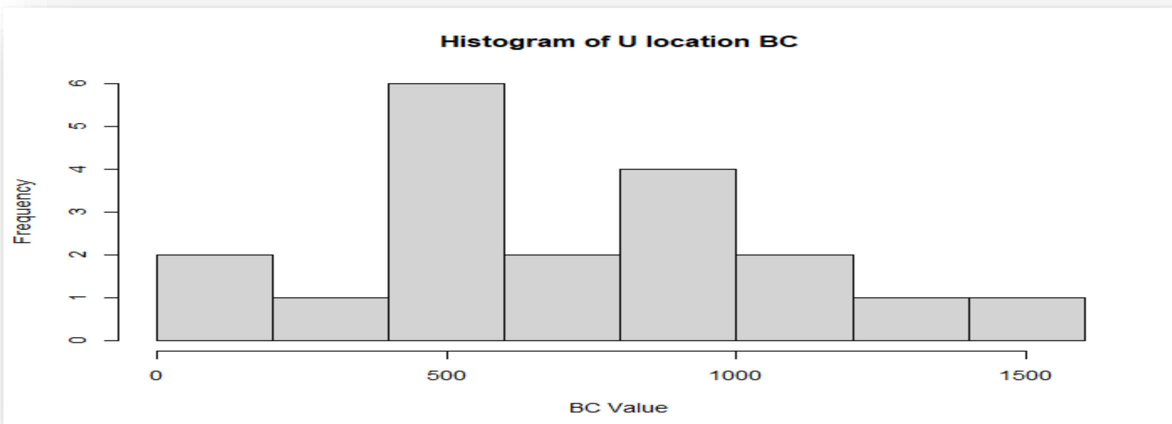


Figure 6a-c: Histograms of IR BC1 Data Recorded at Fifteen-Minute Intervals

Visually, the distribution of the IR BC 1 at most of the locations appeared skewed to the right, both under the 1-minute and the 15-minute data. The only exception was the U location BC data, whose distribution looked like that of a normal curve, compared to the other locations. The Shapiro-Wilk test was also conducted to check for normality across locations and time intervals. The results are outlined below:

Table 6: Results of the Shapiro-Wilk Normality Test for IR BC1 Data

Variables	W Value	P Value
One Minute:		
A location BC	0.72	< 2.2e-16
U location BC	0.90	1.10e-12
D location BC	0.44	< 2.2e-16
Fifteen Minutes:		
A location BC	0.69	1.85e-12
U location BC	0.96	0.48
D location BC	0.52	7.46e-07

The results from the Shapiro-Wilk normality test show that for the one-minute data (all locations), their distribution was significantly different from the normal distribution ($p < 0.05$). The only dataset whose distribution was not significantly different was the U location BC (the 15-minute data). Since it was the only one in that category, all the datasets were classified as being non-normally distributed, qualifying them to be analyzed using non-parametric statistical tests.

<u>Test for Non-Normality: Kruskal-Wallis Test</u>

Table 7: Kruskal-Wallis Test Results for IR BC 1

Variable of concern	Chi-squared	Df value	P-value
One Minute IR BC 1	70.00	2	6.30e-16
Fifteen Minutes IR BC 1	22.75	2	1.15e-05

These results show that there is a significant difference (p value less than 0.05) in the black carbon concentrations both in the one-minute and the fifteen-minute datasets. In a bid to know which of the location pairs differ significantly, Dunn's post-hoc test was conducted.

Table 8: Dunn's Test Results (Bonferroni Method) for IR BC 1

Variable of concern	Locations	Z	P. Unadjusted	P. Adjusted
One Minute IR BC 1	A - D	7.48	7.57e-14	2.27e-13
	A - U	0.48	6.30e- 1	1e+ 0

	D - U	-7.00	2.63e-12	7.88e-12
Fifteen Minute IR BC 1	A - D A - U D - U	4.04 -0.17 -4.21	0.00005 0.86 0.00003	0.0002 1 0.0001

For the one-minute and fifteen-minute datasets, Dunn's post-hoc test results disclosed that the A location BC and D location BC pairs, were not just different as seen through the summary statistics, but these differences were also statistically significant (p value < 0.05) (Jang & Jung, 2023).

4.3.1.4 Summary

The analysis conducted in this sub-section showed that Downwind BC concentrations significantly differed from the Upwind and Apartment locations. Firstly, the summary statistics revealed that the highest concentration value of 34,028 µg/m³ was recorded at the Downwind location, compared to the Apartment and Upwind locations, which recorded values of 664 µg/m³ and 678 µg/m³, respectively. Results from the Kruskal-Wallis test showed that such differences were statistically significant with p values less than 0.05, across the one-minute and fifteen-minute datasets. Also, the 1-minute and 15-minute datasets, tested using Dunn's post-hoc test, revealed that the differences in black carbon concentrations between the Apartment (A), Upwind (U) locations, and the Downwind (D) location were not only obvious but also statistically significant ($p < 0.05$).

Studies like those conducted by Sablan et al. (2024) and Ravi et al. (2018) emphasize the fact that particulate matter concentrations do not disperse quickly Downwind of fires. Such heightened concentrations can have a significant impact on air quality, visibility, and health. This further reinforces the fact that more attention needs to be paid to communities that live

Downwind of these fires, either through policies that limit such burns or community engagement meetings through which the potential air quality risks are effectively communicated. Also, giving such communities tools that they could use to possibly monitor their air quality is quite important, as such measures would inadvertently affect their general health and well-being.

4.3.2 Results of Data Analysis by Research Question

4.3.2.1 Hypothesis Statement 2

H2: Meteorological conditions, specifically wind speed, wind direction, temperature, and relative humidity, will influence concentrations of BC.

4.3.2.2 Descriptive Statistics

To answer the second research question, the table below gives a descriptive statistic of the Meteorological data during the sampling time (prescribed burn).

Table 9: Summary Statistics of Meteorological Over Time on April 21, 2023 (Sampling Time)

Variable	Mean	Median	Mode	Q1	Q3	IQR	Minimum	Maximum
T	25.1	25.2	N/A	24.3	25.8	1.5	23.0	26.8
RH	45.3	46.5	N/A	40.3	50	9.7	35.1	56.7
WS	2.8	2.7	N/A	2.6	3.1	0.5	2.1	3.2

The summary of the meteorological conditions during the sampling period is provided in the table above. Relative humidity is a measure of the amount of moisture air can hold at a specified temperature and pressure. Relative humidity was moderate, with an average of 45.3% and a maximum of 56.7%. Wind speeds were relatively low and consistent throughout the period, with the maximum wind speed of 3.2 m/s very close to the mean wind speed of 2.8 m/s. Ambient temperature ranged from 23.0°C to 26.8°C, which is also a typical temperature for the time of day and time of year. "NA" values in the mode column across variables were not unexpected for the short sampling window.

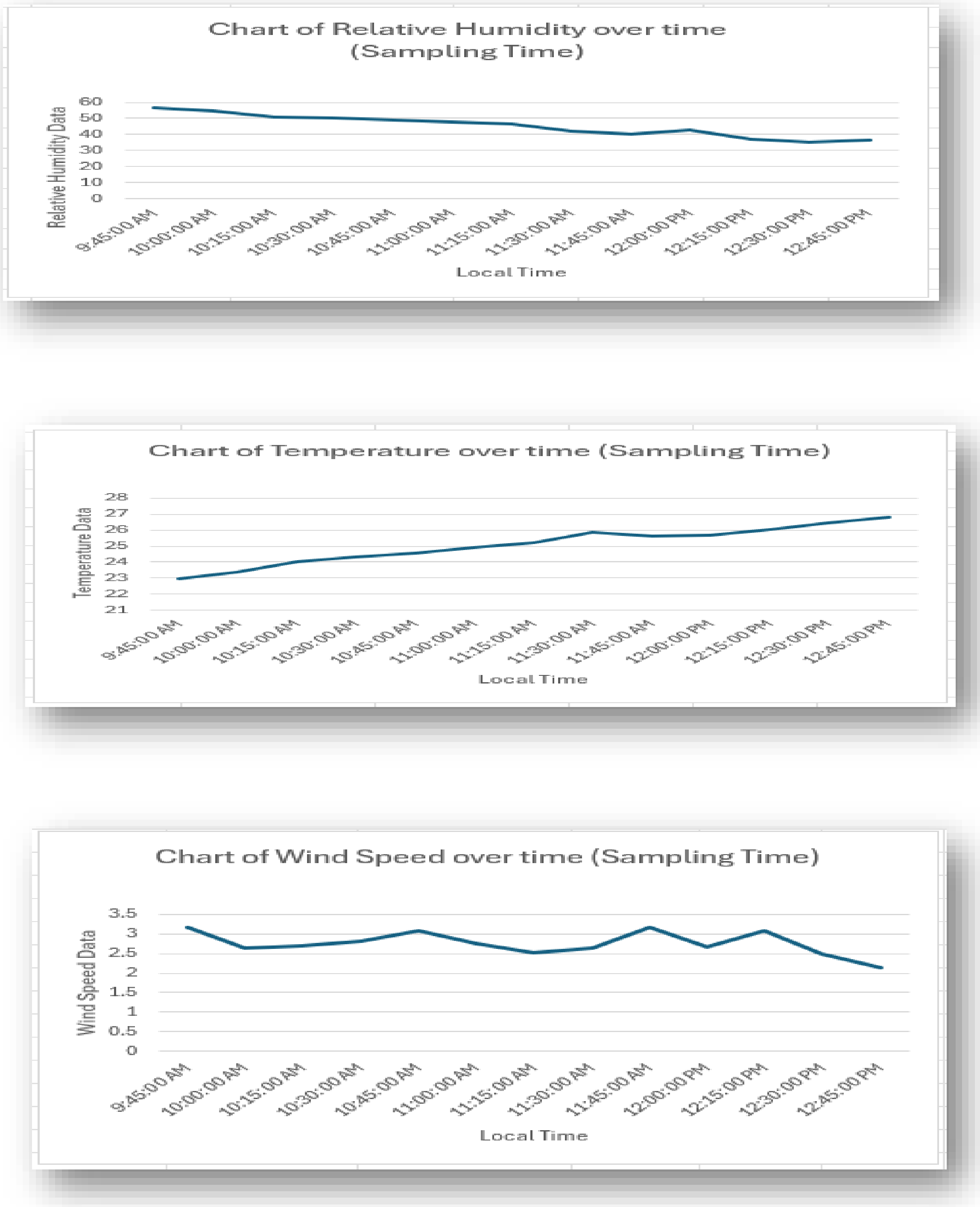


Figure 7a-c: Line charts showing Meteorological data during the sampling period.

The charts above show several interesting trends. Relative humidity has a general trend downward over the sampling period, decreasing from the maximum of 56.7% to approximately 36.7%. Temperature has a general trend upward, from 23.0°C to 26.8°C, which is consistent with the time of day and the spring season in which the burn occurred. The downward trend of relative humidity and upward trend of temperature are expected because warmer air can hold more moisture, which will decrease relative humidity even though the amount of water vapor remains the same. Wind speed exhibited some variation, starting at the maximum of 3.2 m/s and fluctuating throughout the sampling time by 0.5m/s.

Interestingly, Figure 4b shows that the same period (9:45 to 10 am) during which the BC concentrations spiked at the Downwind location coincided with the increase in temperature and wind speed, and a decrease in relative humidity variables. Also, since the Wind Direction variable is a categorical, circular variable, it was grouped into logical bins before running the analysis (linear regression analysis). The bins are shown in the table below:

Table 10: Categorization of Wind Direction

Category	Wind Direction Range (°)
0	0 (Calm winds)
1	0° - 45° (N-NE)
2	45° - 90° (NE-E)
3	90° - 135° (E-SE)
4	135° - 180° (SE-S)
5	180° - 225° (S-SW)
6	225° - 270° (SW-W)
7	270° - 315° (W-NW)
8	315° - 360° (NW-N)

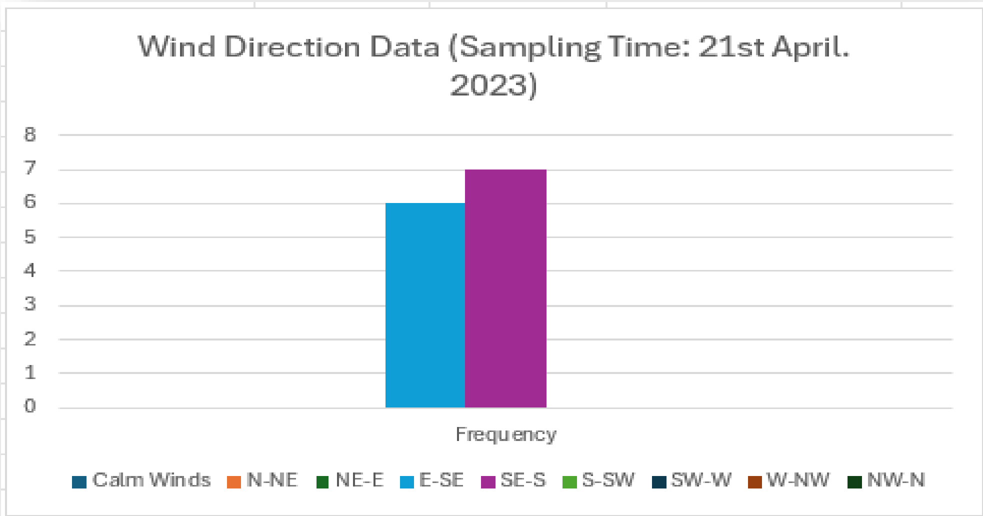


Figure 8: Histogram of Wind Direction Data taken during the Sampling time

The grouped wind direction was also plotted on a histogram, and from Figure 8, categories 3 and 4, indicative of the (E-SE) and (SE-S), were the prominent directions in the sampling time. The wind rose was plotted using the wind speed and wind direction, streamlined to the sampling time, also affirming this as they show the directions that the wind was blowing from the 106.3° to 168.9° range. In addition, the wind class frequency chart shows that the prominent wind speed recorded at that time fell within the class 2.1m/s to 3.6m/s, pointing to decent and constant wind conditions throughout the sampling time.

