Using a Remotely Piloted Aircraft System to Investigate the Relationship between Canopy Temperature Depression and American Beech Health in Southern Ontario

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

The unprecedented spread of invasive pest and pathogens, along with climate change and human activity/development is degrading forest system health. American beech trees are a principal tree species that dominates Ontario's hardwood forests, yet are declining in numbers, primarily due to diseases such as beech bark disease and beech leaf disease, but also because of human development in environmentally sensitive forests. To better monitor American beech (*Fagus grandifolia*) health and identify severely deteriorated trees, innovative technologies such as Remotely Piloted Aircrafts (RPAs) can be utilized to complement the data collected by mid-altitude aerial aircrafts and ground-based surveys. Existing research has demonstrated the potential for RPA based thermography, which measure individual canopy temperature readings, to identify trees that are under water stress because of factors such as drought and foliar, stem and/or root diseases. However, whether American beech trees displaying noticeable signs in decline in health, due to factors such as foliar, stem and/or root diseases, can be differentiated from trees showing little to no sign in decline is yet to be determined by RPA-borne thermal imaging. This paper investigates whether RPA-borne thermal imaging can be a useful tool to monitor American beech tree health in Southern Ontario forests.

The study was located at rare Charitable Research Reserve in Cambridge, Ontario, in semi-naturalized forests. A total of 29 American beech trees across eight different plots were included in the sample for the study and were given a health level of either "healthy", "fair" or "poor" based on the presence/severity of beech bark disease, severity of bark deterioration and limb loss, and canopy coverage estimated as a percentage based on RPA visual imagery. In August of 2020, thermal imagery was collected on five different days: August 6th, 7th, 15th, 19th, and 26th, and in the following year was collected on three different days: August 2nd, 3rd, and 4th. Canopy temperatures of each individual beech tree was retrieved, normalized based on air temperature (canopy temperature depression) and analyzed to determine whether canopy temperature readings significantly differed based on health level. This study found that increasing American beech tree canopy temperatures were not correlated with deteriorating health. The one-way ANOVA performed for most flights showed that canopy temperature readings did not significantly change based on the recorded tree health level.

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Chapter 1. Study Background, Research Objective and Literature Review

1.1. Introduction

The functions and services that forested ecosystems provide are essential for human well-being and the biodiversity found within. Forest ecosystem functions include primary production and decomposition (Ansink et al., 2008; Brockerhoff et al., 2017) and forest ecosystem services include surface and ground water flow regulation, air and water quality enhancement, soil stabilization and erosion control, climate regulation and carbon sequestration and many others (Aust & Blinn, 2004; Food and Agriculture Organization of the United Nations [FAO], 2013; Krieger, 2001; Miura et al., 2015; Nowak et al., 2008). From an economic standpoint, it is estimated that globally, forest ecosystems provide $4.7 trillion dollars annually in goods and services for human well-being (Costanza et al., 1997; Krieger, 2001, p. 3). Given the socio-economic importance of forest ecosystems, any rational decisions made to manage forests need to be based on objective and reliable data (Corona et al., 2011; White et al., 2016).

However, forest monitoring and management is becoming challenging because of the increases in the spread and types of invasive pests and pathogens resulting from ongoing international trade and travel (Aukema et al., 2010; Brockerhoff & Liebhold, 2017; Dash et al., 2017). Invasive pests and pathogens continue to be the greatest ecological threat facing many tree species and forests, with an annual estimated economic impact ranging from $7.7 and $20 billion in Canada (Colautti et al., 2006; Lovett et al., 2016; Venette, 2017). In Canada, over 80 non-native insects or diseases have been identified since 1882, with several that have become invasive and highly destructive to forests (Forest Invasive Alien Species, 2015). Some of the most prominent alien pests and pathogens in Canada include the emerald ash borer, beech bark disease, Dutch Elm disease and the Gypsy Moth (Forest Invasive Alien Species, 2015).

With 400,000 hectares of forests lost every year in Canada from pests (Forest Invasive Alien Species, 2015), effective and efficient monitoring and management strategies are vital for future forest conservation. Monitoring programs and systems are currently in place in Canada to gather data that are of national and international concerns related to forest sustainability

(Wulder et al., 2004). The National Forest Inventory is an example of a collaborative initiative between the federal, provincial, and territorial government agencies that utilizes consistent standards and procedures to determine tree ages, land use, dominant species, and volume of wood (Wulder et al., 2004). Forest health programs have also been implemented in provinces such as in Ontario, where long-term environmental monitoring programs sample forests to determine tree mortality rates, identification of potential stressors, increases or decrease of tree species abundance and changes in tree size distributions (Credit Valley Conservation, 2017).

Ground-based surveys by professional field technicians have formed the foundation of forest health monitoring (Canadian Council of Forest Ministers [CCFM], 2012). Forest surveys of plots are fulfilled either annually or on a variable basis and the forest health factors monitored may change each year (CCFM, 2012; Credit Valley Conservation, 2017). The focus of the forest surveys is to determine dramatic changes in forest composition that arise because of invasive pests and pathogens. The data retrieved from forest monitoring programs can then lead to better planning and policy decisions on the forests being managed and the surrounding areas (Ontario Ministry of Northern Development, Natural Resources and Forestry [NDMNRF], 2021; Wulder et al., 2004). Despite the potential for traditional ground-based survey techniques, there are challenges associated with the spatial coverage that can be attained, the consistency in tree health interpretation and measurements between assessors, and high costs to inventory large forests (Dash et al., 2017; White et al., 2016).

Technological advances in modern remote sensing (e.g., Light Detection and Ranging (LiDAR), Remotely Piloted Aircrafts (RPAs) and satellite-borne and mid-altitude laser scanning) have the potential to complement traditional forest survey methods by providing additional data to assess forest health (Corona, 2016; Dash et al., 2017; Paneque-Galvez et al., 2014; Tang & Shao, 2015). RPA technology has advanced in recent years and has become an attractive complement for researchers and ecosystem managers to gather additional data for their forest health and composition surveys (Berie & Burud, 2018). RPAs can be automated to collect data that is of high spatial resolution at targeted locations over short intervals, which offers users versatility in forest inventory (Berie & Burud, 2018; Dash et al., 2017; Tang & Shao, 2015).

RPAs can come equipped with multi-spectral, hyperspectral, and thermal infrared camera technology and can be used for different applications (Tang and Shao, 2015). Thermal infrared camera technology designed for RPAs is becoming increasingly available for research and monitoring (Kelly et al., 2019). Thermal infrared technology can provide users with temperature measurements that can determine water availability of plants. When impacted by foliar, stem and/or root diseases, plants have shown to be water stressed, leading to lower transpiration rates and increases in canopy temperature (Smigaj et al., 2019; Jones, 1999). Many studies have now examined how thermal imagery with remote sensing tools, such as RPAs, can be used to detect increases in leaf and canopy temperature because of pest related diseases (e.g., Berni et al., 2009; Gonzalez-Dugo et al., 2012; Hais and Kučera, 2008; Smigaj et al., 2019; Smigaj et al., 2015).

To determine water content and subsequently the effects of pest related diseases, thermal "stress indices" are used to normalize environmental variation over different temporal periods (Smigaj et al., 2019). Two prominent thermal stress indices have been used in previous studies: canopy temperature depression and crop water stress index (CWSI). Canopy temperature depression normalizes canopy temperature with reference to air temperature and CWSI "introduces a non-water stressed baseline and a non-transpiring upper baseline" (Smigaj et al., 2019, p. 701). In terms of tree health, the use of thermal imagery and thermal stress indices have shown promising results in monitoring water stress in orchards (Berni et al., 2009; Gonzalez-Dugo et al., 2012), in identifying Verticillium wilt in olive trees (Calderón et al., 2013) and in assessing red band needle blight in Scots pine trees (Smigaj et al., 2019). However, it is unknown if American beech trees impacted by beech bark disease and other diseases are distinguishable from healthy beech trees using RPAs and thermal imagery.

1.2. Study Overview and Research Hypothesis

This study investigates whether diseased American beech trees can be distinguished from healthy American beech trees using an RPA equipped with thermal camera technology. The following hypothesis guides my study:

Research Hypothesis: *American beech trees that are "poor" in "health" will display warmer canopy temperature readings than "healthy" American beech trees, regardless of the day, weather conditions and site characteristics.*

This study investigates whether thermal imagery collected by an RPA can detect canopy temperature increases in American beech trees showing deteriorating health. This research has been conducted at selected forested sites at rare Charitable Research Reserve in Cambridge Ontario. Data collection occurred between the months of July and September of 2020 and 2021. For accurate analysis of results, data collection was prioritized during periods of high net solar radiation and clear skies. Trees were selected which had their full canopy visible from the RPA imagery collected. The thermal stress index canopy temperature depression was calculated to normalize canopy temperature with reference to air temperature (Smigaj et al., 2019). Canopy temperature depression can allow for comparisons between the different hours that canopy temperature data is collected, as the canopy temperature of trees constantly varies due to changes in air temperature and other environmental conditions (Smigaj, et al., 2019).

This research can contribute towards advancing the understanding of the potential for RPAs and thermal imagery technology for more efficient forest monitoring and management. Whether canopy temperature readings for healthy, fair in health, or poor in health American beech trees can be distinguished from one another based on the thermal imagery collected using a RPA, is addressed in this report. Much of the methodology and research builds from the work of Smigaj et al. (2019), where they compared canopy temperature depression readings to red band needle blight disease levels of Scots Pine trees. Although the study by Smigaj et al. (2019) was completed on a monocrop pine plantation, this study consists of American beech trees situated in a semi-natural forested location. A semi-natural forest can be challenging to survey as there are many factors (e.g., water availability, species diversity, elevation, soil type etc.) that cannot be controlled for and may affect the thermal RPA-borne data collected. Therefore, surveying monocrop plantations, where there is less species diversity, water availability is controlled, and the trees are uniformly planted is preferred and has shown some success (Bernie et al., 2009; Calderón et al., 2013; Smigaj et al., 2019), however the applicability of detecting pest and pathogen induced canopy temperature changes in a single tree species located in a semi-natural forest is less well known and needs to be studied further. Moreover, this study relies on data collected over multiple days versus the single day performed by Smigaj et al. (2019). The decision to collect thermal imagery over multiple days was done as a method of technical replication and to determine what factors may be affecting canopy temperature readings should the data show varying correlations between health and canopy temperature.

1.3. Literature Review

1.3.1. Forests Monitoring

Forests are an important ecosystem for terrestrial biodiversity, with the majority of amphibian, bird and mammal species depending on this habitat for survival (FAO and United Nations Environment Programme [UNEP], 2020; Vié et al., 2009), and for society as they provide significant ecological, economic, and cultural benefits (Brockeroff et al., 2017; FAO and UNEP, 2020; Ferretti, 1997). However, forest ecosystem health is being challenged by climate change, invasive pests and pathogens, and human activities/developments (Brandt et al., 2013; Brockeroff et al., 2017; FAO and UNEP, 2020; Ferretti, 1997; Percy and Ferretti, 2004). To prevent further forest loss and degradation, forest management and monitoring techniques must continue to adapt and innovate as local and global conditions continue to change.

Across different political and socio-ecological landscapes, various strategies, frameworks, and methods have been utilized to monitor forest ecosystems. In Europe, forest monitoring programs were implemented under the International Programme on the Assessment and Monitoring of Air pollution Effects on Forest, beginning in 1986 (Lorenz et al., 2007; Nevalainen et al., 2010). Gradually, however, the scope of monitoring expanded from air pollution effects to other factors that included the effects of pests and fungal diseases (Nevalainen et al., 2010). Similarly, in the United States, their Forest Health Monitoring Program began in 1990 to assess forest health and sustainability across all the forested landscape (Bennett and Tkacz, 2008). The current Forest Health Monitoring Program approach has been adapted to include remote sensing data collection (e.g., visual-spectrum optical imagery), as well as traditional in-situ field data focused on aspects such as tree species and diameter, forest type and stand size (Bennett and Tkacz, 2008).

In Canada, forests consist of a large proportion of the terrestrial landscape which contribute numerous ecosystem services to society (Dyk, Leckie, Tinis and Ortlepp, 2015; Gillis, Omule and Brierley, 2005). The significance of forests for social and ecological wellbeing led to the development of programs such as Canada's National Forest Inventory, the National Deforestation Monitoring System and Earth Observation for Sustainable Development of Forests (Gillis et al., 2005; Wulder, 2004). With Canada's National Forest Inventory, data on forest characteristics and quantity are collected and compiled every five years by the provinces and territories into a central database. Although early forest monitoring metrics in Canada's National Forest Inventory focused on wood supply and the performance of the lumber/timber industry, the current framework considers forest health, biodiversity, and forest productivity as major components (Boutin et al., 2009; Gillis et al., 2005; Gillis, 2001; Wulder, 2004).

To support Canada's National Forest Inventory, the Canadian Council of Forest Ministers (CCFM), Natural Resources Canada and the Canadian Food Inspection Agency, have developed a task force to reduce the spread and establishment of invasive pests in Canada (CCFM, 2012; Nienhuis and Wilson, 2018). These parties work to implement a National Forest Pest Strategy to monitor, perform risk analyses, report results and much more, regarding the management of invasive forest pests in Canada (CCFM, 2012).