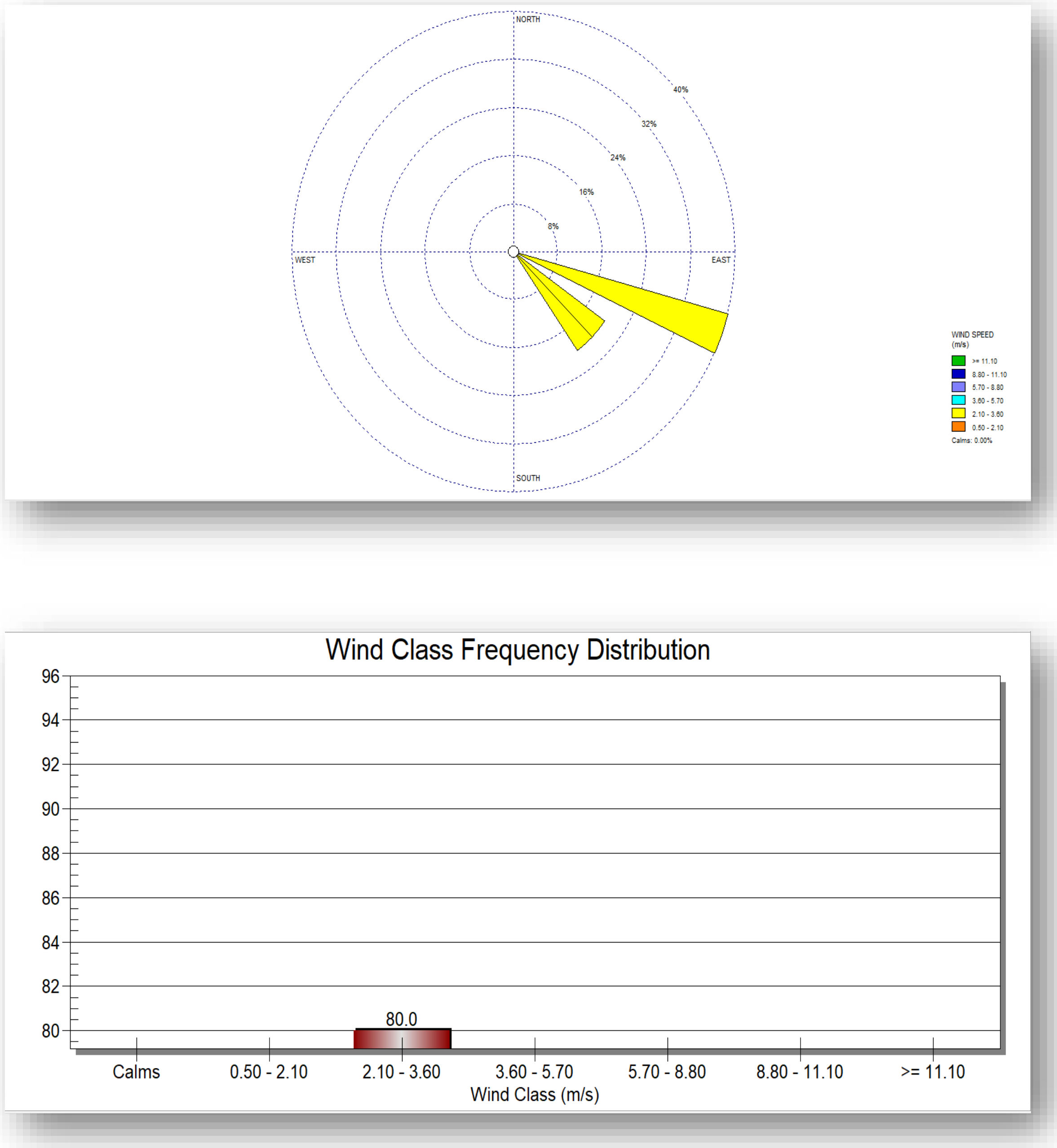


Figure 9a-b: Wind Rose and Wind Class Frequency Distribution during the Sampling Time

4.3.2.3 Inferential Statistics

The results of the logarithmic transformation of black carbon data at one minute and fifteen minutes are shown below.

Table 11: Log Transformation of the non-normal variables (One Minute and Fifteen Minutes)

Transformation Stage	Variables (Skewness values)		
	A (1 Minute)	D (1 Minute)	U (1 Minute)
Pre Transformation	4.80	2.82	1.15
Post Transformation	0.93	-0.14	-0.16
	A (15 Minutes)	D (15 Minutes)	U (15 Minutes)
Pre Transformation	0.27	1.76	0.71
Post Transformation	0.19	0.66	0.37

The next set of results are those that were obtained from the regression models (univariate linear and multiple linear regression models).

Univariate Linear Regression Results

General Univariate Linear Regression Model Formula: ***y = a + bx***

Y: dependent variable, e.g., A location BC, U location BC, D location BC

X: independent variable, e.g. WS, WD (category), RH, T.

logy= a + bx could then be: logA location BC = a + bWS

(This study's univariate linear regression model formula)

Figures 10-12 show scatter plots with regression lines that detail the linearity between black carbon concentrations at A, D, and U sites with the independent meteorological variables (temperature, wind speed, relative humidity) measured at 15-minute intervals.

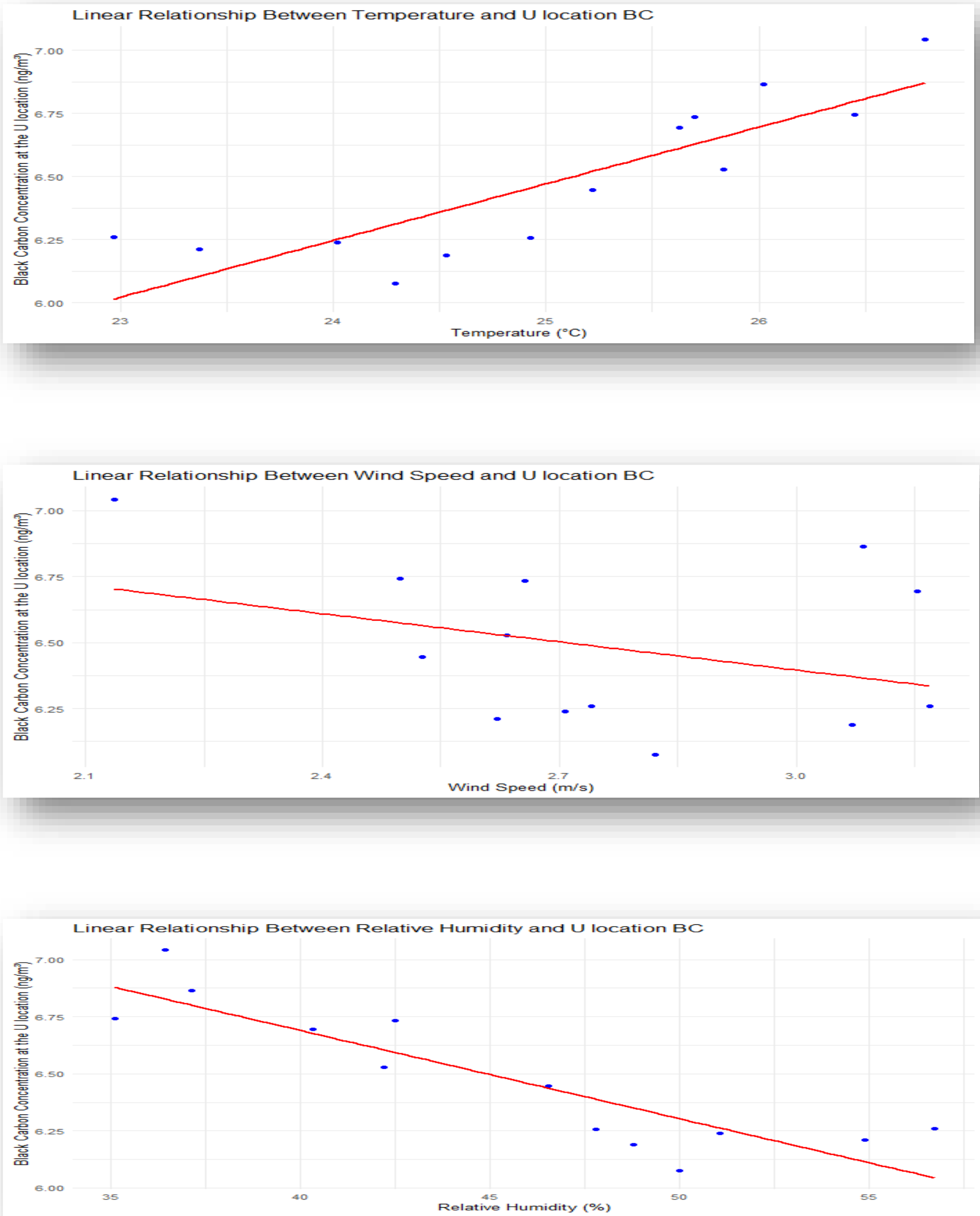
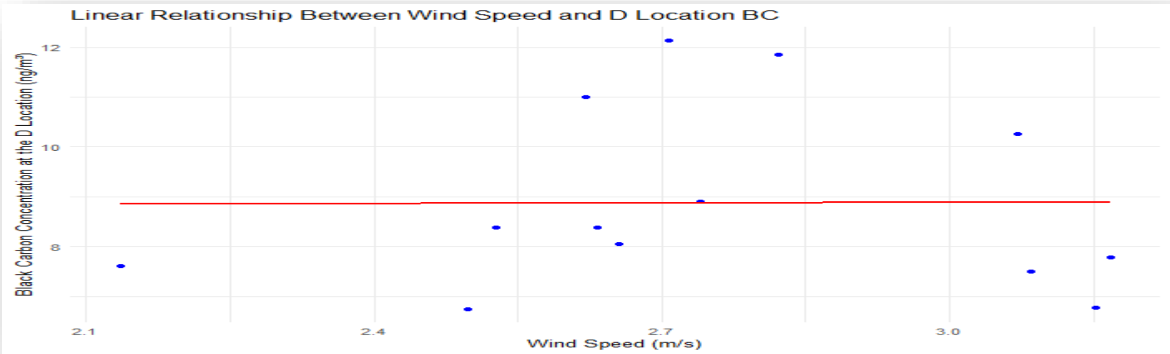
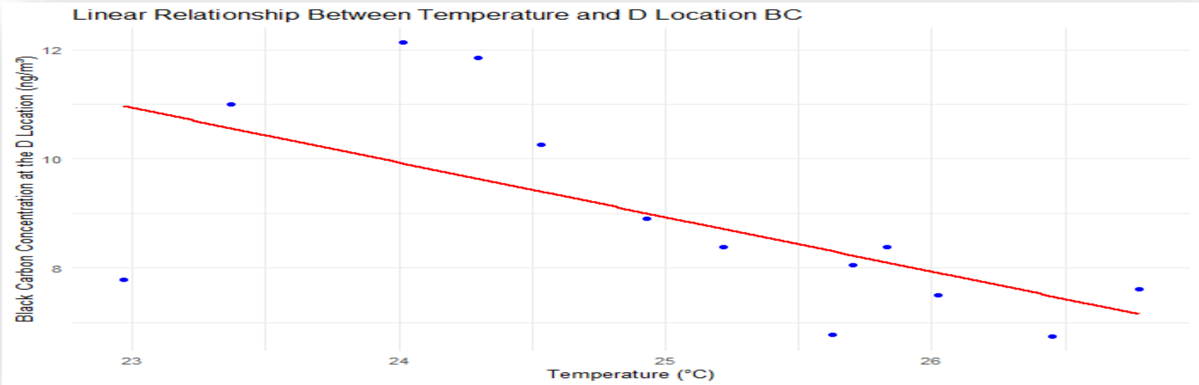


Figure 10a-c: Scatter Plots with Regression Lines for the Upwind (U) Location Showing Relationships Between Black Carbon (BC) and Temperature, Wind Speed, and Relative Humidity (Fifteen Minutes)





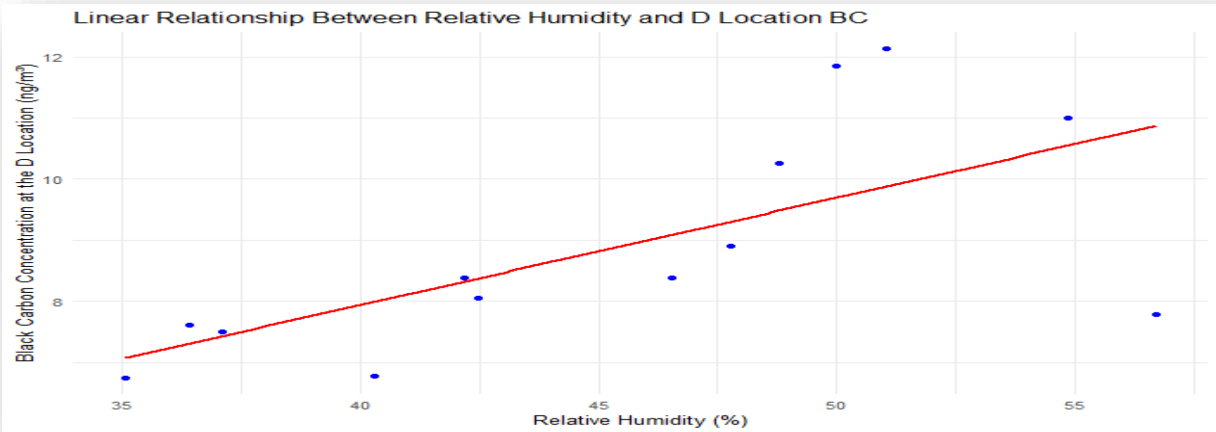


Figure 11a-c: Scatter Plots with Regression Lines for the Downwind (D) Location Showing Relationships Between Black Carbon (BC) and Temperature, Wind Speed, and Relative Humidity (Fifteen Minutes)

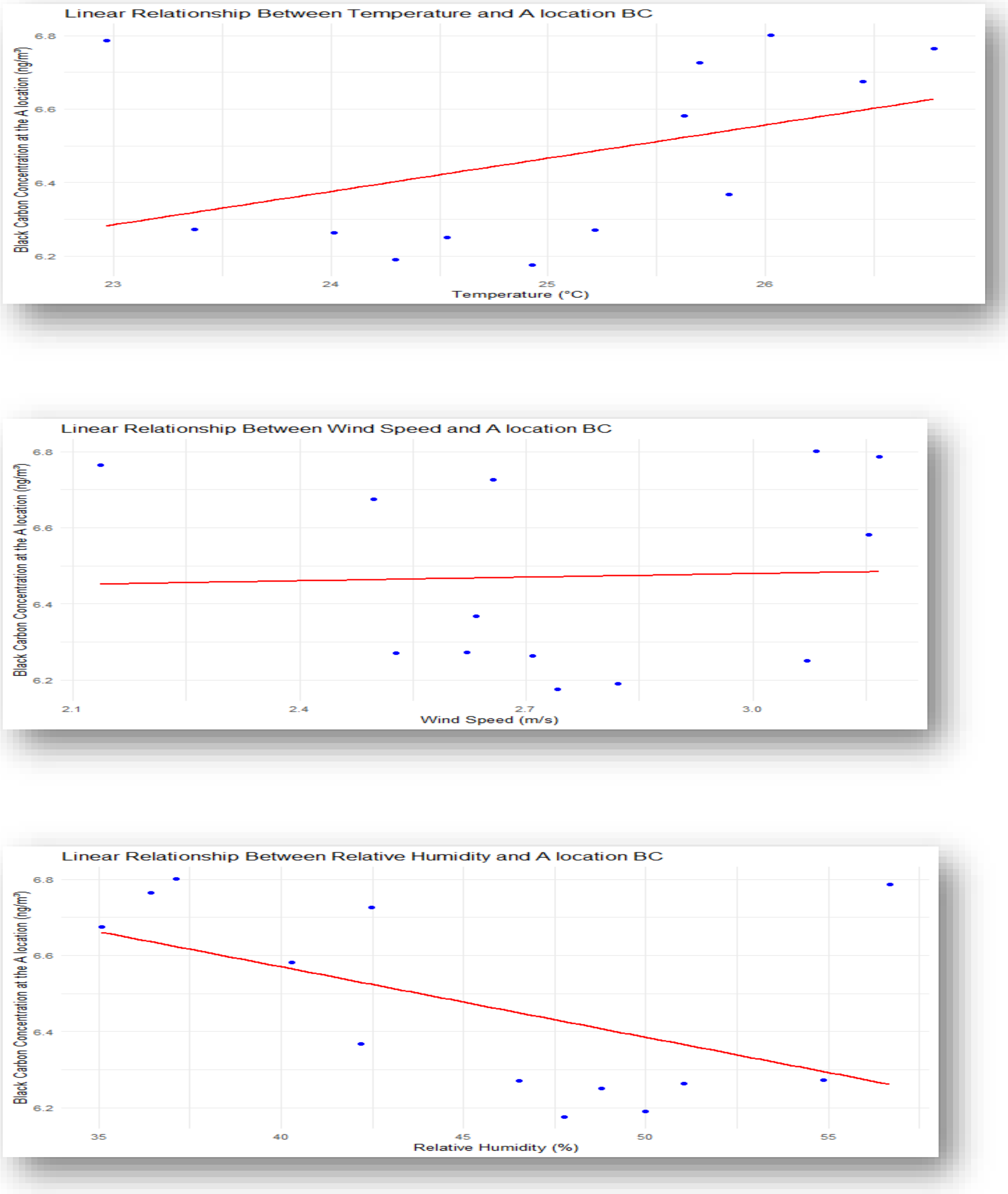


Figure 12a-c: Scatter Plots with Regression Lines for the Apartment (A) Location Showing Relationships Between Black Carbon (BC) and Temperature, Wind Speed, and Relative Humidity (Fifteen Minutes)

Even after the natural log transformation of black carbon concentrations to stabilize variance and to eliminate skewness in the distributions, the regression lines and scatter plots produced from the simple linear regression models exhibited weak linear relationships between the individual predictors and the ln black carbon concentrations. The visual inspection of the individual plotted points, not closely clustered about the fitted regression lines, suggested that the influence of the individual predictor(s) on the log-transformed black carbon concentrations could not be explained in isolation. Acknowledging the cumulative effects and possibly interactions of multiple predictors was necessary. This was the rationale for transitioning to a multiple linear regression (MLR) model and a more expansive model of relationships. Overall, the patterns seen between the one-minute and the fifteen-minute data were similar. The fifteen-minute plots were provided here because they resulted in clearer patterns between the predictor and response variables, unlike the one-minute dataset, which resulted in a closer stacked pattern. The one-minute scatter plots with regression lines are included in Appendix B.

Table 12: Coefficients from the Univariate Linear Model Using 1-Minute Interval Data

Variables	Intercept	Estimate	Standard Error	P-Value
D location BC				
WS	8.67	0.04	0.69	0.95
WD (Category 4)	8.71	0.11	0.35	0.75
T	32.05	-0.94	0.15	1.54e-09
RH	1.38	0.16	0.02	1.07e-09
U Location BC				
WS	7.32	-0.31	0.10	0.001
WD (Category 4)	6.42	0.06	0.05	0.30
T	0.77	0.23	0.02	< 2.2e-16
RH	8.22	-0.04	0.003	< 2.2e-16
A location BC				
WS	6.42	0.01	0.08	0.91
WD (Category 4)	6.47	-0.05	0.05	0.30
T	3.73	0.11	0.02	1.07e-07
RH	7.41	-0.02	0.003	1.22e-10

Table 13: Coefficients from the Univariate Linear Model Using 15-Minute Interval Data

Variables	Intercept	Estimate	Standard Error	P-Value
D location BC				
WS	8.77	0.04	1.85	0.98
WD (Category 4)	9.02	-0.27	1.07	0.81
T	33.97	-1.00	0.37	0.02
RH	0.90	0.18	0.06	0.01
U Location BC				
WS	7.47	-0.36	0.29	0.24
WD (Category 4)	6.44	0.07	0.18	0.69
T	4.20	0.09	0.06	0.15
RH	8.23	-0.04	0.01	6.19e-05
A location BC				
WS	6.38	0.03	0.25	0.90
WD (Category 4)	6.50	-0.05	0.15	0.72
T	4.20	0.09	0.06	0.15
RH	7.31	-0.02	0.01	0.07

While Univariate linear regression models can be used to determine how each meteorological variable influences black carbon (BC) concentrations individually, the decision to focus on Multiple Linear Regression (MLR) is to understand which variables are the strongest predictors of concentrations. The MLR model usually has a larger adjusted R^2 value, meaning it possesses greater explanatory power when also considering the complexity of the model. MLR was used to evaluate the impact of multiple predictors (wind speed, temperature, and relative humidity) at the same time. This shows the complex interactions of various meteorological factors that would influence BC concentration levels.

Analyzing the coefficient estimates of the MLR provided a more accurate measure of how each variable impacts BC concentration. Variables can be considered in isolation; however, when controlling for the influence of all other variables. This ultimately gives a more comprehensive and realistic narrative of the various environmental dynamics surrounding prescribed burns, which gives a better assurance when advising on air quality assessments and exposure assessments.

Multiple Linear Regression Results

General Multiple Linear Regression Model Formula: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon$

Y: dependent variable, e.g., A location BC, U location BC, D location BC

X: independent variable, e.g., WS, WD (sin and cos), RH, T

$\log y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon$ ***could then be:*** $A\ location\ BC = \beta_0 + \beta_1 \cdot WS + \beta_2 \cdot wind\_x + \beta_3 \cdot wind\_y + \beta_4 \cdot T + \beta_5 \cdot RH + \varepsilon$

(This study's Multiple Linear Regression model formula)

Before running the Multiple Linear Regression Model, histograms and QQ plots were used to check for normality. As a result of the large number of such plots, they have been put in Appendix B. The residual figures for one minute and fifteen minutes were also put in the same section. In some models where either all predictors were statistically significant or all were insignificant, the multicollinearity was visually assessed first. These models were each assessed with the Variance Inflation Factor (VIF) analysis that identifies multicollinearity. Variables with large VIF were then removed from subsequent models, so that significant predictors could be more clearly identified.

Table 14: Coefficients Table from the Multiple Linear Regression Model (1-Minute Interval Data)

Location	Estimate	Standard Error	*Pr(>|t|)*
D Location BC			
Model 1-Intercept	47.56	28.55	0.10
WS	-0.61	0.72	0.40
wind_x	-4.89	2.42	0.05
wind_y	8.71	2.50	0.001

T RH	-1.69 -0.09	0.89 0.15	0.06 0.56
A Location BC			
Model 1-Intercept WS wind_x wind_y T RH	19.78 -0.23 1.09 -1.56 -0.31 -0.07	3.73 0.09 0.32 0.34 0.12 0.02	3.34e-07 0.01 0.001 7.14e-06 0.01 0.001
Model 2- Intercept WS T wind_x wind_y	7.11 -0.11 0.09 1.78 -2.19	0.90 0.09 0.02 0.26 0.29	2.21e-13 0.20 1.98e-05 1.77e-10 3.42e-12
Model 3-Intercept wind_x wind_y T	6.23 1.61 -1.99 0.10	0.59 0.23 0.25 0.02	< 2e-16 3.30e-11 1.94e-13 4.77e-08
U Location BC			
Model 1-Intercept WS wind_x wind_y T RH	15.35 -0.24 0.23 -0.64 -0.18 -0.07	3.84 0.09 0.33 0.35 0.12 0.02	9.27e-05 0.01 0.50 0.07 0.13 0.001
Model 2- Intercept WS RH	8.32 -0.04 -0.04	0.21 0.07 0.003	< 2e-16 0.55 < 2e-16

Table 15: Coefficients Table from the Multiple Linear Regression Model (15-Minute Interval Data)

Location	Estimate	Standard Error	*Pr(>|t|)*
D Location BC			
Model 1-Intercept WS wind_x	18.83 -0.57 -5.67	79.06 1.88 6.86	0.82 0.77 0.44

wind_y T RH	8.92 -0.83 0.06	7.16 2.48 2.48	0.25 0.75 0.89
Model 2-Intercept WS wind_x wind_y T	30.04 -0.67 -6.27 9.47 -1.19	17.48 1.65 5.13 5.71 0.40	0.12 0.70 0.26 0.14 0.02
A Location BC			
Model 1-Intercept WS wind_x wind_y T RH	19.27 -0.24 1.36 -1.89 -0.29 -0.06	10.07 0.24 0.87 0.91 0.32 0.05	0.10 0.34 0.16 0.08 0.40 0.29
Model 2-Intercept WS wind_x wind_y T	7.96 -0.15 1.97 2.45 0.07	2.43 0.23 0.72 0.79 0.06	0.01 0.54 0.02 0.01 0.22
U Location BC			
Model 1-Intercept WS wind_x Wind_y T RH	16.60 -0.26 0.06 -0.46 -0.22 -0.08	8.15 0.19 0.71 0.74 0.26 0.04	0.08 0.23 0.94 0.55 0.41 0.12
Model 2-Intercept WS wind_x Wind_y T	2.68 -0.14 0.81 -1.15 0.22	2.16 0.20 0.63 0.71 0.05	0.25 0.52 0.24 0.14 0.002

D Location (Downwind) – One-Minute data

In the one-minute data table, the wind directions of both axes had the greatest estimated values.