To monitor invasive species spread, the CCFM task force utilizes mid-altitude aerial and ground surveys to identify and quantify invasive forest pests (CCFM, 2012). According to CCFM (2012), "approximately 289 distinct ground and aerial surveys are conducted for 75 biotic and abiotic forest health factors across Canada" (p. 6). Of the surveys undertaken, approximately 61% are related to monitoring forest pest populations. The methods used to conduct mid-altitude aerial surveys to monitor forest pests involve piloted helicopters and fixed wing aircrafts, which are usually accompanied by some ground component to verify pest damage and intensity (CCFM, 2012). The mid-altitude imagery collected allows the task force to create maps using GIS software and can be used to monitor forest health and prevalence of pests based on defoliation severity (CCFM, 2012). Remote sensing options are being considered for the future of forest pest monitoring in Canada, though there is a lack of expertise, funding, and research into how new technologies (e.g., RPAs) can be utilized to current programs (CCFM, 2012; CCFM, 2019).

Ground surveys across Canada include the use of over 14,500 permanent or temporary monitoring plots (CCFM, 2012). Sampling occurs at these plots on an annual or variable basis, depending on the pest being monitored. Monitoring methods include pheromone traps to determine adult insect populations (e.g., to monitor eastern spruce budworm), lure formulations (e.g., to monitor jack pine budworm) and quantifying eggs and larvae on trees/branches to extrapolate to a given area (CCFM, 2012). Generally, only one or two pests are monitored at most ground plots and generally only include gypsy moths, eastern spruce budworm, jack pine budworm and forest tent caterpillar (CCFM, 2012). Forest diseases, such as stem and root diseases are also being monitored at ground plots, though not as intensively as pests.

In Ontario, Canada, forest health monitoring is primarily a responsibility of the Ontario Ministry of Northern Development, Natural Resources and Forestry (NDMNRF), as most of Ontario's forests (43 million hectares (ha)) are found on publicly owned crown land (Nienhuis and Wilson, 2018; NDMNRF, 2021). In total, there is approximately 56 million ha of forest and 14 million ha of treed wetland in Ontario (NDMNRF, 2021). With such large, forested areas, obtaining accurate data on forest inventory and health is complicated (Bilyk et al., 2020). In 2015, the Invasive Species Act was implemented to give additional legislative powers to the province to prevent and control non-native species spread. The Invasive Species Act is the first independent piece of legislation that focuses solely on invasive species and allows inspectors to monitor spread and make decisions to quarantine an area to eradicate a species from an area (Nienhuis and Wilson, 2018). Ultimately, collecting high-quality data through monitoring efforts can increase decision-making capacity which can then improve future monitoring methods for more sustainable forests in Ontario, (Figure 1) (NDMNRF, 2021). Therefore, forest monitoring is recognized as an important component for future forest management and sustainability in Ontario.

Figure 1: *The adaptive management cycle that guides forest management, monitoring, policy making and reporting in Ontario (NDMNRF, 2021)*

The NDMNRF monitoring program utilizes mid-altitude aerial mapping, biomonitoring, pest surveys and permanently established plots to inventory forests and monitor overall health (NDMNRF, 2020). The use of RPA technology to inventory and monitor forests has played an increasingly larger role over time in the NDMNRF programs. The use of satellite imagery, GPS receivers, airplanes, Light detection and Ranging (LiDAR) and other technology is being more widely used, which is improving in-situ forest inventory and health monitoring (Bilyk et al., 2020). Other organizations in Ontario that participate in tree and forest monitoring include the Association for Canadian Educational Resources and Conservation Ontario (Association for Canadian Education Resources, 2020; Conservation Ontario, 2018).

Despite the efforts of the NDMNRF and other organizations in monitoring Ontario's forests, invasive pests and diseases are becoming a greater threat to forest survival and health (Nienhuis and Wilson, 2018). Tree species such as, butternut (*Juglans cinecera* L.), American beech and American chestnut (*Castanea dentate*) have significantly reduced in numbers due to butternut canker, beech bark disease and chestnut blight, respectively (Boland et al., 2012; NDMNRF, 2020; Nienhuis and Wilson, 2018; Poisson and Ursic, 2013). Although there is a lack of expertise in remote sensing technologies within the provinces (CCFM, 2012; CCFM, 2019), exploring the use of new technologies, such as RPAs and thermal infrared detection, may lead to better forest management. Recent work has shown promising results in using RPAs equipped with thermal camera technology in monitoring restoration progress (Hamberg, 2020), identifying trees affected by forest pests and pathogens (Calderón et al., 2013; Smigaj et al., 2019) and recording drought responses of specific tree species (Scherrer et al., 2011).

1.3.2. American Beech

American beech (*Fagus grandifolia)* is unique to North America as it is the only species of the *Fagus* genus (Tubbs and Houston, 1990). Although beech trees may have existed over most of North America before the last glacial period, the beech tree species is now only found on the eastern side of North America. In Ontario, beech trees are a principal tree species that have comprised many hardwood forests for centuries (NDMNRF, 2021). The beech tree species can dominate moist soils and late successional forests or can be well integrated into mixed stands (McLaughlin and Greifenhagen, 2012). Beech trees are well adapted to alluvial soils, and although slow growing, can attain ages of 400 years (Tubbs and Houston, 1990). In Ontario, beech trees often reach a maximum age of 250, with a diameter of 80 cm and a height of 27 m (McLaughlin and Greifenhagen, 2012). Furthermore, beech trees are an important component of hardwood forests as their nuts are a source of nutrition for black bears, deer and rodents. Beech wood is also used by humans, commonly for flooring and furniture (McLaughlin and Greifenhagen, 2012; Tubbs and Houston, 1990).

American beech trees have a broad canopy structure and bark that is distinguishably smooth and light grey (Figure 2) (NDMNRF, 2021). The native habitat range of American beech extends as far north-east as Cape Breton Island, Nova Scotia and as far south as Northern Florida and the mountains of northeastern Mexico (Tubbs and Houston, 1990). Beech is well suited to annual precipitation levels between 760 mm to 1270 mm. Beech trees grow on average for 100 to 280 days in a year, and favour temperatures between 4˚ and 21˚ C (Tubbs and Houston, 1990). Beech is also a unique tree species as they use double the amount of water for transpiration and growth than deciduous trees such as oaks (Tubbs and Houston, 1990).

Figure 2: *American beech leaves are narrow, oval with a pointed tip (a); beech bark is generally smooth and appearing light bluish grey in colour (b) (NDMNRF, 2021)*

1.3.3. American beech diseases

Although a significant member of Ontario's hardwood forests, beech trees are threatened by beech bark disease, which is undermining the overall integrity of these forests. As noted in section 1.0, Morin et al. (2007), state that "Beech bark disease is an insect-fungus complex involving the beech scale insect (*Cryptococcus fagisuga)* and one of two canker fungi" (p.726). Of the two canker fungi *Neonectria faginata* is the most significant contributor to beech bark disease in Ontario (McLaughlin and Greifenhagen, 2012). Beech bark disease has spread throughout most of eastern North America, with it being officially confirmed in Ontario in 1999.

The disease begins with the beech scale feeding on the outer bark of beech trees (Kibbe Bonello, 2019). The scale diminishes the integrity and growth of the tree and makes it more susceptible to fungal infection. The feeding of the outer bark of the tree results in the collapse of the host parenchyma cells which creates small fissures in the bark (Koch, Carey, Mason and Nelson, 2009). These fissures allow the fungus *Neonectria faginata* to develop and grow as circular lemon-shaped cankers on the tree, which weakens the inner bark and cambium of the beech tree (Figure 3) (Koch et al., 2009; McLaughlin and Greifenhagen, 2012). The infection usually starts on the lower bole of the tree; however, cankers can encircle the entire surface of the bark and extend into the crown. Mature trees in the stand are usually targeted first and can exhibit crown dieback (Koch et al., 2009; McLaughlin and Greifenhagen, 2012).

Some beech trees exhibit resistance to the insect beech scale and do not experience beech bark disease. However, only 1% of trees in North America have shown to be resistant (Koch et al., 2009; McLaughlin and Greifenhagen, 2012). If identified, the growth of these disease resistant beech trees can be promoted through dispersal of its seed. If disease resistant trees are not identified, other management strategies include culling infected trees and removing beech tree root sprouts to limit spread. Single tree selection of greatly diseased beech trees of over 50 years are usually culled, while retaining relatively low impacted trees. The single tree selection strategy could be a solution to improve disease resistance in forest stands (McLaughlin and Greifenhagen, 2012). Despite these efforts, effective management strategies for beech dominant forest stands have not been identified and must continue to be studied.

Figure 3*: Comparison of the outer bark of a relatively intact American beech tree (a) and a deteriorated American beech tree (b) at rare Charitable Research Reserve in Cambridge Ontario; beech bark disease cankers on the stem of an American beech tree (c); and fruiting bodies on active beech bark diseased cankers (d) (McLaughlin and Greifenhagen, 2012)*

Furthermore, some beech trees in parts of North America are being affected by a new disease known as beech leaf disease (Carta et al., 2020; DiGasparro, 2019; Ewing et al., 2018; Popkin, 2019). Researchers have been reporting effects of beech leaf disease since it was first noticed in 2012 in the state of Ohio (Ewing et al., 2018). Early signs of beech leaf disease “appear as a dark green, interveinal banding pattern on lower canopy foliage” (Ewing et al., 2018, p. 1). Leaves will eventually turn dark and will appear leathery and crumpled. The effects of beech leaf disease can be noticed as soon as bud break, leading researchers such as Ewing et al. (2018), to believe that the disease progresses through the buds. As the disease progresses through the years, affected buds will begin to be aborted, resulting in limited foliage to be produced and leading to tree mortality (Ewing et al., 2018). Early studies suggest that a nematode species, *Litylenchus crenatae,* is the primary cause of beech leaf disease (Carta et al., 2020). No effective control measures have been identified yet, though continually monitoring for the disease, limiting the movement of firewood, and identifying disease resistant trees could lead to future success in limiting beech leaf disease spread (DiGasparro, 2019, Ewing et al., 2018).

1.3.4. Thermodynamics

The structure of forest ecosystems is complex (Holling 2001; Kay, 2000; Kuuluvainen, 2009). In particular, the dynamics of forests are a function of positive and negative feedback loops which create a self-organizing system (Meadows, 2008; Kay, Regier, Boyle and Francis, 1999; Kay, 2000; Kuuluvainen, 2009). Furthermore, forests are open systems which process flows of high-quality energy (exergy) to obtain order from disorder (Brzustowski and Golem, 1976; Kay et al., 1999; Kay, 2000; Kuuluvainen, 2009; Schneider and Kay, 1994a; Schrödinger, 1944). Because of the complexity inherent to forests ecosystems, monitoring tools and methods need to be well adapted to how these systems change for better management and policy development.

To monitor ecosystems, the laws of thermodynamics must first be understood. The first law of thermodynamics states that energy cannot be created or destroyed and that in a closed system, total energy remains unchanged through transformation processes (Schneider and Kay, 1994b). Over time, the quantity of energy remains unchanged in a closed system, yet the quality of the energy (i.e., exergy) may change. However, the first law applies differently to open systems whereby the energy still cannot be created or destroyed but can be exchanged with the surrounding environment and systems. The second law of thermodynamics states that physical or chemical processes in the system will degrade the quality of the energy available (Schneider and Kay, 1994b). However, open systems, such as forest ecosystems, are open to energy flows and are moved away from equilibrium across time and space. Systems like forests maintain structure by exchanging energy and/or matter with the outside world and can be classified as non-equilibrium systems (Kay, 1999; Schneider and Kay, 1994b). A non-equilibrium system can exist in local states that are not at thermodynamic equilibrium by increasing entropy of the larger system it resides in (Kay, 1999). However, these open systems tend to return to an equilibrium state and often tend to resist being moved from equilibrium (Kay, 1999). Therefore, monitoring and managing ecosystems such as a forest is a challenge as ecosystem change can be rapid and understanding what state the system will change to is difficult to predict.

1.3.5. Energy Budget and Leaf Energy Balance

Many biotic and abiotic factors can affect leaf and canopy energy balances. The amount of solar radiation received in each region on Earth plays a major factor in what vegetation can thrive. Overall, the solar radiation received by the Earth equates to about 342 watts per square metre (Wm^{-2}), with about 168 Wm^{-2} being absorbed by the Earth's surface and 67 Wm^{-2} absorbed by the atmosphere (Bonan, 2002). Conversely, the Earth's surface emits 390 Wm^{-2} of longwave radiation which is mostly absorbed by the atmosphere (350 Wm^{-2}), with the remainder escaping to space. The radiation from the atmosphere is emitted in all direction with approximately 195 Wm^{-2} being lost to space. As a result, the net radiation absorbed by the Earth is approximately zero.

Although net radiation equals zero, the distribution of radiation is unequal. Latitudes near the tropics absorb more radiation than the poles. The difference in distribution of radiation, results in a temperature gradient from low latitudes to high latitudes (Bonan, 2002). Therefore, low latitudes are much warmer than higher latitudes as more radiation is absorbed near the equator and less at the poles. However, radiation is not the sole factor determining temperature of a region. The uneven distribution of incoming solar radiation effects air pressure, which produces winds that carries heat from tropical regions to polar regions (Bonan, 2002).