• Wind_x variable, winds blowing from the west, has an estimate of -4.89 and wind_y variable, winds from the north, has an estimate of 8.71. This means that for every 1 increment of wind_x, the BC at location D results in a decrease of 99.24%. Likewise, for every 0.01 increment of wind_y the BC at location D increases by 9.1%. By and large, wind directions on both axes have a large effect on BC at location D, and are also statistically important (p values 0.05, 0.001).

• It is also important to mention that the other variables (except the wind direction) were not statistically significant or exhibited a large degree of collinearity. According to Pearce et al. (2012) Downwind exposures were observed to be influenced most directly by wind direction and distance from the burn site, with the observed emissions from the burn site occurring in correspondence to the burning severity, method, and timing.

Location (Apartment) – One-Minute Data

All predictor variables in Model 1 were statistically significant following the first model.

• wind_x variable (wind blowing east) and wind_y variable (wind blowing south) had the highest coefficients as well, at 1.09 and -1.56, respectively. Therefore, for a 0.1-unit increase in wind_x, BC at location A increased by 11.6%, whereas for a 1-unit increase in wind_y the BC decreased by 79.0%. This may seem minor until reading further below about the impactful effects of wind direction and BC at location A.

• The model prompted us to check for collinearity between the RH and T variables that were both similar enough that the VIF index values revealed that the variable, RH, may not be necessary, with RH being the highest at 52.93. Therefore, RH was excluded from subsequent models.

From the output of the second model:

• Estimates of wind_x (flowing east) and wind_y (flowing west) rose to 1.78 and -2.19, respectively. As such, for each 0.1-unit increase in wind_x and wind_y the effect on the BC at location A where BC increased 19.5% and decreased 19.7% respectively with both wind values yielding statistically significant outputs (p values 1.77e-10, 3.42e-12). This led to the conclusion that wind had a strong impact on BC concentrations. In the third model, all predictors, except for wind speed (WS) and relative humidity (RH), were included. RH was removed from the model due to its VIF value (52.93; Model 1), which suggests multicollinearity. However, WS was omitted based on a lack of statistical significance ($p = 0.20$) when looking at the second model.

• The wind_x (blowing east) and wind_y (blowing south) variables had the highest estimates of 1.61 and -1.99. Therefore, for each 0.1-unit increase in wind_x, the BC at location A increased by 17.5%, whereas for each 1-unit increase wind_y, the BC decreased by 86.4%. For both wind values, these estimates were statistically significant with p values of 3.30e-11 and 1.94e-13, asserting their impact on the BC values. At Location A, wind direction provided impactful insights into this research.

<u>U Location (Upwind) – One-Minute Data</u>

In the first model for the U location BC:

- Wind Speed (WS), wind_x (eastward wind), and wind_y (southward wind) estimated the largest (-0.24, 0.23, -0.64), meaning a 1-unit increase in WS would result in a 21.2% decrease in U location BC; a 1-unit increase in wind_x and wind_y corresponded to a 25.4% increase and a 47.1% decrease in U location BC, respectively.

- Of note, WS and relative humidity (RH) were the only significant predictors, with p values of 0.01, 0.001. In the second model, all insignificant variables were eliminated, while the WS and RH were kept.
- While the WS estimated a greater (-0.04) value, it was insignificant ($p > 0.05$); however, RH estimated a lesser (-0.04) value but was significant ($p < 2e\text{-}16$). This finding yet again further supports the strong effect of RH on BC concentrations found in this study.

D Location (Downwind) – Fifteen-Minute Data

Using all the predictors in the first model:

- The wind_x (flowing to the west) and wind_y (flowing to the east) had the highest estimate values of -5.67 and 8.92, indicating a solid influence from wind direction. In this model, none of the predictors were statistically significant.
- After checking for multicollinearity, the T and RH variables were highly collinear (-0.98), And this was displayed through the VIF analysis. RH had the highest VIF score of 54.04, and so it was taken out of the first model.

In the second model:

- The wind_x (flowing to the west) and the wind_y (flowing to the north) had the highest estimates of -6.27 and 9.47, respectively.
- Interestingly, the T variable was the only variable with a statistical significance of 0.02. It also had the third-highest estimate with a value of -1.19. This means that for every 1-unit increase in T, D location BC decreases by 69.6%, depicting a strong yet inverse relationship on the black carbon concentrations at the D location.

A Location (Apartment) - Fifteen Minutes

At this location, the same multicollinearity problems were observed, and so the RH had to be dropped due to its high VIF value of 54.04.

For the second model:

- The wind_x (wind flowing to the east) and the wind_y (wind flowing to the south) had the highest estimate values of 1.97 and -2.45, meaning that for every 0.1-unit increase in wind_x and wind_y, A location BC increased by 21.8% and decreased by 21.7%. Both variables were also statistically significant (p values: 0.02, 0.01), suggesting that directional airflow plays a major role in influencing BC levels at the Apartment location.

U Location (Upwind) - Fifteen-Minute data

As seen in the other locations, RH also displayed multicollinearity with a VIF value of 54.04, necessitating its elimination from the second model.

In this model:

- The wind_x (wind flowing to the east) and the wind_y (wind flowing to the south) had the highest estimate values of 0.81 and -1.15, meaning that for every 0.1-unit increase in wind_x and wind_y, U location BC increases by 8.4% and decreases by 10.8%. Interestingly, none of the wind direction variables were statistically significant.
- Surprisingly, T was the only variable with a statistical significance of p value = 0.002 and the third highest estimate value of 0.22. Meaning that for every 1-unit increase in T, the U location BC decreases by 19.6%, suggesting a moderately strong, yet statistically significant impact on the black carbon concentrations at the U location.

From the results stated above, the wind direction seemed to be quite prominent, especially in the A location (1 minute and 15 minutes), where the wind was flowing towards the south and the east direction. It is suggested that the wind direction might be instrumental in the transport of BC concentrations at this location. This may be owing to the spot where the sensor was placed (at the screen porch) and its exposure to winds blowing in the southeastern direction. Similarly, the D location for the one-minute data portrayed the same trend but in the opposite direction, with wind flowing towards the west and the south directions, pinpointing the prevailing winds' role in conveying fire emissions to close locations (Jaffe et al., 2020). Its 15-minute data had temperature as the strongest variable of interest, and this might be due to the heavy influence that the heat from the burn and that of the environment had on the BC concentrations at that location (Liu, 2014; Odman et al., 2018).

At the U location BC, RH was significant in the 1-minute data, but in the 15-minute data, temperature was significant. This might be underlining the strong influence and collinearity that T and RH have on the BC concentrations at the Upwind location. Also, since this location was on the upper part of the fire, this site might have retained more moisture owing to factors such as topography, cooler temperatures, which promote the aggregation of BC, especially in hotter environments (Balachandran et al., 2013; Miller et al., 2019).

These trends spotlight the influence and importance of meteorological conditions when it comes to understanding the dynamics of BC concentrations across locations. Such findings align with previous research endeavors that show the influence of conditions such as wind, temperature on the transport of pollutants during biomass burns (Sadia Afrin & Garcia–Menendez, 2020; Petralia & Potosnak, 2024; Liu et al., 2021). Also, having site-specific meteorological conditions helps to improve the accuracy of regression models in air quality studies.

Table 16: Multiple Linear Regression Model Outputs (Continued) – 1- and 15-Minute Interval Data

One Minute	Adjusted R-Squared	P-value
D location BC		
Model 1	0.38	5.32e-15
U Location BC		
Model 1	0.53	< 2.2e-16
Model 2	0.48	< 2.2e-16
A Location BC		
Model 1	0.39	< 2.2e-16
Model 2	0.35	< 2.2e-16
Model 3	0.35	< 2.2e-16
Fifteen Minutes		
D Location BC		
Model 1	0.44	0.10
Model 2	0.51	0.04
U Location BC		
Model 1	0.78	0.01
Model 2	0.73	0.01
A Location BC		
Model 1	0.51	0.07
Model 2	0.49	0.05

For the One Minute data:

• At the U location, the adjusted R^2 for the original model was 0.53, whereas the second model had an adjusted R^2 of 0.48, which suggests that the original model with all predictors explained the variability in U better than the second model.

• At the A location, the original model had the adjusted R^2 of 0.39, which was greater than the adjusted R^2 of the second model of 0.35 and the third model of 0.35. This indicates that the original model, which included all predictors, explained the variability in A better than the second model.

For the Fifteen Minutes data:

• At the D location, the original model had an adjusted R^2 of 0.44, which is lower than the second model, which had an adjusted R^2 of 0.51. This indicates that the original model with all predictors did not explain the variability in D as well as the second model did.

• At the U location, the original model had an adjusted R^2 of 0.78, which is greater than the second model, which had an adjusted R^2 of 0.73; therefore, the original model, which included all the predictors, better explained the variability in U compared to the second model.

• At the A location, the original model had an adjusted R^2 of 0.51, which was higher than the adjusted R^2 for the second model (0.49). As a result, the original model, which included *all* the predictors, explained the variability in A better than the second model.

It is important to note that the original models had the highest adjusted R^2 values for all the locations and periods, except for the D location in the Fifteen Minutes data set. This also reflects an important idea that even a model with statistically significant and non-collinear predictors can sometimes be deficient in explaining the variance in that model.

Table 17: ANOVA Test Results (One Minute and Fifteen Minutes)

Location / Model	Res. Df	RSS	Df	Sum of Squares	F	*Pr(>F)*
One Minute						
A: Model 1 Model 2 Model 3	 183 184 185	 11.45 12.21 12.32	 -1 -1	 -0.76 -0.11	 12.18 1.77	 0.001 0.19
U: Model 1 Model 2	 183 186	 12.12 13.64	 -3	 -1.52	 7.65	 7.64e-05
Fifteen Minutes						

D: Model 1 Model 2	 7 8	 13.41 13.45	 -1	 -0.04	 0.02	 0.89
A: Model 1 Model 2	 7 8	 0.22 0.26	 -1	 -0.04	 1.34	 0.29
U: Model 1 Model 2	 7 8	 0.14 0.21	 -1	 -0.06	 3.09	 0.12

Table 19, identified in the previous section, contains several interesting findings relating to this research.

- At site A, the first regression model produced a statistically significant result indicated by the F statistic of 12.18 and a p value of 0.001. The first regression model removed several meteorological variables, leading to a deviation in the second model. This means that the first model that included all predictors was the better model choice. The results on regression model three contained an F statistic of 1.77 with a $p > 0.05$ (0.19).
- At the U site, only two regression runs were conducted and showed a F statistic of 7.65 with a p value of 7.64e-05 or <0.0001; which means that the meteorological variables removed (wind_x, wind_y, and T) were important and should be retained as predictors.
- For the fifteen-minute data, the final regression models were statistically insignificant with F values of 0.02, 1.34, 3.09, and p values greater than 0.05. These results suggest that taking out some of the collinear variables, like RH, was beneficial, seeing that the models did not significantly lose their explanatory power at the A, U, and D locations.

4.4 STRENGTHS AND LIMITATIONS OF THE STUDY

This study comes with many strengths that contribute to its importance in the field of air quality and prescribed fire research. Firstly, it can be noted that it is one of the few studies to characterize real-time black carbon (BC) during a real prescribed burn, while using portable, low-cost and easily deployable equipment. By taking time-resolved measurements and incorporating meteorological data into the study, it provides a practical approach to understanding how local environmental factors (wind direction and temperature) impact the dispersion of pollution.

In addition, this study presents clear methods where the steps taken to tackle multicollinearity and the importance of the variables within the regression models are detailed, which strengthens the rigor of the statistical analysis. The use of multiple sensor locations (Upwind, Downwind, Apartment) gives a spatial component to the observed pollution trends, which will allow for better exposure assessments and inform future placements of the sensors. While the study is geographically and temporally limited, it establishes a starting point for a larger, more comprehensive study using portable and low-cost sensors in the real world.