At the canopy level, leaf energy balance is affected by many biological factors, including transpiration rates, leaf structure and size, canopy structure and much more (Still et al., 2019). Each of these factors can have significant effects on leaf energy exchange and can cause significant fluctuations in leaf temperature (Ehleringer et al., 1976; Smith and Carter, 1988). “The net radiation balance for a leaf, R_{net}, is a function of absorbed solar shortwave radiation (SW, in W/m2) and the net of absorbed and emitted longwave radiation (LW, in W/m2).” (Still et al., 2019, p. 4). Sensible and latent heat exchanges balances leaf net radiation. As sensible heat increases, latent heat decreases to balance net radiation of a leaf, and vice versa (Fuchs, 1989; Still et al., 2019). The equation for the energy balance of a leaf is

$$R_{net} = \alpha SW_{in} + \varepsilon_{IR}(LW_{in}) - 2\varepsilon_{IR}\sigma\left(T_{leaf}\right)^4$$

where SW_{in} represents the reflected and scattered shortwave radiation absorbed from the leaf from both sides, α is the leaf absorptivity of SW radiation (0.6), LW_{in} is longwave radiation from the sky and surrounding leaves and branches that is absorbed by both sides of the leaves, ε_{IR} is the leaf absorptivity of LW radiation (0.96) which is equal to its emissivity and T_{leaf} is the LW radiation emitted by the leaf where σ is the Stefan-Boltzmann constant ($5.67 \times 10{-}8$ W·m−2·K−4) (Nobel, 2009; Still et al., 2019, p. 4).

However, plant canopies are much more complex than single leaves, as they comprise of the soil, branches, bark, stems and more of the entire plant (Campbell and Norman, 2000, p. 230). The orientation and inclination of the branches and leaves that make up the canopy can influence the temperatures produced by the leaves (Fuchs, 1989). Therefore, the dynamics of canopy temperature are affected by the individual leaf energy exchange with the atmosphere and the architecture of the canopy itself (Still et al., 2019).

1.3.6. Canopy Temperature as an Indicator of plant health

Current research utilizing canopy temperature to evaluate plant health because of factors such as disease and drought have been studied and have mostly shown significant correlations (e.g., Berni et al., 2009; Calderon et al., 2013; Iizuka et al., 2018; Ludovisi et al., 2017 Smigaj et al., 2019). However, extensive research early in physics and technology were the primary reasons why canopy temperature is seen as an indicator of plant health today (Moran, 2004). Notably, using canopy temperature as an indicator of ecosystem and plant health was recognized when Monteith and Szeicz (1962) identified that canopy temperature is a function of energy balance components. Before the work by Monteith and Szeicz (1962), research was either focused on the relationship of evaporation and energy balance or leaf and canopy temperatures (Moran, 2004).

Understanding and calculating potential evaporation from single leaves and vegetation canopies was pioneered by many such as Bowen (1926), Penman (1948; 1953), Monteith (1965) and Rijtema (1965). The theoretical work on evaporation by such authors was adopted by hydrologists, irrigation specialists, and agriculturalists (Moran, 2004). Work on evaporation led to research by Vidal and Devaux-Ros (1995) which identified the importance of canopy evapotranspiration as a key metric in determining plant water status and the ability of the plant to effectively exchange energy. Hatfield (1997) also identified that plant-water relations are important to understand for plant health as water deficits can lead to reduced growth and impaired photosynthesis and respiration.

The rate of transpiration can be affected by multiple factors, such as solar radiation, humidity, and wind speed (Bonan, 2002). Systems that are exposed to high solar radiation, dry air conditions and high winds will experience greater transpiration rates (Bonan, 2002). Other factors that can affect transpiration rate include, soil type and associated hydraulic properties (e.g., conductivity) and vegetation type (e.g., stomatal conductance). Generally, woody plants will have a lower stomatal conductance, whereas natural herbaceous and agricultural plants will have higher conductance (Bonan, 2002; Kelliher et al., 1995; Körner, 1995). However, measuring evaporation experimentally with equipment such as weighing lysimeters, portable assimilation chambers and remote sensing techniques is limited as they can only determine point values of evaporation, which makes research that cover large areas challenging (Moran, 2004).

Transpiration plays a vital role in determining plant temperature and for monitoring ecosystem health at the canopy scale. Early studies showed that temperatures of plants would generally be cooler than air temperature (e.g., Asari and Loomis, 1959; Eaton and Belden, 1929;

Miller and Saunders, 1923; Waggoner and Shaw, 1952). However, Gates (1964) was one of the first to identify that transpiration played a role in energy budget of plants and the temperatures recorded. The work by Gates (1964), led to the understanding that vegetation temperature was inversely correlated with transpiration rate and stomatal conductance (Fuchs, 1990; Fuchs and Tanner, 1966; Hernández-Clemente et al., 2019; Möller et al., 2006; Smigaj et al., 2017). As a result, remote sensing tools have now began utilizing thermal infrared sensors to collect leaf and canopy temperature measurements as research identified a link between transpiration and temperature (Monteith and Szeicz, 1962; Moran, 2004).

When plants are under water stress by disease or infection, transpiration rates are reduced because of stomatal closure, which increases leaf temperature and reduces photosynthetic activity (González-Dugo, Moran, Mateos and Bryant, 2006; Smigaj et al., 2017; Smigaj et al., 2019). Using vegetation temperature in this case can be an indicator of vegetation health. With the current successes in identifying disease spread and impacts of drought on tree species (e.g., Calderón et al. 2013; Smigaj et al., 2019; Scherrer et al., 2011; Twidwell et al., 2016), ecosystem managers and governments may look to include RPAs with thermal camera technology in forest monitoring strategies.

1.3.7. Remotely Piloted Aircrafts and Thermal Infrared Cameras

In terms of forest monitoring and management, remote sensing and RPA technology can become an attractive complement to mid-altitude aerial and satellite-based data (Tang and Shao, 2015). Remote sensing technologies began to significantly advance in the 1980s and 1990s following the launch of the first Landsat satellite in 1972. The Landsat program has been popular for forestry sectors as ecosystem managers can have access to images that cover large areas, year after year (Tang and Shao, 2015). Using RPA technology is also becoming a popular tool among ecosystem managers as it can allow for more timely data collection as well as opportunities for new natural resource management applications (Tang and Shao, 2015). RPAs can be relatively low cost and come equipped with high resolution remote sensing cameras that can gather data on forest composition, growth, and much more. They can also be programmed to fly autonomously by users for consistent data collection (Berie and Burud, 2018).

RPAs can be used for many applications depending on what they can carry. They can be mounted with multi-spectral, hyperspectral, and thermal cameras, audio monitoring devices, liquid sprayers, GPS devices and much more (Tang and Shao, 2015). Within ecological restoration and ecosystem monitoring, RPAs have been applied in wildlife and freshwater habitat studies (Sandbrook, 2015), evaluating ecological restoration progress (Hamberg, 2020) identifying diseased trees and others (Smigaj et al., 2019). In terms of directly supporting restoration and conservation practices, RPAs can be used to deliver seeds for forest restoration projects, monitor illegal deforestation activities and identify illegal hunting practices (Sandbrook, 2015).

Moreover, thermal infrared camera technology designed for RPAs is becoming increasingly available for research and ecosystem monitoring (Kelly et al., 2019). Thermal infrared technology can provide users with temperature measurements that can determine water stress and evapotranspiration levels in vegetation, soil moisture and much more. Thermal infrared cameras measure radiation in the 8-13 µm wavelengths (Campbell and Norman, 2000, p. 230). However, cameras can cost $15,000 or more, depending on resolution and accuracy of radiometric calibration (Kelly et al., 2019). Cheaper thermal cameras are also usually not radiometrically-calibrated, which means that they can only be used to compare relative temperature differences represented in raw digital numbers (Kelly et al., 2019). For cross-image comparison, data normalization or radiometric correction is required as weather conditions can change rapidly, which can alter the canopy temperatures recorded.

Thermal cameras that have radiometric calibration built in can still have a low temperature accuracy of ±5˚C. The thermal camera sensors that are made for RPAs usually have their sensor (focal plane array) composed of uncooled microbolometers (Kelly et al., 2019; Olbrycht, Wiecek and De Mey, 2012). An uncooled microbolometer is a common type of infrared radiation detector that is relatively low cost and simple. However, thermal drift, which are variable offset shifts in the microbolometers' characteristics, occur which changes to the radiation energy readings (Olbrycht et al., 2012). As a result, non-uniformity correction of the thermal signal is required to harmonize the signal response of the focal pane array by taking an image of the shutter, which is assumed to be identical to the rest of the camera's structure

(Kelly et al., 2019; Olbrycht et al., 2012). Yet, Kelley et al. (2019), note that during actual flight time, the non-uniformity correction can be inaccurate as the exterior of the camera is more exposed to wind. These factors and others such as changes in ambient temperatures, humidity and object emissivity can affect temperature measurements of uncooled infrared cameras that must be corrected for.

Nonetheless, uncooled thermal cameras have been successfully utilized to compare the spatial and temporal variations in canopy temperature of trees (Berni et al., 2009; Gonzalez-Dugo et al., 2012; Smigaj et al., 2019). In terms of beech bark disease, the only current effective method at identifying the disease is through in-situ visual inspection of each individual beech tree. The use of RPAs and miniaturized thermal infrared cameras may become a new strategy at identifying diseased beech trees at greater scales, as only relative temperatures between healthy and sick trees need to be compared.

1.3.8. Thermal Stress Indices

Using thermal imagery and stress indices as a method to investigate the effect of water stress or disease on vegetation surface temperatures is becoming more common practice (e.g., Berni et al., 2009; Calderón et al., 2013; Pineda, Barón and Pérez-Bueno, 2021; Smigaj et al., 2019; Still et al., 2019). For example, research has utilized thermal stress indices to measure canopy temperature increases in orchard trees under water stress (Ballester et al., 2013; Berni et al., 2009; Gonzalez-Dugo et al., 2012). Other studies have used remote thermal sensing methods to identify different land cover types and the effect of heating and cooling on peatland forest (Iizuka et al., 2018) and to demonstrate the potential of restoring temperate wooded ecosystems to lower daytime surface temperatures (Hamberg, 2020). With regards to more naturalized forested areas, studies have shown some success with utilizing thermal stress indices. To determine drought tolerance in a forested stand, Scherrer et al. (2011) used canopy temperature depression for their analysis and recorded significant differences in temperatures of different trees. With regards to using thermal imagery to determine diseases in trees, Smigaj et al. (2019), found statistically significant correlations between red band needle blight and canopy temperature depression. Bernie et al. (2009), used the crop water stress index (CWSI) to measure the effect of different water treatments on olive trees. These remote sensing studies indicate that thermal infrared cameras could complement in-situ methods that evaluate plant stress and health (González-Dugo et al., 2006, Moran, 2004).

As mentioned previously, plant temperature is also affected by a variety of other environmental variables such as air temperature, wind and soil moisture. Depending on the type of study, a certain thermal stress index is utilized which provides a relative measure of plant health by normalizing canopy temperature readings by a certain standard (Leinonen et al., 2006; Moran, 2004; Pineda et al, 2021). The most used indices include the CWSI and canopy temperature depression. The CWSI measures the relative transpiration rate at a given point in time to normalize against other environmental effects (Idso et al., 1981; Jackson et al., 1981). According to Pineda et al. (2021), the CWSI relies on "two baselines: $(T_{canopy} - T_{air})_{wet}$ as the estimated difference for a well-watered plant, and $(Tc_{anopy} - T_{air})_{dry}$ for a dry (non-transpiring) plant" (p.2). Canopy temperature depression is another common thermal stress index that can be used which normalizes canopy temperature to air temperature (Smigaj et al., 2019). Many other stress indices have been used which have obtained scientific acceptance and those include the stress degree day, the maximum temperature difference, and the water deficit index (Idso et al., 1977; Jackson et al., 1977; Lindenthal et al., 2004; Moran et al., 1994; Moran, 2004).

With regards to studies utilizing RPAs equipped with thermal imaging technology, the literature available at the time of writing is becoming increasingly common. Those that have used RPAs with thermal infrared imaging cameras have focused on monitoring water stress in orchards and monoculture tree plantations (Berni et al., 2009; Iizuka et al., 2018; Ludovisi et al., 2017), identifying the effects of disease in orchards and monoculture trees plantations (Calderon et al., 2013; Smigaj et al., 2019), determining the effect of ecological restoration on surface temperature readings (Hamberg, 2020) and analyzing drought tolerance in a mixed deciduous forest stand (Scherrer et al., 2011). However, the methods used, and flight campaigns conducted by these researchers varied.

Table 1 details some relevant literature that have investigated the potential of RPAs and thermal imaging technology to study how changes in vegetation health or ecosystem structure impacted canopy temperature readings. The type of species or ecosystem being studied, varied: some studies examined the effect of a specific treatment on surface temperature change of olive trees (Bernie et al., 2009) and experimentally restored plots (Hamberg, 2020); others investigated the impact of an invasive pest or pathogen on tree canopy temperature change (Calderón et al., 2013; Smigaj et al., 2019); and some investigated how drought (Ludovisi et al., 2017; Scherrer et al., 2011) and spatiotemporal changes (Iizuka et al., 2018) effected temperature readings of trees. Depending on the study and RPA technology available at the time, the number of RPA flights undertaken varied. Most notably, Bernie et al. (2009), only completed one RPA flight campaign for their study, whereas Hamberg (2020), completed five RPA campaigns in July of 2019 and four in September of 2019. For each flight campaign, Hamberg (2020) took images twice per hour at 12, 2, 4 and 8pm. This difference in flights conducted between Hamberg (2020) and the others could have been a result of a variety of factors; however, the study from Hamberg, required relatively more images to determine the effects of ecosystem change from restoration over time and to confirm the consistency of the data collected. Studies by Bernie et al. (2009) and Smigaj et al. (2019) required less image collection and flights as conclusions on surface temperature variations between subjects could be determined in a shorter time frame. Lastly, not all studies utilized a thermal stress index (Hamberg, 2020; Iizuka et al., 2018), however those that did, studied the effects of drought (Bernie et al., 2009; Ludovisi et al., 2017; Scherrer et al., 2011), or pathogens (Calderón et al., 2013; Smigaj et al., 2019) on canopy temperature change.