Nonetheless, there are limitations with this study that affected the interpretation of the results. Firstly, although the MA-200 can be used in Dual Spot mode, not all the sensors were used in that manner. For this analysis, therefore, the BC levels from the Single Spot (IR BC 1) were used, thus introducing variability from the unstable flow rates, filter loading artifacts, and shifts in location. Secondly, there were no post-processing steps to refine the data or use noise-reducing methods (ONA, LPR, and CMA). Furthermore, there was no Drinovec et al. (2015) correction factor provided. The first three algorithms were provided by AethLabs (https://aethlabs.com) (Liu et al., 2021) and are widely implemented in environmental research, but none were used to remove noise, based on a modest sample size and low levels of noise. Noise was only recorded on two occasions in the downwind location of MA-200 0422: (1) A couple of 0 values recorded while advancing the tape were removed from the dataset, and (2) a "Flow Unstable" notice was reported at 12:58 PM, resulting in negative values at 1:00 PM, which continued until sampling ended at 1:32 PM. Even after going through AethLabs' post-processing algorithms, the negative values remained the same and were kept as reported.

Finally, the scope of this study was limited, as data were collected from just three sites during one burn event. This limits the applicability of the findings because they are only relevant in this context. Despite this, the findings nevertheless contribute to an understanding of the impact of meteorological factors upon BC levels during a prescribed burn and provide a reference for future studies.

4.5 SUMMARY

In conclusion, the results of this study reaffirm the importance of assessing variable contributions both statistically and contextually. Some variables otherwise may have not been statistically significant when considered independently, however all together they can contribute to improving the overall performance of the model, especially in cases of multicollinearity, which illustrates the importance of selecting a statistical method that incorporates analytical methods such as ANOVA, adjusted R^2 values, and VIF to determine the best column of predictors. Additionally, the results from the Univariate Linear Regression and Multiple Linear Regression Models address all variables, and there were several variables, wind direction, temperature, and relative humidity, that represented redundancy throughout the data.

This further supports the need for additional research that examines the interaction of climate change effects on temperature and relative humidity, and how these interactions are reflected in contemporary prescribed fire practices. Additionally, having regulatory policies in place to minimize human-related activities, waste management, burning of fossil fuels (e.g., coal, oil, natural gas), deforestation, and animal manure will be fundamental to reducing global warming to minimizing the intensification of wildfires (United Nations, 2025).

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

This thesis investigated black carbon (BC) concentrations relative to a controlled burn at the Jones Center at Ichauway, Georgia - a biologically diverse area and regularly burned area of the Southeastern United States (The Jones Center at Ichauway, 2024; Jang & Jung, 2023). Prescribed burning creates significant sources of particulate matter emissions, and Georgia is one of the states that performs the most prescribed burns. The goal of this research was to contribute to the knowledge of a combustion-specific element that scientists have not investigated significantly: the spatial distribution of black carbon in relation to controlled burn events. This dissertation utilized three MA-200 portable and low-cost aethalometers to measure black carbon concentrations at three distinct micro-environment locations:

(1) an outdoor location Downwind of the controlled burn.

(2) an outdoor location Upwind of the controlled burn; and

(3) an outdoor location located on the screen porch of the Apartment. Furthermore, weather data, including wind speed and direction, temperature, and relative humidity, was collected using a weather station on location. The average data was analyzed to explore the following two questions:

1. Relative to the prescribed burn, how do concentrations of black carbon vary across the locations?

2. What effects do meteorological variables have on the concentrations of black carbon?

Employing both a 1-minute and a 15-minute resolution dataset and various models of analysis, including descriptive statistics, methods of non-parametric tests (Kruskal-Wallis and Dunn's post hoc), and univariate linear and multiple linear regression modeling, suggested that black carbon (BC) levels exhibited significant spatial differences. This study confirmed the hypothesis that locations that are Downwind would generally experience the highest concentrations of black carbon, supporting previous findings that communities located Downwind faced higher exposure risks (Considine et al., 2019). Additionally, this study concurred with prior studies identifying projected pollutant transport due to wind after a fire event (e.g., Pearce et al., 2012; Ravi et al., 2018; Xu et al., 2018). It was also determined that weather variables had effects, but again, these effects were site-dependent and time-relevant. Wind direction (both x and y) was determined to be a statistically significant predictor of BC concentrations at both Downwind and Apartment sites, with additional finding temperature and relative humidity being significant, especially at the Upwind site - relative humidity was statistically significant in the one-minute dataset, and temperature was the main variable in the 15-minute model. These findings show how localized atmospheric dynamics associated with burn intensity, topography, and weather conditions influence air pollution exposure at a micro scale.

Of significance, the study addressed the need for portable and low-cost sensor technology to be used in conjunction with meteorological-type monitoring to arrive at a good understanding of pollutants and their spatial and temporal resolution. This is particularly relevant in rural areas, which do not have the robust air quality coverage that regulatory networks provide. The work also illustrated the extent to which meteorological markers can create differences in prescribed burns and air quality that are important for adaptation to climate change and public health assessment. In conclusion, this research filled a significant gap in the fire and air quality literature by providing real-time black carbon data from several locations with the specificity of combustion and environmental context, which delineated the exposure conditions. The findings underscored the need for air monitoring strategies in community settings while advancing the task of reconciling ecological fire management with human health protections, especially for at-risk populations closest to and Downwind of smoke exposure.

5.2 RECOMMENDATIONS

Using the findings from this work as a context, the following recommendations are proposed for future research efforts:

- Models such as Blue Sky could be incorporated into studies such as this in a bid to arrive at more detailed conclusions. Some studies have reported that the Bluesky Model could either underestimate or overestimate BC concentrations and so running it side by side with such ground-based data could help to cross-check its performance for black carbon.
- Also, collocating the MA-200 with reference grade sensors such as the AE-33, filter-based gravimetric samplers could help to assess the overall functionality, credibility, and shortcomings of the sensors under real-world fire scenarios.
- Additionally, further studies could investigate the influence of other seasons, such as winter and its weather conditions, on BC concentrations. These would be interesting to see, as seasonality does not just dictate burn decisions but would also greatly impact the dispersal of BC particles.

Ultimately, this research survey offers basic knowledge of prescribed fire's impact on black carbon levels across different locations and weather impacts on this variability. The results may apply to future projects related to environmental monitoring, fire management techniques, and public education, particularly in locations where prescribed burning is used regularly.

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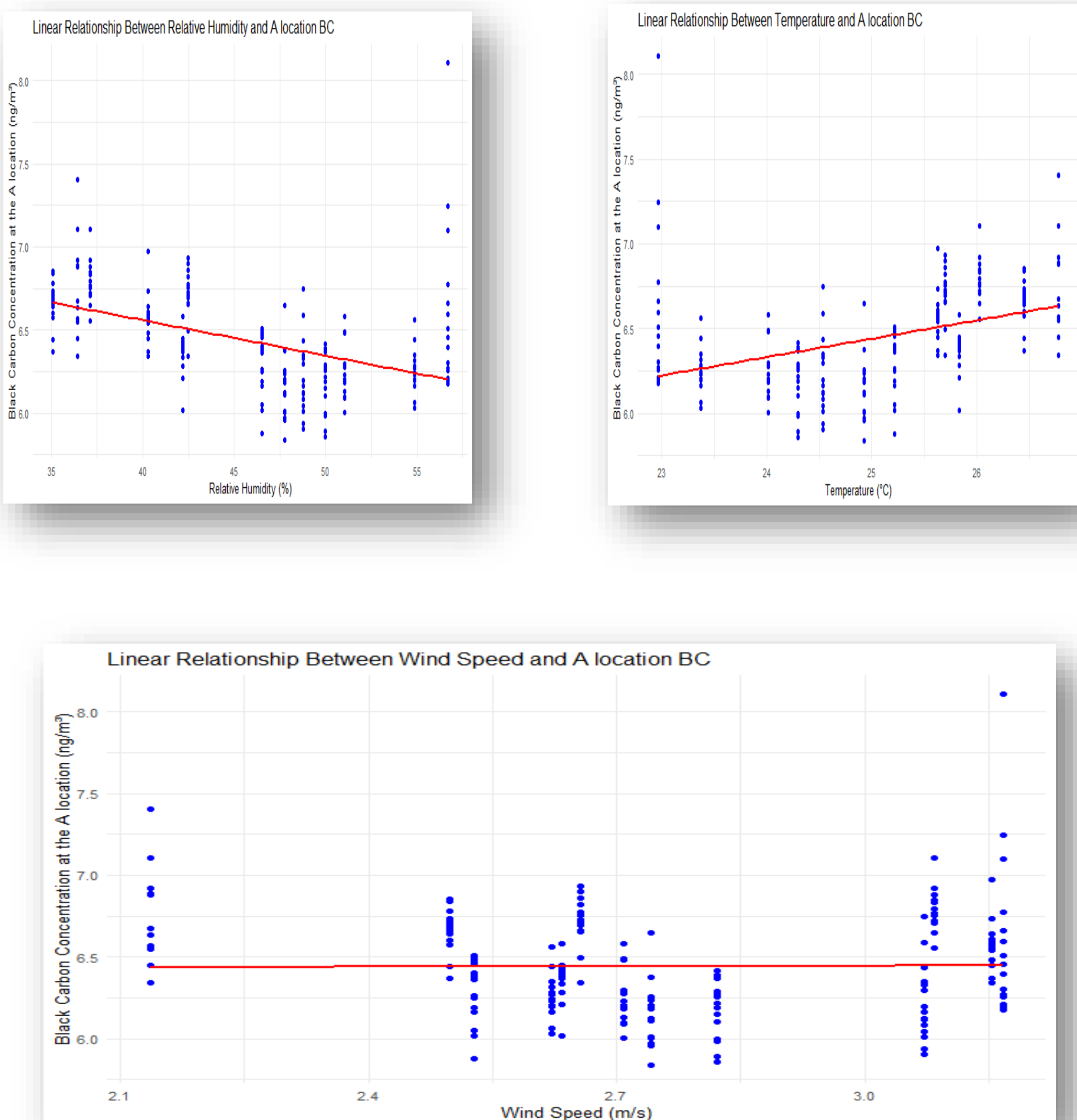
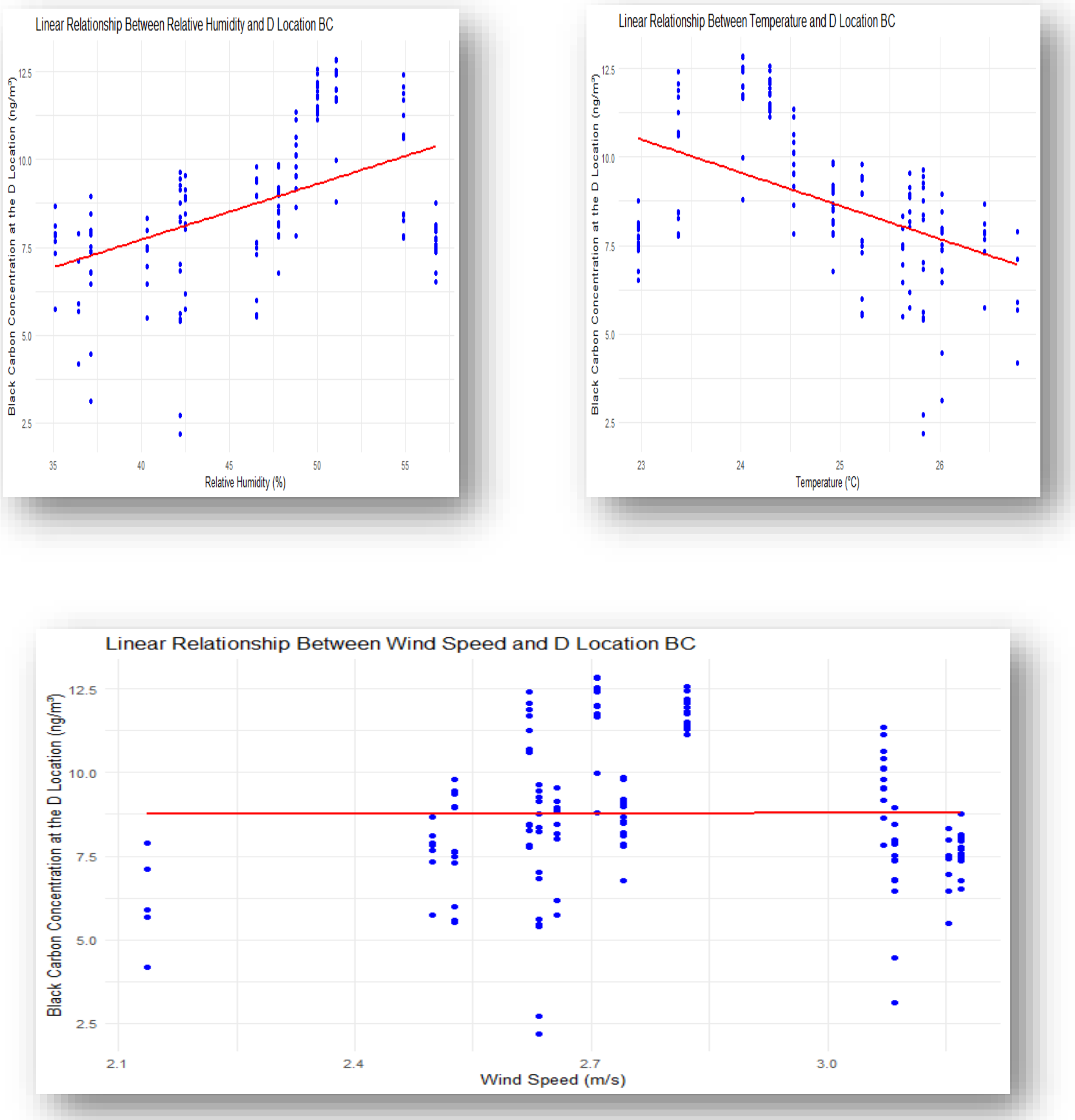
Appendix A

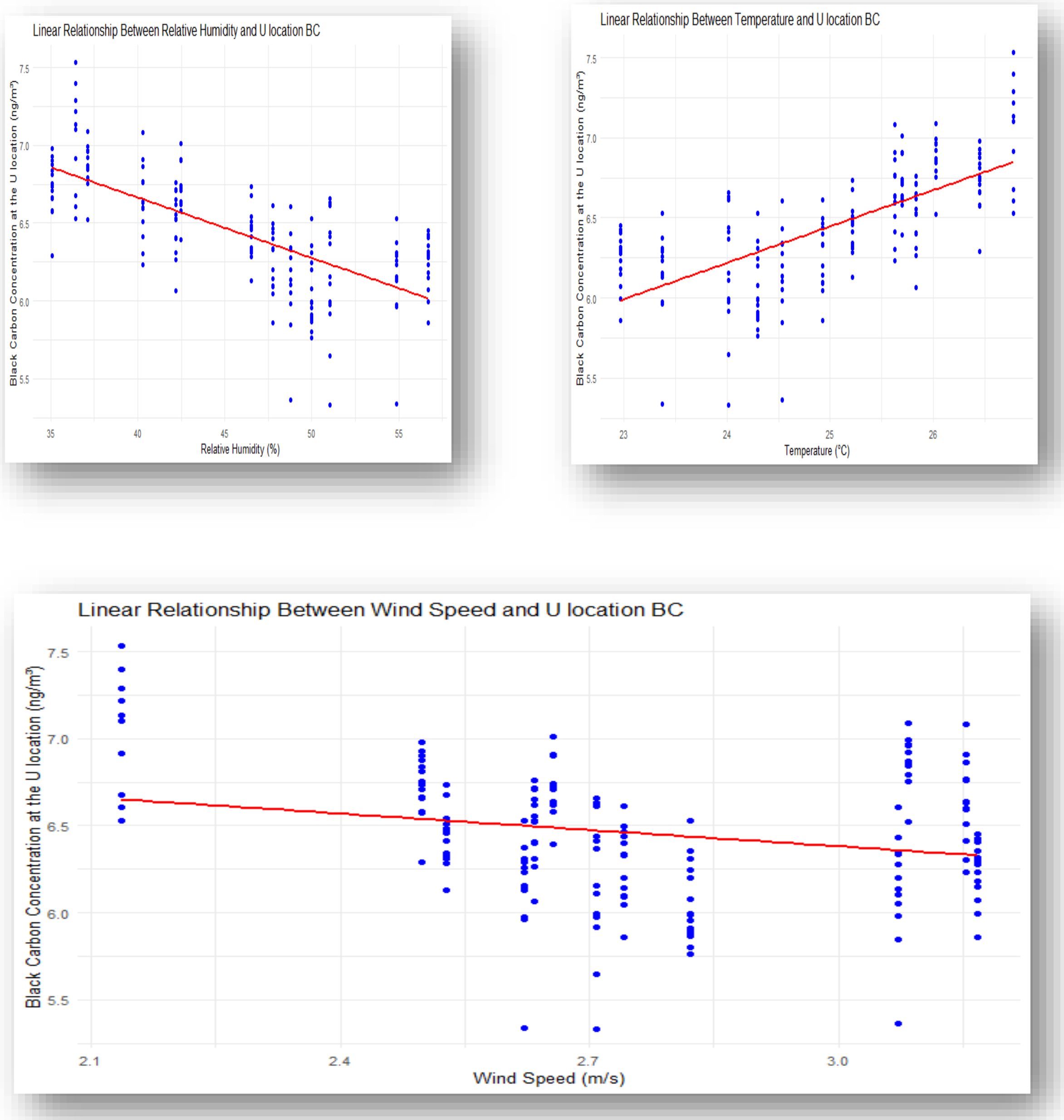
Univariate Linear Regression Model Results



Scatter Plots with Regression Lines for the Apartment (A) Location Showing Relationships Between Black Carbon (BC) and Temperature, Wind Speed, and Relative Humidity (One Minute)



Scatter Plots with Regression Lines for the Downwind (D) Location Showing Relationships Between Black Carbon (BC) and Temperature, Wind Speed, and Relative Humidity (One Minute)

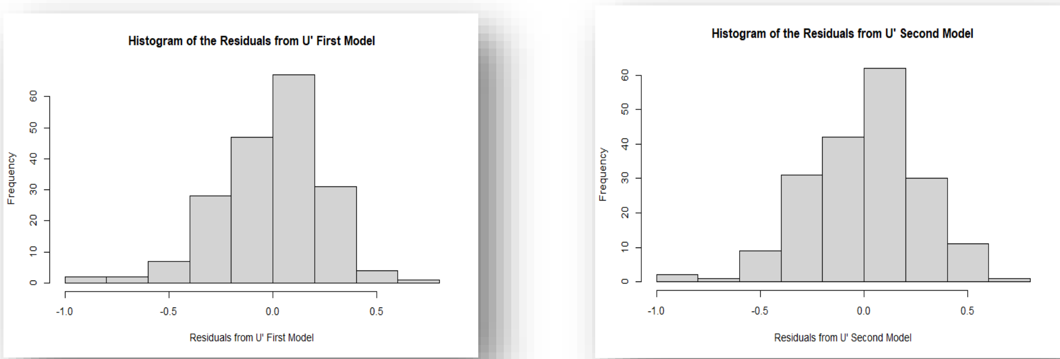


Scatter Plots with Regression Lines for the Upwind (U) Location Showing Relationships Between Black Carbon (BC) and Temperature, Wind Speed, and Relative Humidity (One Minute)

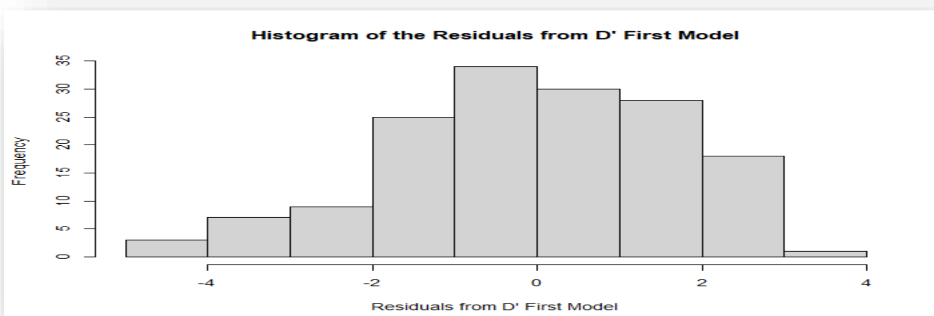
Appendix B

Multiple Linear Regression Results

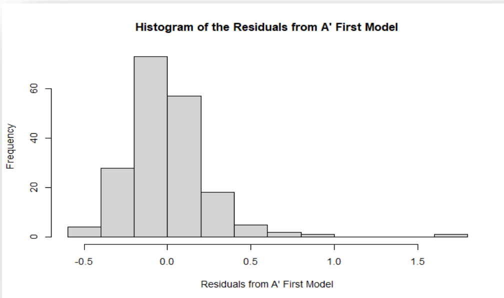
Histogram Charts for the Model Residuals (Check for Normality)

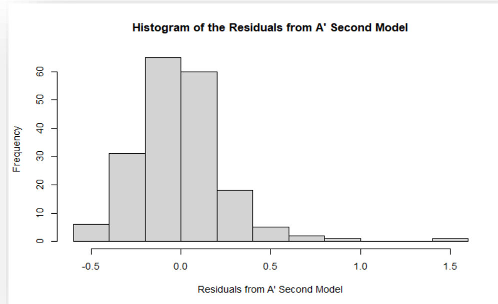


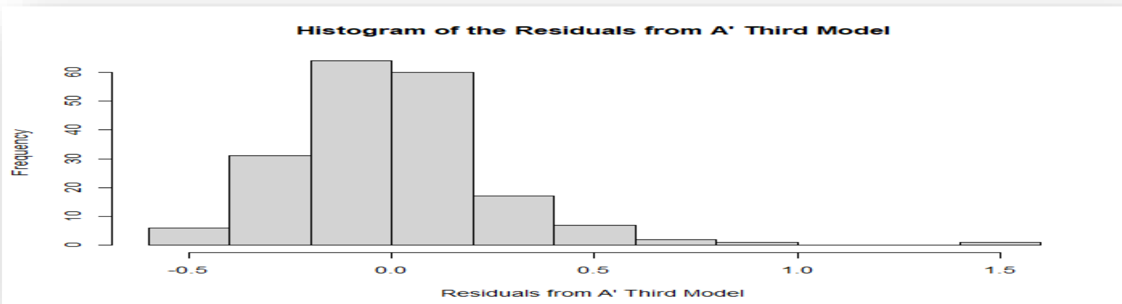
Histogram Charts of Residuals for the Upwind (U) Model – Models 1 and 2 (One Minute)



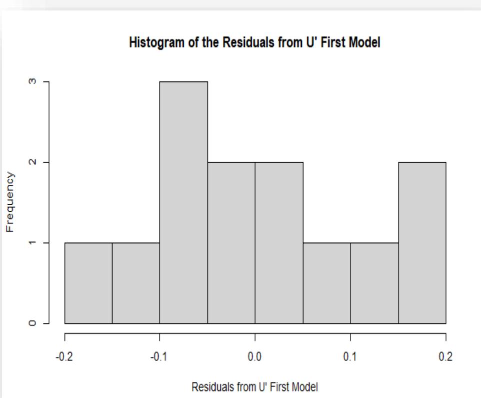
Histogram Charts of Residuals for the Downwind (D) Model – Model 1 (One Minute)

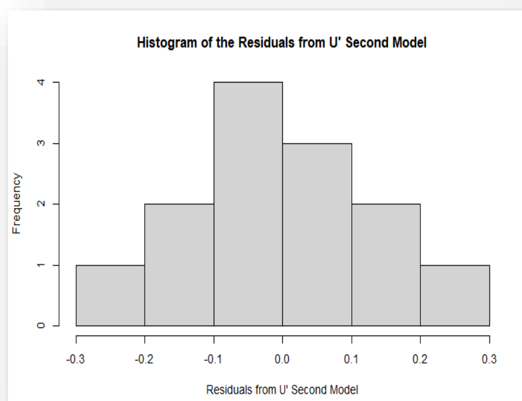




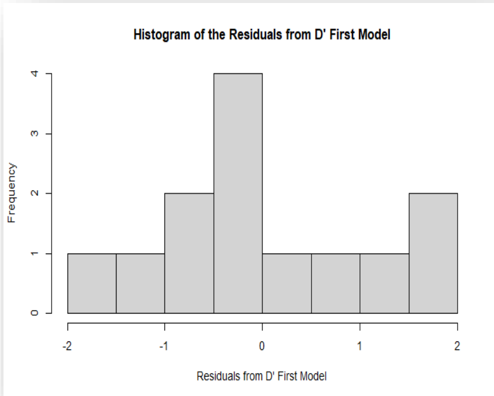


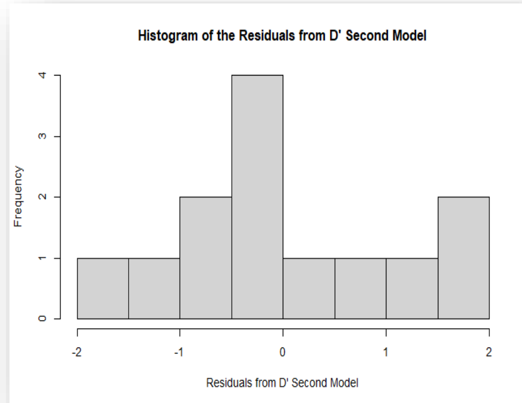
Histogram Charts of Residuals for the Apartment (A) Model – Models 1,2 and 3 (One Minute)