***Table 1**: Studies that have investigated the use of RPAs and thermal camera technology on vegetation, the number of flights conducted and the thermal stress index that was used*

Authors	Study	Species/ecosystem studied	Sample size/observation area	Number of flights	Thermal Stress Index Used
Iizuka et al., 2018	Visualizing the Spatiotemporal Trends of Thermal Characteristics in a Peatland Plantation Forest in Indonesia: Pilot Test Using Unmanned Aerial Systems (UASs)	Monoculture Tree Plantation of Northern Wattle (Acacia crassicarpa)	The size of the study site was about two acres	Four flights in two days	Not applicable
Calderón et al., 2013	High-resolution airborne hyperspectral and thermal imagery for early detection of Verticillium wilt of olive using fluorescence, temperature and narrow-band spectral indices	Olive trees *(Olea europaea* L cv. 'Arbequina'*)*	A total of 25 trees; each given a health rating on a scale of 0 to 4.	10 flights over three years	Crop Water Stress Index and Canopy Temperature Depression
Bernie et al., 2009	Mapping canopy conductance and CWSI in olive orchards using high resolution thermal remote sensing imagery	Olive Trees (Olea europaea L cv. 'Arbequino')	A total of 108 trees. Trees were categorized based on one of the three drip-irrigation treatments applied.	One flight	Crop Water Stress Index
Ludovisi et al., 2017	RPA-Based Thermal Imaging for High-Throughput Field Phenotyping of Black Poplar Response to Drought	Black poplar (*Populus nigra* L)	Two separate water treatments on a population of 4603 trees.	Two flights in one day	Stress Susceptibility Index
Smigaj et al., 2019	Canopy temperature from an Unmanned Aerial Vehicle as an indicator of tree stress 2 associated with red band needle blight severity	Monoculture tree plantation of Scots pine (*Pinus sylvestris*)	A total of 60 trees in a 1200m^2 area	Six flights in one day	Canopy Temperature Depression
Hamberg, 2020	The effect of ecosystem change, restoration, and plant diversity on thermally imaged surface temperature	Experimental restored plots of temperate wooded ecosystems	A total of 20 experimentally restored plots and 35 control plots	98 flights across nine days	Not directly identified
Scherrer et al., 2011	Drought-sensitivity ranking of deciduous tree species based on thermal imaging of forest canopies	Six deciduous tree species (*Acer pseudoplatanus, Fagus sylvatica, Tilia platyphyllos, Fraxinus excelsior, Prunus avium* and *Quercus petraea)*	Four study sites consisting of diverse tree species (two 'dry' and two 'moist' sites). A total of 184 trees were sampled.	Three flights over four weeks	Canopy Temperature Depression

Applications of thermography in forests have been limited because of the low-resolution imagery captured by satellites (Smigaj et al., 2019). Airborne piloted aircrafts have been used to gather higher resolution data; however, it is expensive and time restricted (Smigaj et al., 2019). Fortunately, RPAs that can gather high spatial resolution data are becoming more inexpensive and more accessible. Much of the literature reviewed here has proven the potential of thermal imagery and thermal stress indices to identify diseased and water stressed vegetation. Research continues to expand with novel work by Hamberg (2020), which shows the potential of this method to investigate the effects of ecological restoration and reorganization on surface temperature readings. However, with regards to the monitoring of invasive pests and disease spread in forests, more research is needed. Furthermore, the majority of RPA and thermal imagery-based research has investigated the effects of pests and disease in monocrop plantations (Calderón et al., 2013; Smigaj et al., 2019), rather than in more naturalized forest settings. Other forest pests and diseases, such as the emerald ash borer, hemlock woolly adelgid and beech bark disease, and the effects on surface temperature changes have not yet been studied using RPAs and thermal imaging technology.

Revolutionizing forest pest and disease monitoring requires additional research on the potential of RPA and thermal imaging technology. In Canada, remote sensing options are being considered, though there is still a lack of guidance on the potential for RPA and thermal camera technology to monitor the numerous pest and disease spread in various tree species (CCFM, 2012; CCFM, 2019). With the spread of invasive forest pests and disease not slowing, evaluating the success of RPAs with thermal camera technology for monitoring is needed. This study builds on the research reviewed in this chapter to investigate the use of RPAs and thermography to determine the relationship of American beech tree health and canopy temperature depression. The results gathered from this study can guide the NDMNRF and the CCFM on whether RPAs equipped with thermal camera technology may be a useful tool for monitoring American beech tree health in Canada.

Chapter 2. Study Design, Results and Conclusions

2.1. Methodology

2.1.1. Conceptual Framework

RPA-borne thermal imagery can assist ecosystem managers in identifying diseased and dying trees. American beech trees take in incoming shortwave radiation from the sun for photosynthesis. This energy is used primarily for transpiration and to regulate the internal temperature of the tree (Hoffmann et al., 2016; Smigaj et al., 2019). To study the effect of deteriorating health, an RPA was used to compare how the canopy temperature of healthy beech trees differ to diseased beech trees. Generally, when vegetation has been under water stress by factors such as drought and pest infestation, transpiration rates will be reduced and will increase leaf temperature (González-Dugo et al., 2006; Smigaj et al., 2017; Smigaj et al., 2019). American beech tree health was recorded using a health ranking system developed by Griffin et al. (2003). Canopy temperature depression was calculated, which normalized canopy temperature readings to air temperature for the analysis (Smigaj et al., 2019). Canopy temperature depression was then compared against tree health using scatter plots, ANOVA and post-hoc tests. The analyses showed whether canopy temperatures for beech trees characterized as healthy differ significantly in comparison to those characterized as fair and poor in condition. The results from this study can inform ecosystem managers and conservationists on the potential of this methodology to better detect diseased American beech trees and to improve forest management. The framework for this study design is depicted in Figure 4.

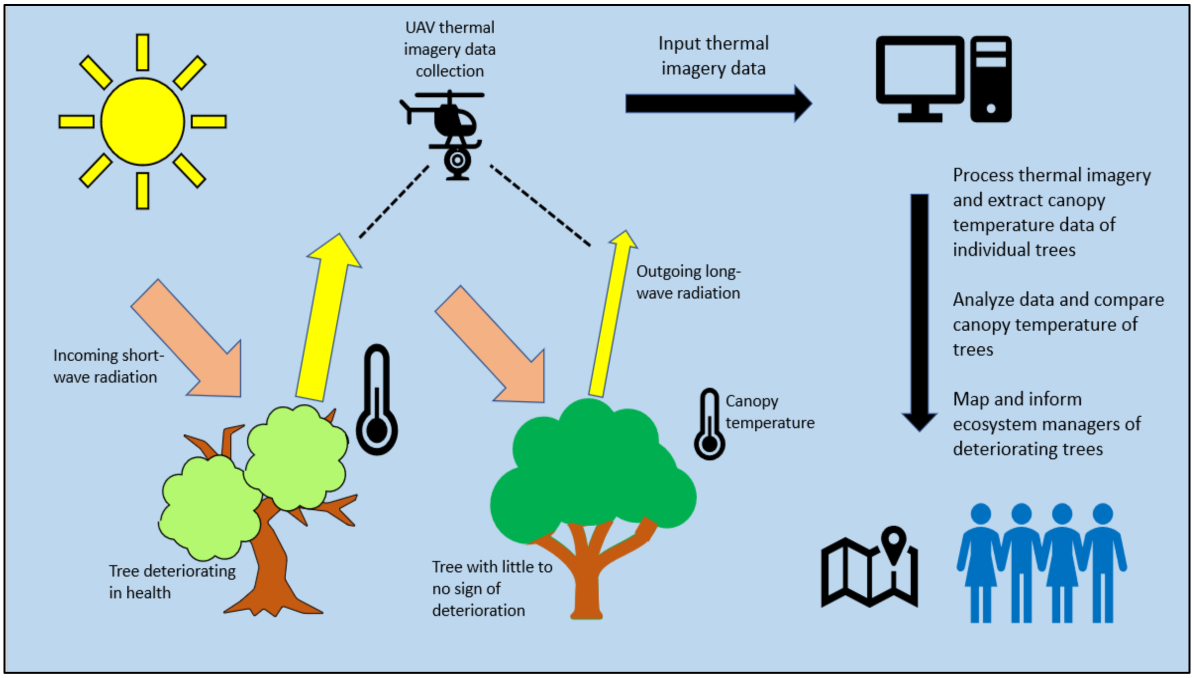

Figure 4: *Conceptual framework of tree health monitoring using RPA and thermal infrared technology*

2.1.2. Study Site

This study was located in the *rare* Charitable Research Reserve in Cambridge, Ontario (Figure 5). The *rare* Charitable Research Reserve is an urban land trust and environmental institute that is managed by staff and volunteers, and is funded through grants, individual donations, and foundations. Staff and volunteers manage and maintain over 365 hectares of sensitive landscape such as woodlands, meadows, marshes, and swamps. The plots established in this study were located in the Cliffs and Alvars, which is classified as a Maple-Beech deciduous forest, and the Ancient Woods, which is classified as a Sugar Maple-Oak deciduous forest (Woodcock et al., 2020) (Figure 5). The Cliffs and Alvars forest contain a variety of trees species, shrubs, and wildflowers on a limestone plain, that is directly adjacent to the Grand River; whereas the Ancient Woods combines a deciduous-mixed swamp and an old-growth upland forest, consisting of red and white oaks, pine, and beech trees (Figure 5).

Within the research reserve, eight sampling plots with American beech trees were established in this study. In the summer of 2020, plots one to four were set up, consisting of a total of 20 beech trees (Figure 5). In the following year, an additional four plots were established, increasing the total number of beech trees sampled and analyzed to 29. Seven plots were established in the Cliffs of Alvars forest (Figure 5b), whereas only one was established in the Ancient Woods (Figure 5a). Each of the eight plots were established using an adaptive cluster sampling approach. An adaptive cluster sampling approach was used to maximize the number of American beech trees sampled for this study. Most of the trees in plots two and three consisted of only beech trees whereas the other plots consisted of maple, cherry, birch and oak as well. Additionally, the approach used to create the plots aimed to include an even distribution of healthy and diseased trees to better understand the relationship of canopy temperature with American beech tree health.

Originally, two plots were established in the Ancient Woods in the summer of 2020 (Figure 5a), but plot five had to be removed from the study as identifying the beech trees in the RPA imagery proved difficult. Furthermore, plot eight, which was set up in the summer of 2021 (Figure 5b), originally consisted of five sampled beech trees; however, only one tree was identified in the RPA imagery which was used in the final analysis. Several factors led to the exclusion of plot five and the four beech trees in plot eight: the beech trees were not the dominant canopy cover and the full canopy could not be identified in the final imagery; the surrounding trees were similar in height to the sampled beech trees yet only portions of the tree canopy could be visible in the final imagery; and some of the sampled beech trees could not be accurately delineated as the canopy layer was densely compacted with various other tree species.