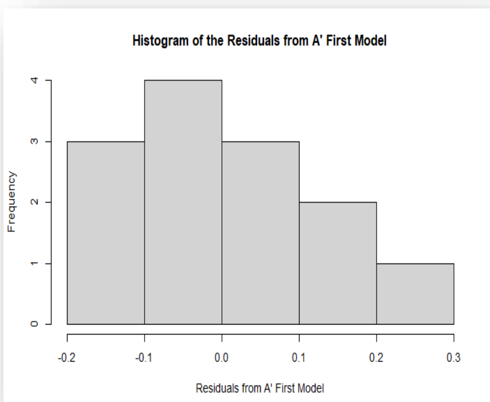


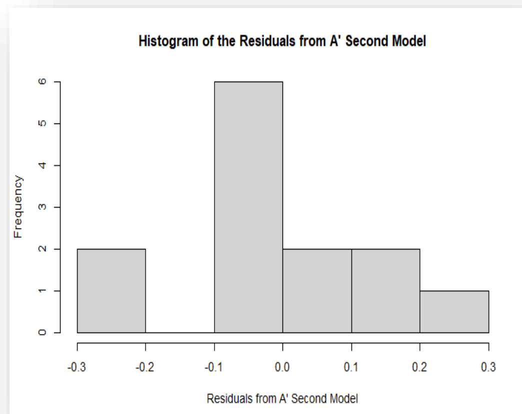
Histogram Charts of Residuals for the Upwind (U) Model – Models 1 and 2 (Fifteen Minutes)





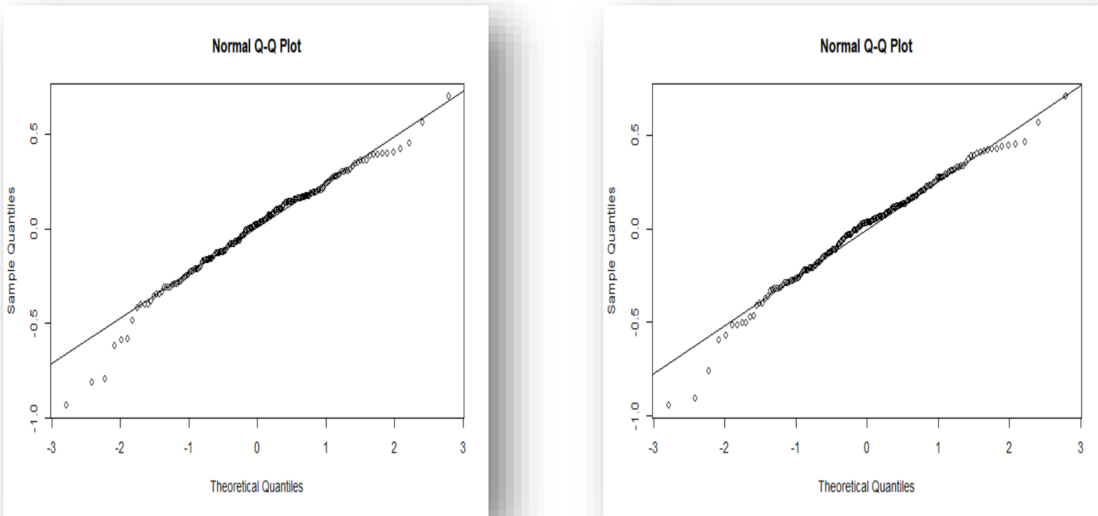
Histogram Charts of Residuals for the Downwind (D) Model – Models 1 and 2 (Fifteen Minutes)



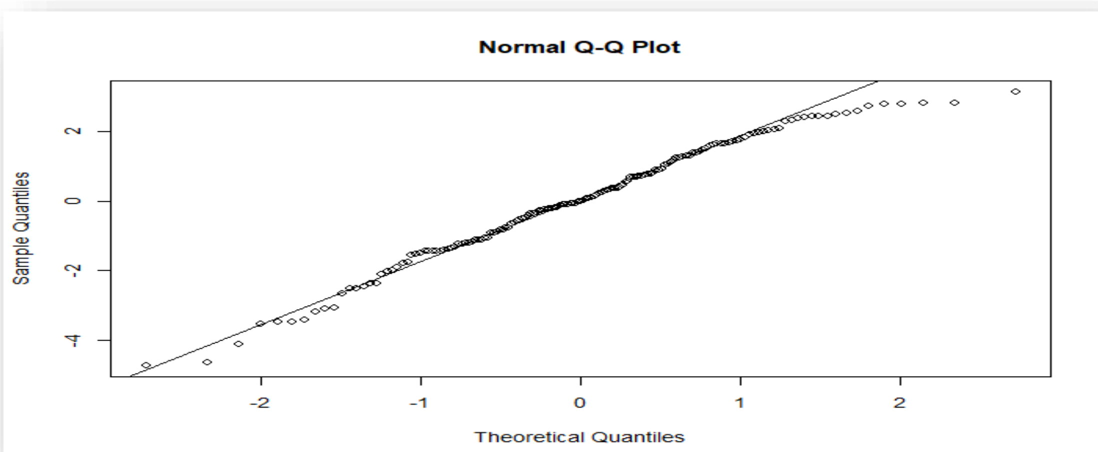


Histogram Charts of Residuals for the Apartment (A) Model – Models 1 and 2 (Fifteen Minutes)

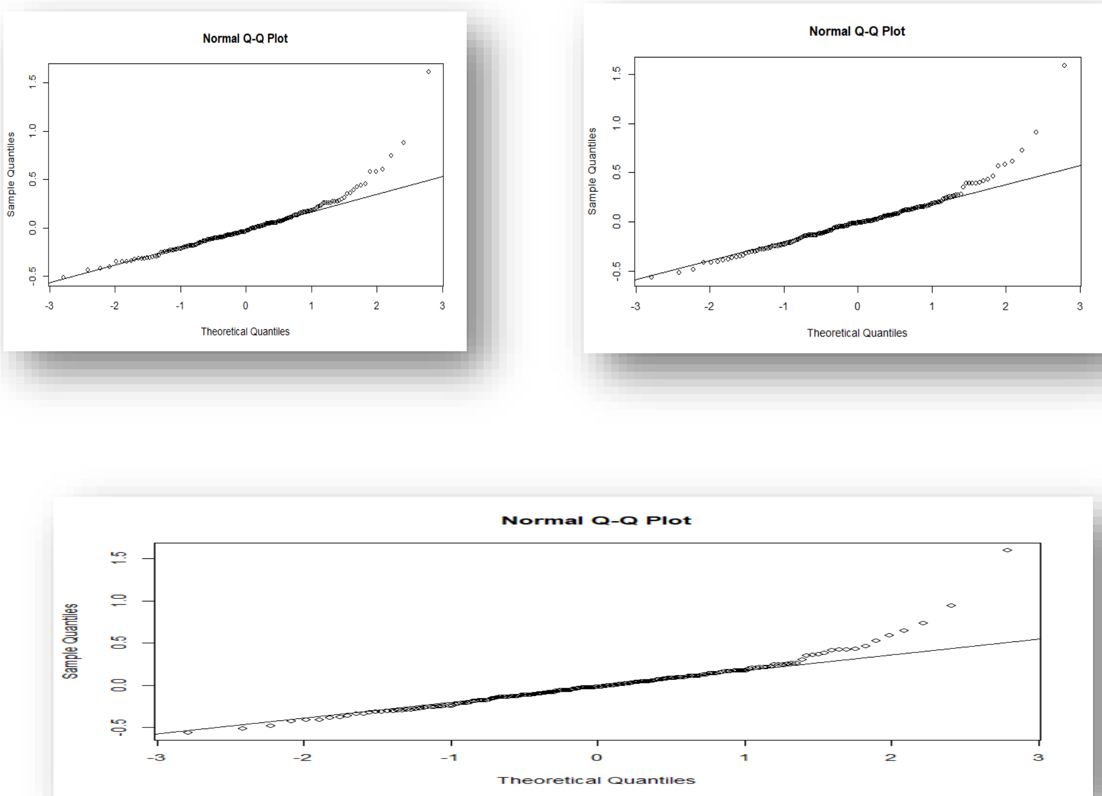
QQ Plots for the Model Residuals (Check for Normality)



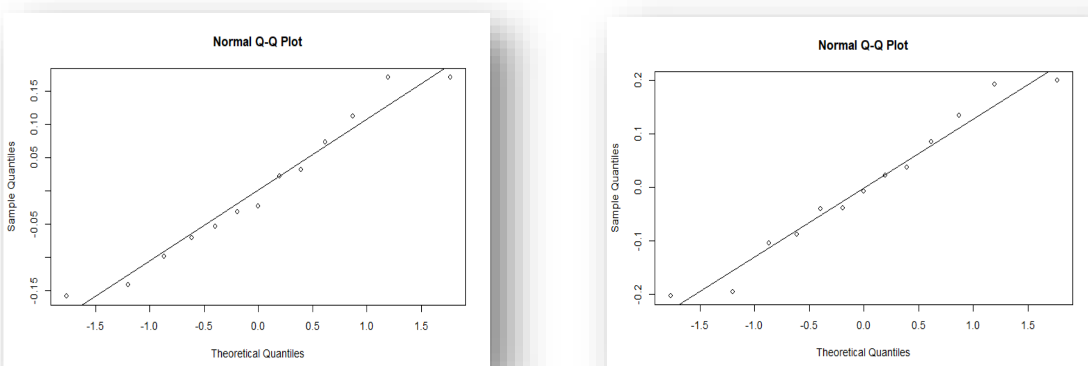
QQ Plots of Residuals for the Upwind (U) Model – Models 1 and 2 (One Minute)



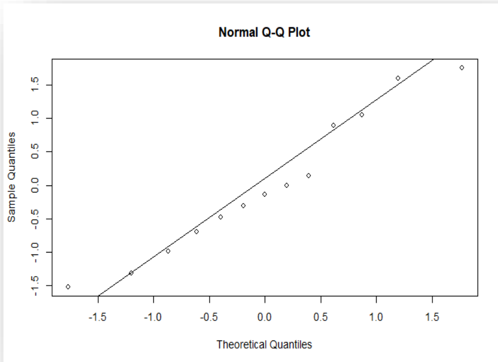
QQ Plots of Residuals for the Downwind (D) Model – Model 1(One Minute)

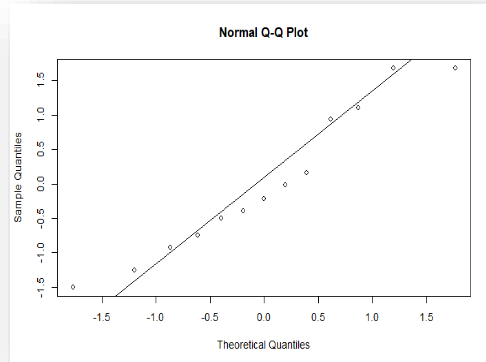


QQ Plots of Residuals for the Apartment (A) Model – Models 1, 2, and 3 (One Minute)

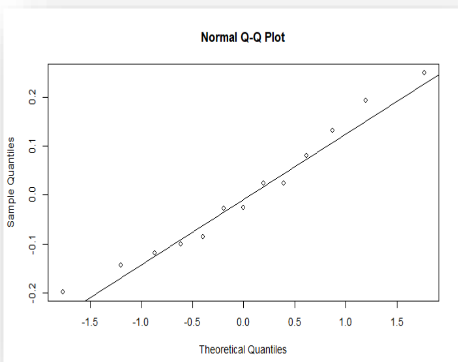


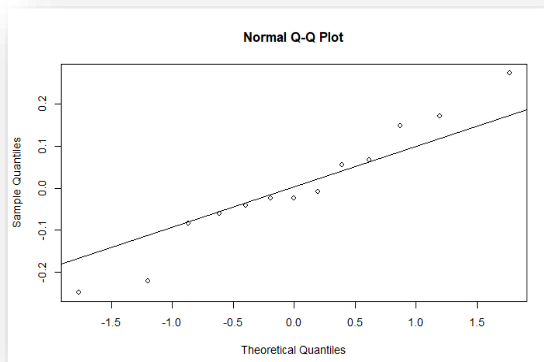
QQ Plots of Residuals for the Upwind (U) Model – Models 1 and 2 (Fifteen Minutes)