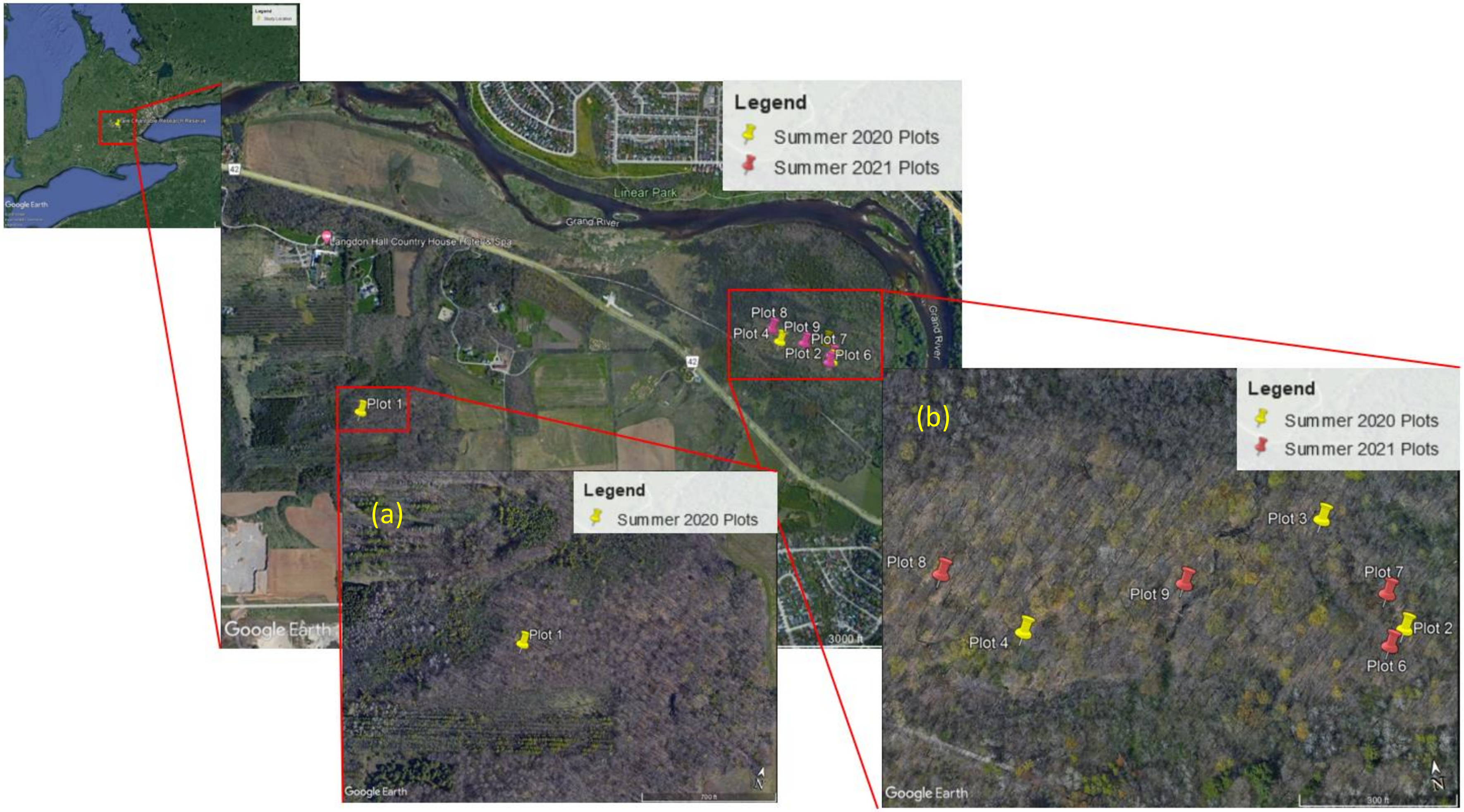

Figure 5: *Location of research at Rare Charitable Research Reserve in southern Ontario, Canada, along with plots with identified beech Trees for the study. Yellow pushpins represent plots established in 2020. Red pushpins represent plots establish in summer 2020. Red pushpins represent plots establish in summer 20201. Plot 1 was established in Ancient Woods (a). The remaining seven plots were established in the Cliffs and Alvars forest (b)*

2.1.3. Canopy Temperature and Weather Data Acquisition

A DJI Matrice 200 Series V2 RPA-equipped with the DJI Zenmuse XT2 gimbal and camera-housing system was used for this study. A FLIR Tau 2 radiometrically calibrated uncooled micro bolometer thermal camera was used to collect canopy temperature measurements. The thermal camera had a 640 x 512 resolution, 30 hertz frame rate, a 13 millimeter wide-angle focal length and a 45 x 37˚ field-of -view. The thermal camera operated in the single 7.5-13.5 micrometer (μm) spectral band, had a pixel pitch of 17μm and a noise equivalent temperature difference of <50 millikelvin. In addition, the Zenmuse XT2 was fitted with an optical camera operating in the visual spectrum, allowing for visual imagery to be captured simultaneously with the thermal imagery. Simultaneous visual imagery collection was beneficial as it allowed for the images captured to be directly compared with the thermal imagery and to accurately delineate individual tree canopies in the imagery. The RPA was flown at a relative altitude of 80 meters above the take-off location. The size of the pixels from the thermal images collected was approximately 9-11cm^2.

Since detection of disease severity in woody plants by RPA has only recently been considered, few studies have indicated the number of RPA campaigns required for accurate analysis of data. Based on recent literature, RPA flights completed per study ranged from just one to over 90 (Berni et al., 2009; Calderon et al., 2013; Hamberg, 2020; Iizuka et al., 2018; Ludovisi et al., 2017; Smigaj et al., 2019). The aim for this study was to complete as many flights as possible to determine the relationship of CTD and American beech tree health. In August of 2020, thermal imagery was collected at Rare Charitable Research Reserve, over four different plots containing a total of 20 unique trees. Thermal data was retrieved on five different days: August 6th, 7th, 15th, 19th, and 26th. In the following year, an additional four plots were added to the study and brought the total number of trees sampled to 29. Thermal imagery was collected over eight different plots in 2021 on three different days: August 2nd, 3rd, and 4th.

For this study, the RPA was flown at two different times during the day to coincide closely with solar noon. Depending on cloud cover, wind speeds and other weather conditions, flights generally occurred between the hours of 1230-1330 and then at 1330–1430. Smigaj et al.

(2017), indicated that thermal imagery should be captured when solar radiation levels and ambient temperatures is greatest, as evaporative demand is theorized to be at a maximum. Capturing imagery when these levels are greatest is ideal as this will maximize the temperature differences seen between tree canopies (Simgaj et al., 2019). RPA flights for this study were completed on days with varying weather conditions, though most days consisted of relatively little cloud cover, high temperatures and low winds. However, on August 26th, 2020, only one flight between 1230-1330 was completed due to the onset of inclement weather later in the afternoon. Similarly, on August 2nd at 1330-1430, the cloud conditions rapidly changed during the flight, which affected the temperature readings, and had to be excluded from the final analysis. Air temperature measurements were extracted from a meteorological weather station at the Region of Waterloo Airport, which was located approximately 8.9 kms away from the site.

2.1.4. American Beech Tree Health Interpretation

One of the most prominent diseases impacting American beech trees in North America is beech bark disease (BBD). Most of the trees sampled in this study either show current infection or previous indications of infection from BBD. Beech bark disease can be separated into three distinct phases: 1) beech scale infestation, 2) pimple development and 3) *Nectria* fungi cankers. Initially, the beech scale insect will create small feeding wounds into the bark of the tree. This scale insect is only mobile when it is a crawler, which is the immature stage of its life cycle and the first phase of BBD (McLaughlin and Greifenhagen, 2012). Following the infestation stage, the crawlers will develop into its adult form and will subsequently be covered in a “white wool” or pimples on the outer bark of the tree. This second phase of the disease can be present on the tree for 2-10 years before the last phase begins which is where the *Neonectria* fungus infection develops in the feeding wounds of the beech scale. The development of cankers is the last phase and can be characterized as “dead spots” that will manifest on the main stem and branches of the tree. Fruiting bodies of the fungus, also known as *perithecia*, will also develop on the cankers in the late summer and fall. These fruiting bodies will enlarge the size of the canker and further diminish the vigor of the tree. Symptoms of this disease is wide ranging but can generally lead to outer bark loss, limb loss, reduced foliage in the upper canopy and severe bark cracking (McLaughlin and Greifenhagen, 2012).

To determine whether a beech tree is healthy or declining in health, a visual inspection of the tree was performed. If the tree was declining in health, various characteristics were noted: the phase of BBD was identified (i.e., beech scale infestation, pimple development and *Neonectria* cankers) and the percent that it covered four meters up the main tree stem from the bottom was recorded based on visual observation; estimates were taken on the number of dead and decaying middle and upper branches of the tree; bark cracking/girdling was estimated up to about 12-15 meters of the main stem from the bottom; and canopy coverage was estimated as a percentage based on RPA visual imagery. By evaluating the various health characteristics of each sampled beech tree, a health level was given on a scale between 0-3, as represented in Figure 6. This ranking system was adopted from Griffin et al. (2003), which guides this research on evaluating American beech tree health.

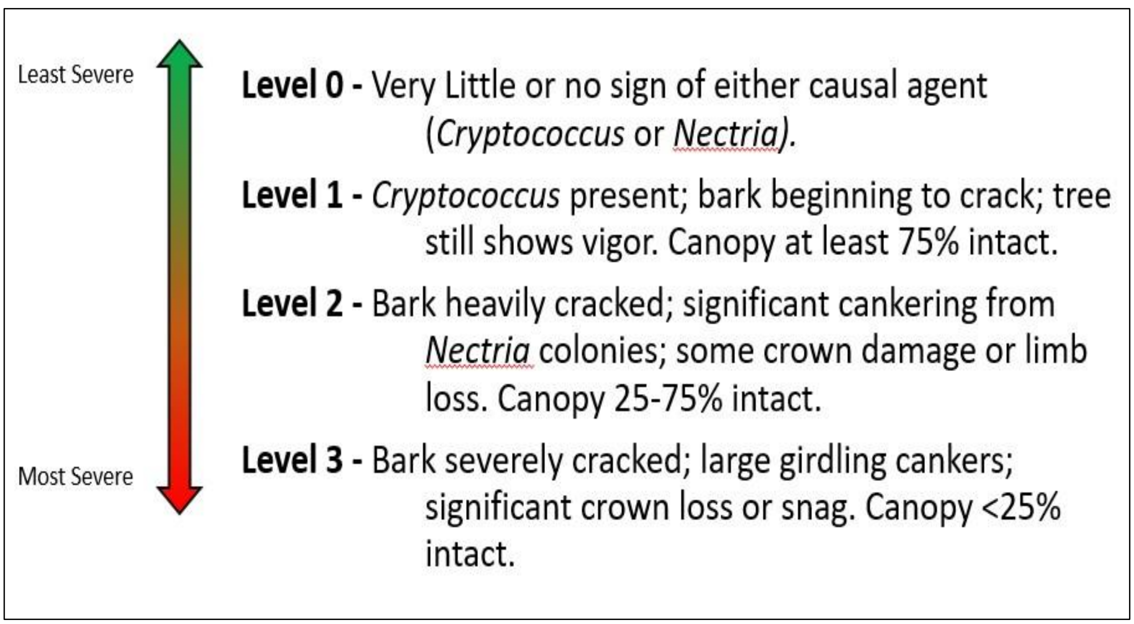

Figure 6: *Ranking of BBD level adopted from Griffin et al., 2003*

Trees that were given a health ranking in 2020 were revaluated again in 2021 to identify any significant changes from the trees. All trees except for two trees in plot 1 were adjusted to a “Level 2” ranking from “Level 1”, as the canopy appeared less than 75% intact in the second year of RPA data collection (Figure 7) (Griffin et al., 2003). This change was applied in the data analysis for the RPA data collected in 2021. Of the 29 identified trees for this study, six were given a “Level 1” ranking (considered as “Healthy”), 13 a “Level 2” ranking (considered as “Fair”) and ten a “Level 3” ranking (considered as “Poor”). No trees were given a “Level 0” ranking in this study.

Figure 7: *The two trees which had their health level adjusted from “Level 1” in 2020 (a) to “Level 2” in 2021 (b) as the canopy appeared less than 75% intact in 2021*

2.1.5. Data processing and Statistical Analysis

The software used to perform the data processing and analysis was FLIR Thermal Studio and R Studio. To delineate individual tree canopies from one another, thermal images were overlaid on to the corresponding visual images to identify the beech tree canopies. To avoid temperature influence from understory vegetation, a buffer was used to exclude canopy edges of the tree. Smigaj et al. (2019), used a buffer of at least two pixels for the tree canopy, which was applied here. Once trees were delineated, average temperatures of the canopies were extracted. Canopy temperature depression, which normalizes canopy temperature with reference to air temperature, was calculated for each tree by performing the calculation $T_{canopy} – T_{air}$ (Smigaj et al., 2019). Since this study is investigating relative temperature differences in canopies, absolute temperature readings were not necessary for this study. Using these data, the relationship between canopy temperature and beech tree health was identified.

2.1.6. Delineating Beech Tree Canopies

Beech tree canopies were delineated manually using the Flir Thermal Studio software. To avoid edge effects and effects from understory vegetation, canopy temperature data was extracted from areas that were fully covered by leaves and away from canopy edges using a buffer of at least two pixels (Smigaj et al., 2019). During each flight campaign two pictures were taken over each plot with approximately a one-minute gap between each picture that was captured over the same plot. Images that were taken over the same plot, during the same flight hour of the same day were extracted and averaged before analysis as a method of technical replication. Many of the more diseased trees had several gaps in their tree canopies, along with dead branches. To get an accurate sense of the canopy temperature of the tree, the gaps and dead

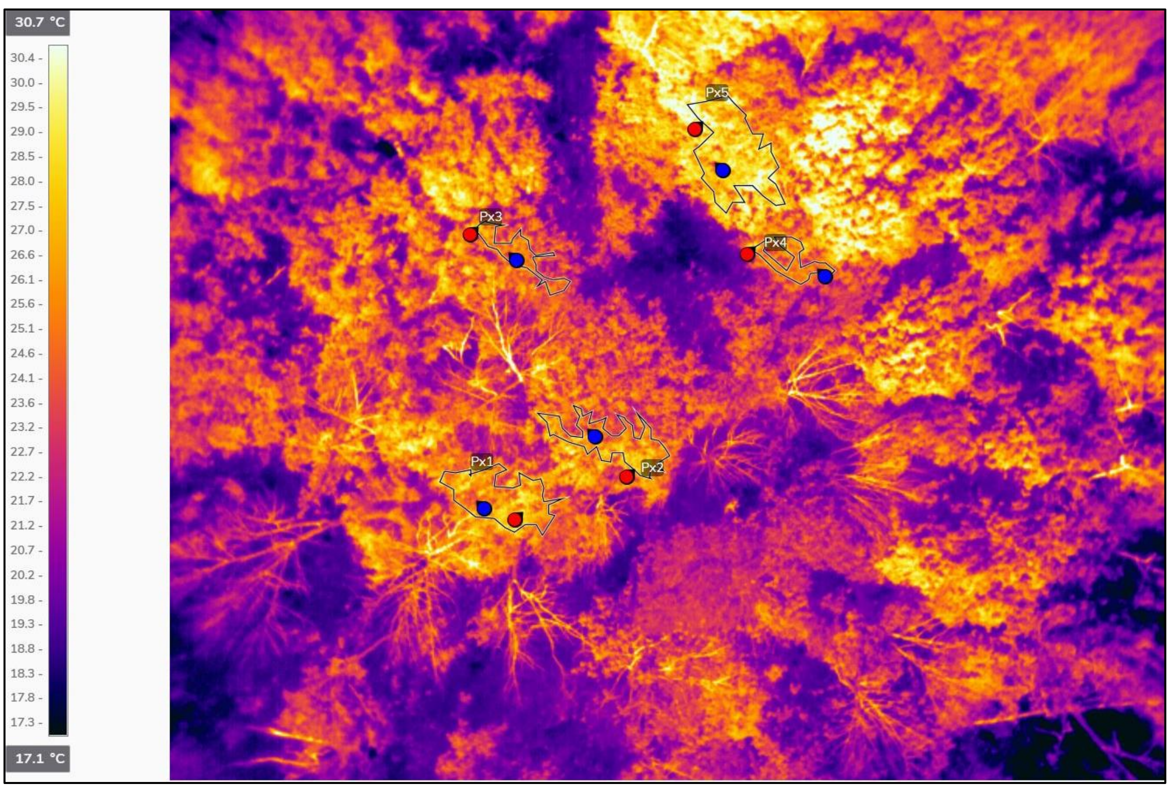

Figure 8: *An example of how canopy temperature measurements of each tree were extracted. The outlines in black indicate an individual American beech tree canopy. Blue dots are displayed where temperatures are coolest and red dots displayed where temperatures are warmest on each canopy*

branches were avoided when extracting canopy temperature measurements. An example of how canopy temperature of each individual American beech tree in each plot was extracted is presented in Figure 8.

2.2. Results

2.2.1. Testing Assumptions

To determine whether a parametric or non-parametric statistical test was used to analyze the data, the assumptions of normality and equal variances were tested. The Shapiro-Wilk test was used to test normality as sample size of trees analyzed in 2020 and 2021 was small (20 and 29, respectively). Although the power of the Shapiro-Wilk test may be weak with smaller sample sizes, it performs the best compared to other normality tests (Razali and Wah, 2011). Based on the results in Table 1, the assumption of normality is met for all flight campaigns, except for the flight completed on August 7th at approximately 1330-1430.

Table 2: *Testing normality of the canopy temperature depression sample data with the Shapiro-Wilk test. Sig. (p) value is compared to the alpha level (a priori). A p < 0.05 indicates that the null hypothesis is rejected, and the sample is non-normally distributed*

Date and Approx. Time of Flight	Shapiro-Wilk	
	Statistic (W)	**Sig.**
August 6, 2020: 1230-1330	0.946	0.315
August 6, 2020: 1330-1430	0.937	0.209
August 7, 2020: 1230-1330	0.956	0.469
August 7, 2020: 1330-1430	0.825	**0.002**
August 15, 2020: 1230-1330	0.963	0.608
August 15, 2020: 1330-1430	0.927	0.137
August 19, 2020: 1230-1330	0.909	0.061
August 19, 2020: 1330-1430	0.950	0.363
August 26, 2020: 1230-1330	0.955	0.456
August 2, 2021: 1230-1330	0.986	0.954
August 3, 2021: 1230-1330	0.989	0.989
August 3, 2021: 1330-1430	0.951	0.190
August 4, 2021: 1230-1330	0.944	0.127
August 4, 2021: 1330-1430	0.960	0.322

To test the assumption of equal variance, the Levene's test was used (Gastwirth, Gel and Miao, 2009). Based on the results in Table 2, the assumption of equal variance was met for all flight campaigns, except for the flight campaign completed on August 7 at approximately 1330-1430 and August 15 at approximately 1230-1330 for the 2020 field season.

Table 3: *Testing the homogeneity of variances for the canopy temperature depression sample data using Levene's Test. Sig. (p) value is compared to the alpha level (a priori). A p < 0.05 indicates that the null hypothesis is rejected, and the assumption of equal variance is violated*

Date and Approx. Time of Flight	Levene's Test		
	Df	**F-value**	**Sig.**
August 6, 2020: 1230-1330	2	1.02	0.38
August 6, 2020: 1330-1430	2	0.61	0.56
August 7, 2020: 1230-1330	2	1.14	0.34
August 7, 2020: 1330-1430	2	3.92	**0.04**
August 15, 2020: 1230-1330	2	8.64	**<0.01**
August 15, 2020: 1330-1430	2	1.06	0.37
August 19, 2020: 1230-1330	2	1.47	0.26
August 19, 2020: 1330-1430	2	1.45	0.26
August 26, 2020: 1230-1330	2	0.27	0.77
August 2, 2021: 1230-1330	2	0.29	0.76
August 3, 2021: 1230-1330	2	2.51	0.10
August 3, 2021: 1330-1430	2	0.17	0.85
August 4, 2021: 1230-1330	2	0.68	0.52
August 4, 2021: 1330-1430	2	1.50	0.24

2.2.2. Canopy Temperature Depression and Health Level

The canopy temperature depression values ($T_{canopy} - T_{air}$) of each individual American beech tree were extracted for each flight and compared against their associated health level. Scatterplots comparing the relationship of CTD to American beech health levels for the 2020 and 2021 field seasons are displayed in Figure 9 and Figure 10, respectively. The colour of the dots in each scatterplot are used to identify which forest plot the tree is from. To identify trends, the coefficient of determination (R^2) was identified for each flight, which showed weak correlations overall between CTD and American beech tree health levels. The R^2 values for each flight ranged from -0.25 to 0.29, indicating no clear relationship between canopy temperature depression and beech tree health level.

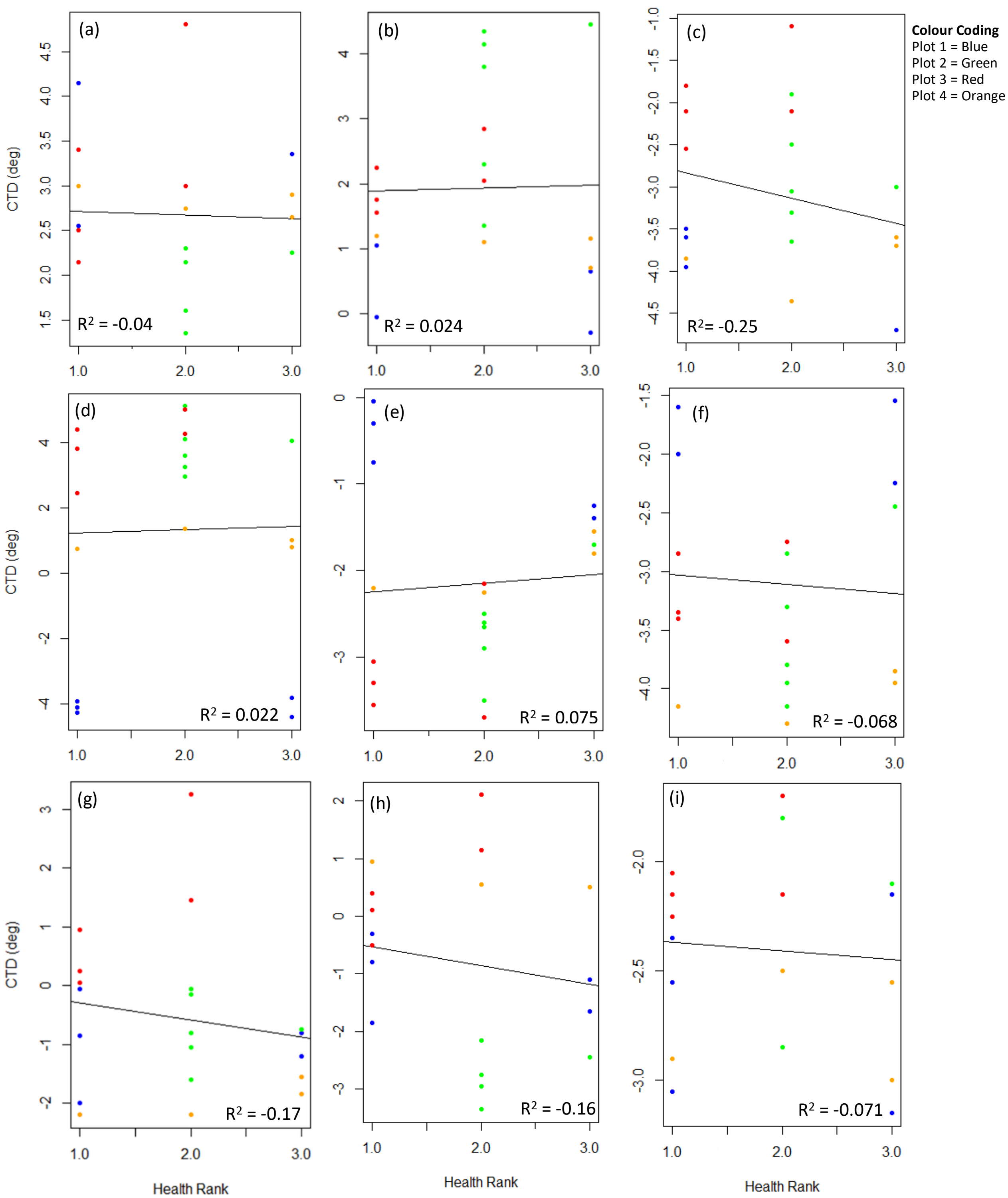

Figure 9: *Scatterplots displaying the canopy temperature depression values against estimated health level of American beech trees, as well as their respective R2, at Rare Charitable Research Reserve in 2020 at approximate times: (a) August 6th at 1230-1330; (b) August 6th at 1330-1430; (c) August 7th at 1230-1330; (d) August 7th at 1330-1430; (e) August 15th at 1230-1330; (f) August 15th at 1330-1430; (g) August 19th at 1230-1330; (h) August 19th at 1330-1430; (i) August 26th at 1230-1330*

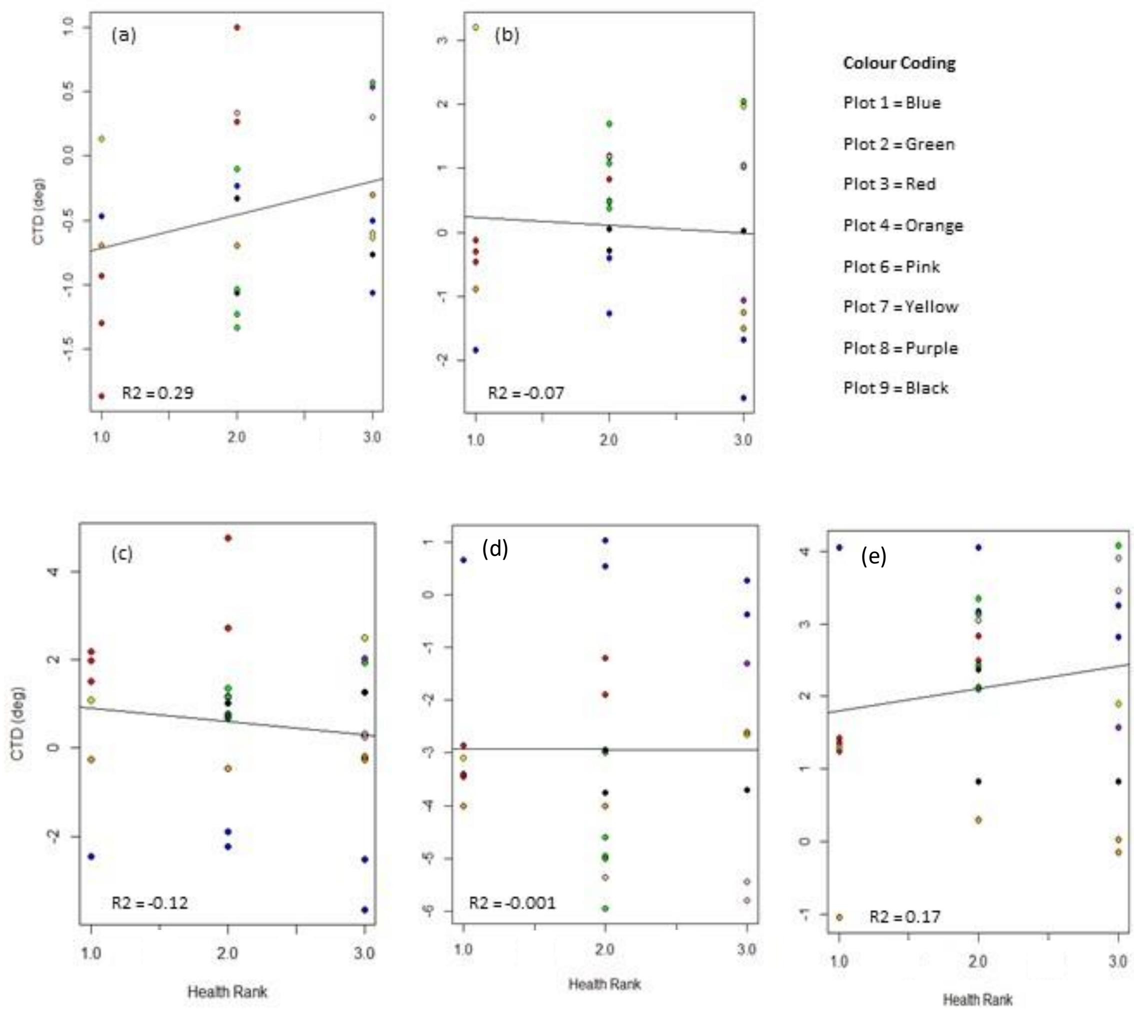

Figure 10: *Scatterplots displaying the canopy temperature depression values against estimated health level of American beech trees at Rare Charitable Research Reserve in 2021 at approximate times: (a) August 2nd at 1230-1330; (b) August 3rd at 1230-1330; (c) August 3rd at 1330-1430; (d) August 4th at 1230-1330; (e) August 4th at 1330-1430*

2.2.3. Analysis of Variances

After determining the distribution of the data and the equality of the variances, a parametric or a non-parametric test was used to evaluate whether the different health levels differed from one another with regards to the canopy temperature depression values recorded. For this study, a one-way Analysis of Variance (ANOVA) was used for the analysis if the Shapiro-Wilks test indicated no significant differences in the raw data and the Levene's test showed the variances were equal (Table 3). However, if the variances were not equal (i.e., the Levene's test failed) then a Welch's ANOVA was used (Table 4). A post-hoc test (i.e., a pairwise t-test) was used for data from the ANOVAs that showed statistically significant (Sig. < 0.05) differences in canopy temperature depression readings between the three separate health levels (Table 5).