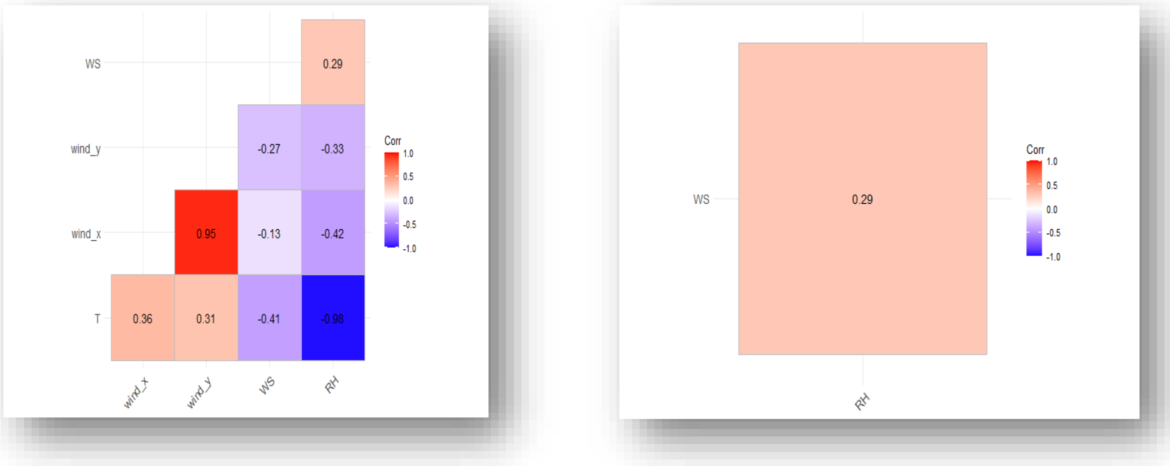
QQ Plots of Residuals for the Downwind (D) Model – Models 1 and 2 (Fifteen Minutes)



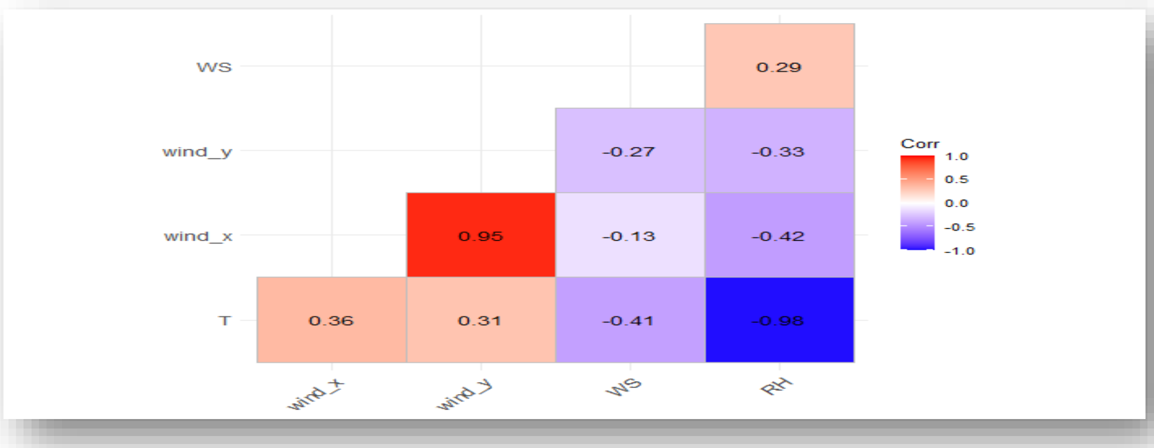


QQ Plots of Residuals for the Apartment (A) Model – Models 1 and 2 (Fifteen Minutes)

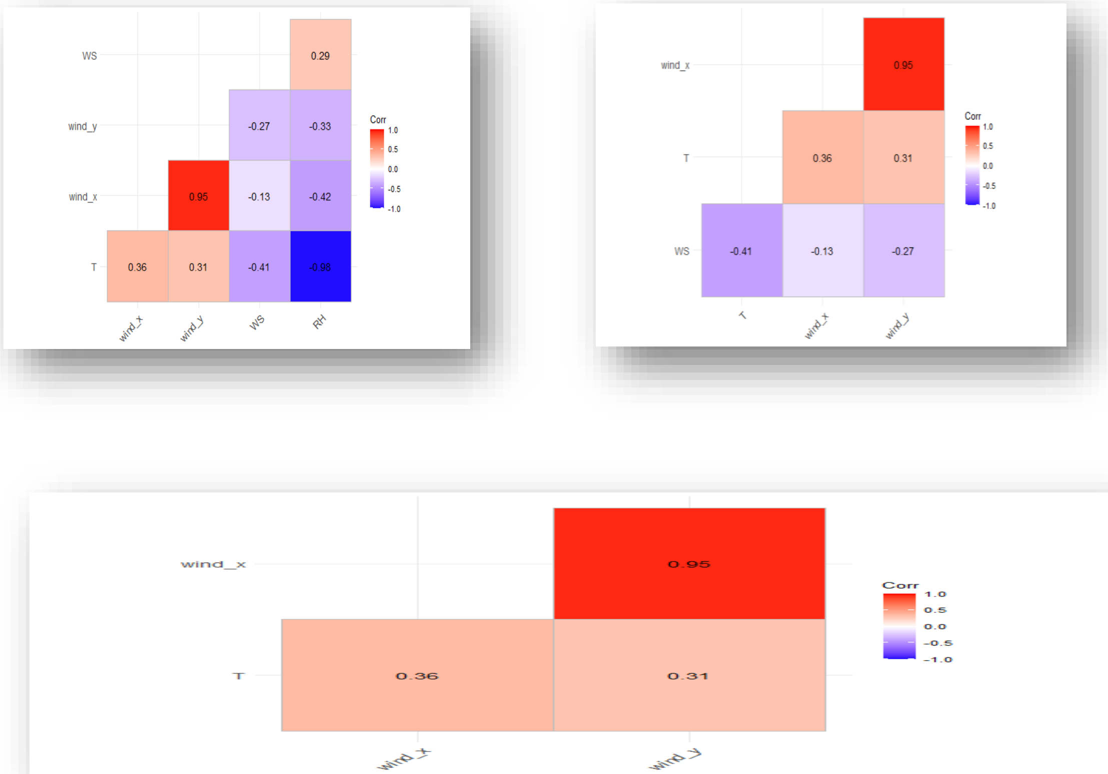
Multicollinearity Assumption Check



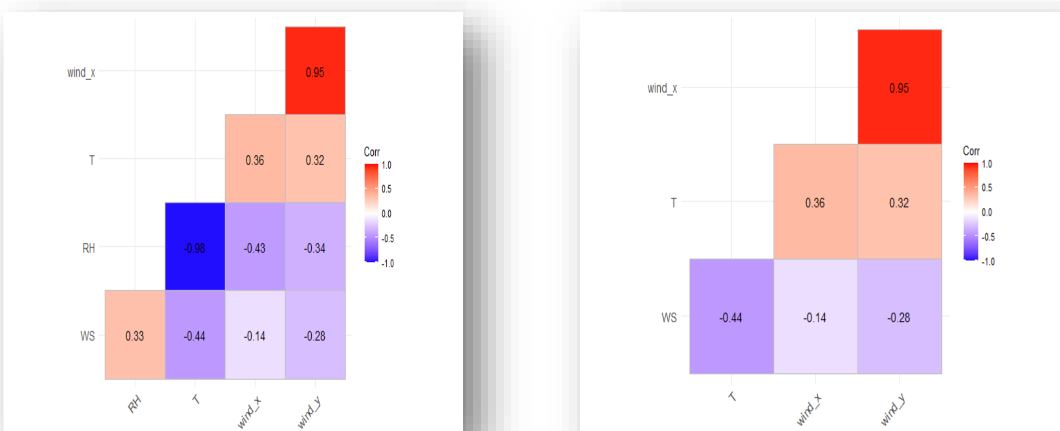
Correlation Matrix for the Upwind (U) Model – Models 1 and 2 (One Minute)



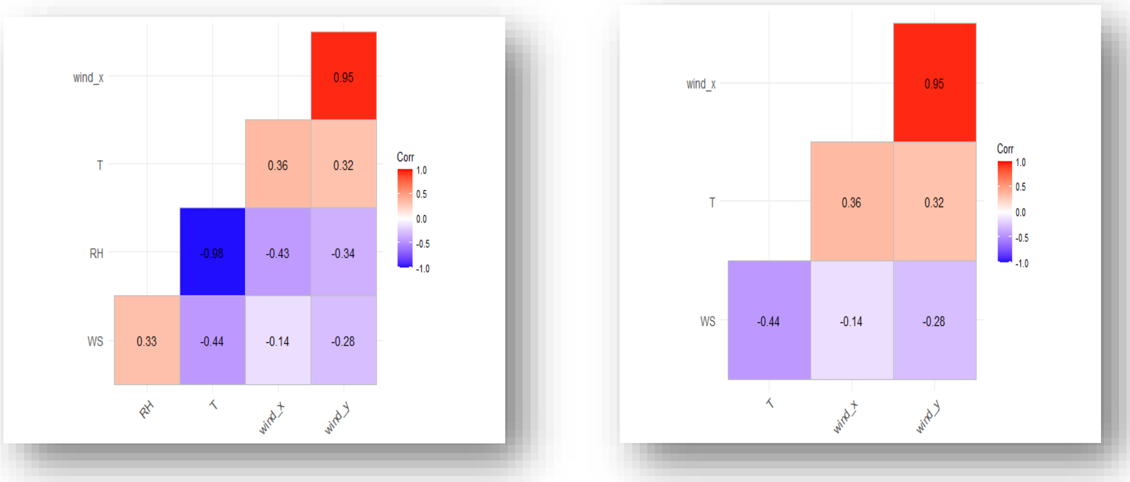
Correlation Matrix for the Downwind (D) Model – Model 1 (One Minute)



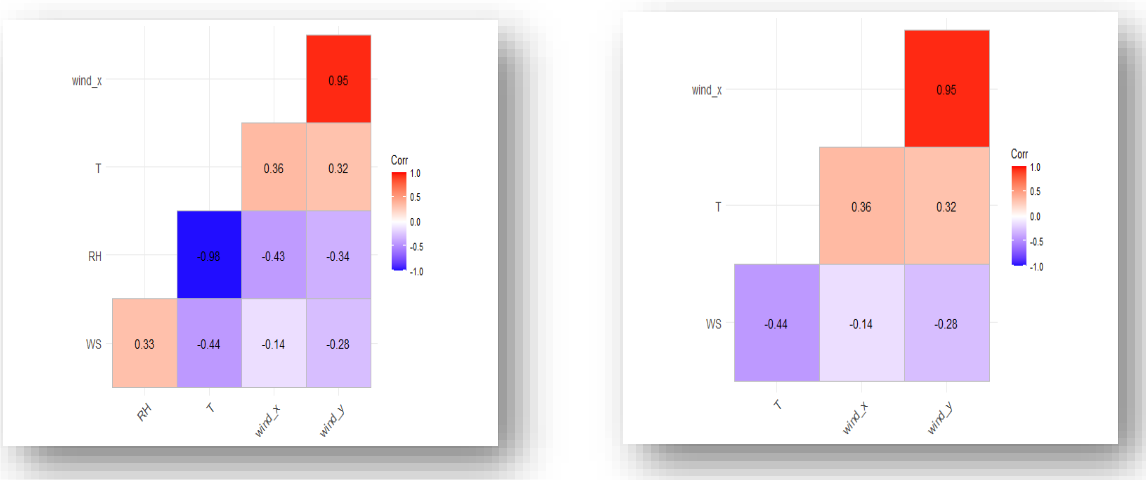
Correlation Matrix for the Apartment (A) Model – Models 1, 2 and 3 (One Minute)



Correlation Matrix for the Upwind (U) Model – Models 1 and 2 (Fifteen Minutes)



Correlation Matrix for the Downwind (D) Model – Models 1 and 2 (Fifteen Minutes)



Correlation Matrix for the Apartment (A) Model – Models 1, 2 and 3 (Fifteen Minutes)

Multiple Linear Regression Model: Residuals table (One Minute)					
	Minimum Value	***1st Quartile***	***Median***	***3rd Quartile***	***Maximum Value***
D Location					
Model 1	-4.7391	-1.1490	-0.0064	1.3018	3.1444
U Location					
Model 1	-0.93553	-0.15795	0.02166	0.16637	0.69895
Model 2	-0.9456	-0.1772	0.0333	0.1697	0.7080
A Location					
Model 1	-0.51429	-0.14079	-0.03141	0.10486	1.61283
Model 2	-0.5680	-0.1401	-0.0117	0.1204	1.5885
Model 3	-0.56084	-0.14002	-0.01922	0.11289	1.59550 76

Multiple Linear Regression Model: Residuals table (Fifteen Minutes)					
	Minimum Value	***1st Quartile***	***Median***	***3rd Quartile***	***Maximum Value***
D Location					
Model 1	-1.5224	-0.6934	-0.1394	0.8937	1.7538
Model 2	-1.5015	-0.7502	-0.2137	0.9431	1.6784
U Location					
Model 1	-0.15902	-0.07116	-0.02335	0.07330	0.17097
Model 2	-0.20279	-0.08846	-0.00653	0.08600	0.20028
A Location					
Model 1	-0.19880	-0.09998	-0.02654	0.08069	0.24952
Model 2	-0.24865	-0.06186	-0.02490	0.06754	0.27353 77