The results from the one-way ANOVA show no statistically significant (*Sig.* < 0.05) differences in canopy temperature depression readings between the three distinct health levels on the dates presented in Table 4. Therefore, there is no sufficient evidence to suggest that there is a statistically significant difference between the means of the three groups.

Table 4: *One-way ANOVA analyzing the differences between the means of Healthy, Fair and Poor American beech trees for the flights where all assumptions were met*

Date and Approx. Time of Flight		*Df*	*Sum of Squares*	*Mean Square*	*F*	*Sig.*
August 6, 2020: 1230-1330	*Health Level*	2	0.72	0.36	0.49	0.62
	Residuals	17	12.54	0.78		
August 6, 2020: 1330-1430	*Health Level*	2	8.86	4.43	2.68	0.10
	Residuals	17	28.14	1.65		
August 7, 2020: 1230-1330	*Health Level*	2	3.08	1.54	1.89	0.18
	Residuals	17	13.85	0.82		
August 15, 2020: 1330-1430	*Health Level*	2	3.11	1.56	2.21	0.14
	Residuals	17	11.94	0.7		
August 19, 2020: 1230-1330	*Health Level*	2	3.63	1.82	0.99	0.39
	Residuals	17	30.99	1.82		
August 19, 2020: 1330-1430	*Health Level*	2	3.79	1.90	0.71	0.50
	Residuals	17	45.27	2.66		
August 26, 2020: 1230-1330	*Health Level*	2	0.46	0.23	1.29	0.30
	Residuals	17	3.05	0.18		
August 2, 2021: 1230-1330	*Health Level*	2	1.44	0.72	1.66	0.21
	Residuals	26	11.30	0.43		
August 3, 2021: 1230-1330	*Health Level*	2	2.08	1.04	0.58	0.57
	Residuals	26	47.05	1.81		
August 3, 2021: 1330-1430	*Health Level*	2	2.41	1.21	0.35	0.71
	Residuals	26	88.73	3.42		
August 4, 2021: 1230-1330	*Health Level*	2	1.21	0.60	0.15	0.86
	Residuals	26	108.43	4.17		
August 4, 2021: 1330-1430	*Health Level*	2	4.90	2.45	1.34	0.28
	Residuals	26	47.49	1.83		

Statistically significant (*Sig*. < 0.05) differences in canopy temperature readings between the three separate health levels on August 7th and August 15th at approximately 1230-1330 and 1330-1430 were observed, respectively (Table 5). Therefore, we reject the null hypothesis and conclude that there is a statistically significant difference between the canopy depression means between at least one of the three groups.

Table 5: *Welch's ANOVA analyzing the differences between the means of Healthy, Fair and Poor American beech trees on August 7th and August 15th at approximately 1230-1330 and 1330-1430*

Date and Approx. Time of Flight		***Num. Df***	***Denom. Df***	***F***	***Sig.***
August 7, 2020: 1330-1430	*Canopy Temperature Depression against Health Level*	2	7.31	5.39	**0.036**
August 15, 2020: 1230-1330	*Canopy Temperature Depression against Health Level*	2	10.14	14.81	**0.001**

A post hoc pairwise t-test indicated that the health level 2 ("Fair") is most different from health level 3 ("Poor") and level 1 ("Healthy") based on canopy temperature measurements taken on August 7th at approximately 1330-1430 (Table 6). However, these values do not indicate a statistically significant difference, given an alpha level of 0.05. Canopy temperature depression measurements of "Fair" beech trees ranged from 1.35˚C to 5.1˚C; -4.1˚C to 4.4 ˚C for "Healthy" beech trees; and -4.4˚C to 4.05˚C for "Poor" beech trees (Figure 9). Given an alpha level of 0.05, American beech trees that are "Fair" in health are significantly different to "Poor" American beech trees on the August 15th flight at approximately 12:30-13:30 (Table 6). CTD measurements of "Fair" beech trees ranged from -3.7˚C to -2.15˚C and -1.8˚C to -1.25˚C for "Poor" beech trees (Figure 9).

Table 6: *Post hoc Pairwise t-test evaluating which health group(s) is/are significantly different based on canopy temperature depression means. Values presented in the table are the Sig. (p) values comparing one group against the other. P-value adjustment method: Bonferroni*

Date and Approx. Time of Flight		***Healthy***	***Fair***
August 7, 2020: 1330-1430	***Fair***	0.12	-
	Poor	1	0.17
August 15, 2020: 1230-1330	***Fair***	0.53	-
	Poor	1	**0.01**

2.3. Discussion

2.3.1 Relationship of American Beech Health and Canopy Temperature

Increasing American beech tree canopy temperatures were not observed in trees with deteriorating health conditions. Weak correlations between canopy temperature depression and health level may indicate that the health characteristics measured (i.e., presence of beech bark disease, canopy crown damage/loss, loss of tree limbs and bark cracking/girdling) has little to no effect on increasing temperatures (Figure 5 and Figure 6). The one-way ANOVA performed for most flights (12 out of 14) showed that canopy temperature readings did not significantly change based on the recorded tree health levels. For the two flights that showed statistically significant differences in canopy temperature readings between the three separate health levels, the flight on August 7th at approximately 1330-1430 showed that trees with the health level "Fair" was most different from "Poor" and "Healthy" and the flight on August 15th at approximately 1230-1330 showed that "Fair" in health trees were significantly different to "Poor". However, no meaningful conclusions were drawn from these results, as these were the only two flights that showed any significant differences and were not consistent with one another. These findings contrast studies that found strong correlations with declining tree/plant health and increasing surface temperature readings in woody plants (Calderón et al., 2013; Hais and Kučera, 2008; Smigaj et al., 2019).

The scatterplots in Figure 5 and Figure 6 also provide no evidence of a correlation between deteriorating tree health and increasing canopy temperatures as some charts indicated canopy temperatures decreasing with declining beech tree health and others indicated increasing canopy temperatures with declining beech tree health. It was anticipated that declining tree health would be associated with higher canopy tree temperatures, particularly in trees showing severe impacts from beech bark disease. Diseases effecting the stem, roots and canopy of the plants can lead to water stress, resulting in leaf stomatal closure (Burdon, 1987; Jones, 1999). Diseased plants tend to experience stunted growth, reduced leaf area and diminished vigor compared to healthy individuals (Burdon, 1987). As a result, canopy temperatures of plants rise as transpiration rates are reduced by disease-induced water stress (Fuchs, 1990; González-Dugo et al., 2006; Idso et al., 1981; Jackson et al., 1981; Smigaj et al., 2017; Smigaj et al., 2019).

However, results from this study may indicate a disconnect between the canopy temperatures gathered and factors such as beech bark disease, bark deterioration and limb loss of beech trees. Despite aggressively impacting some trees, severe effects, such as late-stage beech bark disease, did not lead to a significant increase in canopy temperature readings. This may indicate a lag in the time it takes for beech bark disease and other bark related damage to affect the canopy temperature, or it is possible that impacts to the bark and tree limbs do not significantly impact leaf temperature. It is also likely that individual tree health is being impacted by the surrounding environment, such as the other tree species, the soil conditions and canopy architecture (Fichtner et al., 2017; Kimes, 1980; Morin et al., 2011).

In previous studies that examined the effects of disease and pathogen spread in plants, there has been a focus on impacts at the leaf level and the subsequent effect on canopy temperature. Berdugo et al. (2014), found higher maximum temperature differences from powdery mildew disease spread on cucumber leaves than viral diseases. Another related study performed by Smigaj et al. (2019), found increasing correlations of increased tree foliage damage from a tree pest and canopy temperatures using a UAV. Calderón et al. (2013), also discovered a significant relationship between increasing *Verticillium* wilt severity and increasing canopy temperature readings in olive trees. Similarly, Hais and Kučera (2008) were able to use satellite thermal imagery to distinguish healthy spruce forests with those infested with bark beetles. Although bark beetles attack the stem of the spruce trees, the foliage of the tree becomes noticeably wilted and then brown after 18 months (Natural Resources Canada, 2015). The results from these studies may indicate a stronger correlation with leaf damage/wilting and canopy temperature readings versus bark deterioration, limb loss and reduced canopy area. To better understand the relationship of overall American beech tree health and canopy temperature, future research must consider whether characteristics such as outer bark deterioration and limb loss have a detectable effect on canopy temperature readings or not.

To improve upon the current study design, limiting confounding factors may improve our understanding of the relationship between American beech tree health and canopy temperature. For example, early studies have shown that air temperature, relative humidity and wind can affect canopy temperature readings (Ansari and Loomis, 1959; Eaton and Belden, 1929; Smigaj et al., 2019; Waggoner and Shaw, 1952). Generally, increasing air temperature, decreasing relative humidity, and increasing wind speeds can increase transpiration rates of vegetation (Smigaj et al., 2019; Spellman, 2014). Because of the many factors effecting transpiration, it is ideal to capture the entire sample of trees in one image to avoid the effects of weather-related confounding variables. However, due to the large study area size, it was not possible to capture the entire sample in a single image for each flight campaign. Capturing all the sampled trees in one image would have required a special flight operations certificate as the RPA would have to fly over the 122-metre limit set out by Transport Canada for those holding a basic operations pilot certificate (Government of Canada, 2021). Going forward, acquiring a special flight operations certificate to capture the entire sample set of trees in single images could be explored and can lead to a better understanding of the relationship of canopy temperature and American beech tree health.

Since thermal images are captured over each plot at short intervals during each flight, determining the effects of certain weather and site variables on canopy temperature depression readings would require future researchers to collect weather measurements for each plot at the time of image capture. Although air temperature has great influence on canopy temperature readings, other factors such as wind and vapor pressure deficit may influence measurements. Wind speeds can influence the air boundary layer surrounding the leaves of a plant which can affect the heat exchange between the air and the leaves (Nobel, 2020). Vapor pressure deficit can also result in increased plant water stress as transpiration rates increase with increasing atmospheric vapor pressure deficits up to a point (Grossiord et al., 2020). For example, Smigaj et al. (2019), found that the differences in canopy temperature readings of healthy versus diseased Scots pine trees were most attenuated at times of peak wind speeds and vapor pressure deficit values. Going forward, it would be beneficial to examine the effects of wind, vapor pressure deficit and other variables on American beech tree canopy temperatures by running statistical tests, such as a multiple regression or a partial least squares regression, to determine whether these variables have a significant impact on canopy temperature readings or not. Factors such as wind, vapor pressure deficit and others were originally considered, however constraints in time and access to equipment during the Covid pandemic limited further data collection on these variables.

Apart from weather effects on image capture, study site characteristics can influence canopy temperature measurements. Although the setting of this study took place in semi-natural mixed forest stands in Cambridge, Ontario, performing a similar study in a more controlled environment could lead to more consistent results and less effects from confounding variables. However, the setting for this study was chosen by design, as results from semi-naturalized locations can better inform ecosystem and forest managers of the tree monitoring possibilities with drones and thermal imaging in similar settings. Sites in Mississauga, Ontario was also selected for this study but had to be excluded as Covid-19 protocols restricted travel to locations outside of my public health unit. Furthermore, additional tools could have been applied, such as LiDAR and hyperspectral sensing and DNA analysis techniques to identify and confirm tree fungi. However, Covid-19 protocols made it challenging to access additional equipment and to collaborate with others.

Furthermore, it may be beneficial to undertake thermal imaging campaigns over a longer time frame during the growing season to get a better understanding on the factors effecting canopy temperatures of beech trees. RPA flights were performed in August of 2020 and 2021 for this study. However, taking thermal measurements during spring may have yielded different results, given that there are less hours of sunlight, generally lower air temperatures, and higher soil water availability due to recent snow melt. For example, Scherrer et al. (2011), found that relatively high canopy temperature readings can be associated with increased drought conditions in a deciduous forest. Although soil water potential and availability were not measured during the flights performed for this study, drought conditions could have influenced the canopy temperature measurement recorded. Therefore, future research can consider taking thermal measurements in the spring, following leaf-out, to better understand the effect of soil water availability and potential on canopy temperature readings of beech trees. Leaf colour changes may also lead to changes in canopy temperature measurements, especially later in the summer/early autumn. Monteiro et al. (2016), found that lighter leaf colours were associated with lower plant temperature readings in *Heuchera* and *Salvia* genotypes due to an increase in short-wave radiation reflectance. American beech trees that are infested with beech bark disease and experiencing significant crown die-back will become yellow in color in late summer (McCullough et al., 2001), which can affect the amount of reflected incoming short-wave radiation by the leaves, and subsequently canopy temperature. Therefore, collecting thermal images following leaf-out in the spring when soil water availability may be high, during a drought period in the summer and in the late summer when leaf colours of diseased and healthy beech trees diverge, may lead to a clearer signal on the factors effecting canopy temperatures of beech trees.

Monocrop plantations of mature American beech trees may also yield distinct results when comparing pest infected trees to unaffected trees, as explored by similar studies investigating canopy temperature readings of a monocrop plantation (e.g., Calderón et al., 2013; Smigaj et al., 2019). Monocrop plantation may be a better alternative in comparison to the site used for this study, as each plot established in the mixed forest stands in Cambridge, Ontario, consisted of different tree, sub canopy and understory species. The elevation of each plot in this study also varied slightly when compared to one another, along with the density of all trees and distance to roads and forest edges. Previous research has shown that individual trees can be either positively or negatively affected by the surrounding trees depending on the diversity and types of tree species (Chamagne et al., 2017; Fichtner et al., 2017; Potvin and Dutilleul, 2009; Pretzsch, 2014). For example, the competition for light in mature mixed forest stand can positively affect primary productivity at the community level and can affect the microclimate of an area (Fichtner et al., 2017, Morin et al., 2011). It is also possible that certain plots may have had lower or higher extractable soil water that may have affected some plots and beech trees rather than others (Bréda et al., 2006; Hais and Kučera, 2008). Kimes (1980), indicates that the geometric structure of the canopy, soil temperature and the surface temperature distribution of vertical foliage can also affect canopy temperature readings.

It is also important to consider the challenges of forest boundary delineation, and the potential influence of edge effects on the measurements recorded. Attempting to classify individual forest boundaries can be done using aerial image interpretation, however, distinguishing between different forest types and non-forested segments is subjective (Wang and Boesch, 2007). Without accurate delineation of forests and the study area, edge effects can go unnoticed and alter the canopy temperatures recorded by the thermal sensor. Different forest types, ecotones, and man-made structures adjacent to the study sites can alter the micro-climates of nearby forests. (Fortin et al., 2000). For example, there are roads that have been established around the study sites, as well as walking trails that run through the forests that can affect the light, temperature, and humidity of the area (Delgado et al., 2007; Forman et al., 2003). For these reasons, conducting research in a controlled environment (i.e., a monoculture plantation woodland of American beech trees) can give further insights into the relationship of American beech tree health and canopy temperature.

Furthermore, taking thermal imagery in forests consisting of a variety of tree species and non-uniform site conditions can influence the raw data collected by the camera sensor. Reflections from the surrounding vegetation, the sky, and the water vapor in the air and in between the vegetation and the camera can all affect the signal of the thermal sensor

(Aubrecht et al., 2016; Möllmann and Vollmer, 2010). The reflected thermal energy that is recorded by the thermal sensor is difficult to quantify for an entire canopy as it depends on the structure and orientation of the tree being imaged, the structure, orientation and amount of the reflected sources of energy, as well as meteorological conditions (Aubrecht et al., 2016; Campbell and Norman, 2000). Calculating how much energy is reflected by the canopy is difficult to measure and future research is needed to understand whether this reflected energy can significantly alter the extracted canopy temperatures for individual trees (Aubrecht et al., 2016).

Despite the challenges identified above, there has been success with using thermal imagery to identify trees that are declining in health in natural forest settings. For example, Scherrer et al. (2011), collected thermal imagery from a helicopter to determine the effect of drought on a mixed deciduous forest and obtained significant results. The authors hypothesized that different tree species would have specific canopy temperature responses to water shortage over a four-week drought period because of differing plant/root structures and physiological traits (Scherrer et al., 2011). The final analysis showed tree species such *as Acer pseudoplatanus* (sycamore) and *T. platyphyllos* (large leaved lime) having consistently higher canopy temperatures than tree species such as *F. excelsior* (European ash) and *P. avium* (wild cherry) in both their “moist” and “dry” condition sites (Scherrer et al., 2011). The authors concluded that canopy structure and leaf morphology were the most likely explanations for the differences in canopy foliage temperatures as their findings were consistent regardless of site conditions and when thermal imaging campaigns were undertaken.

Hais and Kučera (2008), also performed their study in a national park and obtained significant results when comparing healthy spruce forests against decaying and clear-cut spruce forests. The authors used thermal imagery obtained by a satellite to compare and model surface temperature values and found an increase in the surface temperature of bark beetle infested spruce forests and clear-cut forests. From 1987 to 2002, clear-cut forests had a mean surface temperature increase of 5.2˚C versus a 3.2˚C increase for decaying spruce forest (Hais and Kučera, 2008). The authors concluded that surface temperature increases in clear-cut forests were greater due to lower evapotranspiration rates and increases in reflectance from dead trees (Hais and Kučera, 2008). Although there are similarities to the study design presented in this report, Hais and Kučera (2008) did not image a mixed forest environment and were focused on the effects of bark beetle infestation at the landscape scale. Regardless of the differences in the two reports, the successes of Scherrer et al. (2011), and Hais and Kučera (2008), led to the undertaking of a thermal RPA-based remote sensing analysis of American beech trees in a semi-naturalized forest setting.

2.3.2 The Future of RPA and Thermal Imaging Technology

Despite the statistically insignificant results found in this study, the use of remote sensing data from unmanned aerial systems continues to be adopted in real world applications and in research (Chabot, 2018). Recent developments in remote control capabilities, power storage, and materials used have allowed engineers and researchers to develop RPAs capable of surveying different environments with a variety of sensors (Ghamisi et al., 2017; Hassanalian and Abdelkefi, 2017; Tang and Shao, 2015). As a result of the recent developments in unmanned aerial systems, research in areas such as wetlands, agriculture, forest, mining, and healthcare continues to advance to understand the potential applications of this technology (Chabot, 2018; Mogili, 2018; Shahmoradi et al., 2020; Tang and Shao, 2015).

Recent advances in sensor technology have allowed for more accurate data collection and analysis. For example, large areas of land can be imaged that provide rich spectral and spatial information because of the recent advancements in hyperspectral imaging sensors (Ghamisi et al., 2017). With the availability of cloud computing, processing and analyzing high quality hyperspectral images is now viable and more widely adopted in research (Ghamisi et al., 2017). Furthermore, newer software can improve data collection with a RPA by solving for the variations in elevation over large areas. For example, eMotion 3 software can use digital terrain models to create 3D flight paths to adjust drone height to record and capture images at a uniform distance above the sample surface (Manfreda et al., 2018).

RPAs using airborne laser scanning, LiDAR technology, digital photogrammetry and structure-from-motion techniques are also becoming more affordable and increasingly utilized over traditional ground-based sampling techniques in forest systems (Goodbody, Coops and White, 2019; Mohan et al., 2017; Rodríguez-Puerta et al., 2022; Tang and Shao, 2015; Zhang et al., 2016). Notably, these tools can be used to expand and support the data collected for forest inventory purposes by observing the composition and structure of forests (Hudak et al., 2013; Mohan et al., 2017; Zellweger et al., 2013; Zhang et al., 2016). For example, Sankey et al. (2017), used a combination of LiDAR and hyperspectral sensors to capture images to detect forest structure change and identify tree species.

Research that utilizes RPAs and thermal camera technology in forested environments are also increasing in adoption due to the reduced costs and higher spatial resolution of sensors. The use of thermal imagery and thermal stress indices have shown to be effective methods at identifying ecosystem structure composition changes following ecological restoration of a temperate wooded ecosystem (Hamberg, 2020). RPAs with thermal sensor technology has also shown to be an effective method at determining the effect of drought on different deciduous tree species found in a semi-natural forest (Scherrer et al., 2011). Thermal imaging has also shown to be an effective method at monitoring plantations and orchards to identify trees that are affected by pest and pathogen spread, and water loss (Bernie et al, 2009; Calderón et al., 2013; Smigaj et al., 2019). Given the variety of functions trees and forest systems provide, such as air and water quality control, climate regulation and decomposition (Ansink et al., 2008; Brockerhoff et al., 2017; Krieger, 2001; Miura et al., 2015; Nowak et al., 2008), utilizing RPA and thermal imaging technology can further our abilities to monitor and manage these systems.

However, challenges remain for the future adoption of RPA technology in government organizations and in various private sectors. Firstly, the methods employed in current research that utilizes RPA technology vary greatly from one another and as a result there is a lack of standardization in the methodologies adopted. For example, there are various sensors that perform well at certain tasks yet perform poorly at others. Thermal sensors are appropriate for determining the physiological state of vegetation yet offer poor spatial resolution and cannot determine structural parameters of the terrain and vegetation. LiDAR sensors perform well in classifying and measuring structural organization of terrain; however, they do not give insight into the physiological state of the vegetation. For every type of sensor, there are different models and manufacturers that vary in quality and costs, and the images retrieved may require excessive computational power for image processing. Given these challenges, it is important to identify unifying principles and to create a standard for individuals that use RPAs to better guide their use in current forestry and government practices (Manfreda et al., 2018).

Although RPAs can provide a cost-effective solution for monitoring and managing areas of concern, there are meteorological and technical limitations that hinder the collection of data. For example, weather constraints such as strong wind, cloud cover and rainy condition can reduce the quality and quantity of the images taken. Areas of uneven terrain, high elevation and high temperatures can also affect the images collected. Furthermore, there are limitations with the sensors used that can affect the quality and consistency of images taken. Some RPA-compatible sensors need to be radiometrically and atmospherically calibrated to record correct surface reflectance values (Manfreda et al., 2018). Current RPAs also have relatively short flight times, and depending on the manufacturer and weight, are unable to carry certain sensors. RPAs with extended flight times and increased carrying capacity can be purchased, however, they will likely cost more (Mozaffari et al., 2019). With the challenges presented from the weather, geographical conditions and current RPA capabilities, environmental and government organizations may be hesitant to adopt RPA technology in its current state.

Adopting RPA technology in current environmental practices may also be limited by certain regulations and by user operating knowledge. In Canada, you must have a drone pilot license when operating a RPA that weighs over 250 grams, and restrictions can apply on where drones are legally allowed to fly. For example, individuals are not able to fly within a 9km radius of an international airport unless permission from air traffic control is given and an advanced operations pilot license is obtained (Government of Canada, 2021). Furthermore, operating a RPA requires practice and knowledge on its operation. Although the controller for most drones can be easy to operate, maneuvering in narrow or crowded locations can be challenging. Some organizations may be unwilling to adopt RPA technology if they are not technologically savvy or unable to hire a skilled RPA technician if they have limited funds available. Therefore, flight regulations and the learning curve presented in operating RPA technology may deter potential forestry governmental organizations from integrating RPA technology in their regular operations.

Going forward, rare Charitable Research Reserve can expand on the work done in this study by exploring the effects of other variables, such as soil water availability, weather variables such as humidity and wind, and the influence of leaf color change on canopy temperature measurements. It may also be beneficial to acquire an advanced operations RPA license to take images over a larger geographical extent to limit the effects of confounding variables on canopy temperature measurements. Future canopy temperature measurements can also be complemented with the use of additional sensors and analyses such as the Normalized Difference Vegetation Index (NDVI) by using a Near Infrared Red, Green and Blue sensor to determine canopy greenness. By addressing confounding variables and collecting canopy greenness data, rare Charitable Research Reserve may be able to better identify the variables that are contributing to increases or decreases in canopy temperature readings, which can lead to improved management of beech tree health in their forests.

3.0. Conclusion

Identifying and monitoring forest system health is important because of the various socio-ecological functions provided by forests. However, the increased spread of various types of invasive forest pests and pathogens requires ecosystem managers and conservationists to quickly obtain objective and reliable data to make rational decisions on how to manage invasive species spread. Current ground-based surveying methods have been foundational for forest health monitoring in Canada and are generally completed on an annual basis. Although there can be high accuracy with identifying diseased tree stands with ground-based sampling approaches, the spatial coverage that can be surveyed is small, time consuming and can be costly. Remote sensing tools can provide those who monitor forest health conditions and composition an alternative to ground-based surveying. RPAs are a remote sensing tool that can be automated to collected high resolution imagery, such as multi-spectral, hyperspectral, and thermal infrared data over large areas of forested land. To detect water stress in trees from invasive pest and pathogen spread, thermal imaging sensors have shown to be a viable alternative to ground-based sampling techniques.

This study examined the use of RPA-borne thermal imagery to identify canopy temperature increases in American beech trees because of factors including the severity of beech bark disease, loss of limbs, bark cracking/girdling and declining crown coverage. Of the total 14 flights conducted in this study, only two flights showed a relatively significant correlation between canopy temperature depression and American beech tree health. However, no meaningful conclusions were drawn from these results as one indicated canopy temperatures decreasing with declining beech tree health and the other indicated increasing canopy temperatures with declining beech tree health. Similarly, the one-way ANOVA performed for most flights (12 of 14) showed that canopy temperature readings did not significantly change based on the recorded tree health levels. Given the lack of significant results found in this study, future research should be explored that makes use of different sensors, additional beech trees with varying health conditions and possibly a more controlled landscape (e.g., a monocrop plantation of American beech trees) to investigate the relationship between tree health and canopy temperature.

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