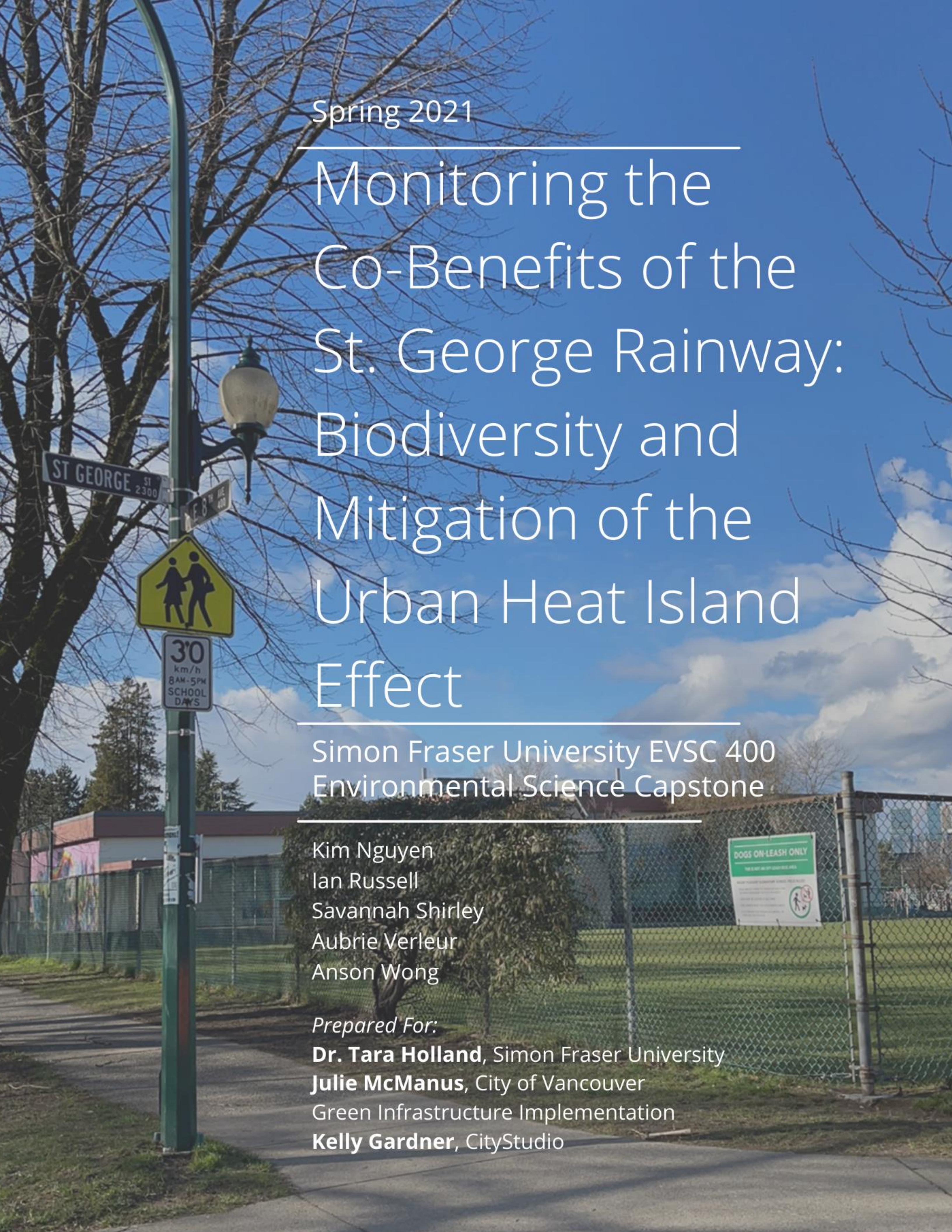

Spring 2021

Monitoring the Co-Benefits of the St. George Rainway: Biodiversity and Mitigation of the Urban Heat Island Effect

Simon Fraser University EVSC 400
Environmental Science Capstone

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Executive Summary

In Vancouver, the conventional method for managing rainwater flow has been through a system of wastewater treatment plants and pipes, referred to as grey infrastructure. Green rainwater infrastructure (GRI) is an emerging alternative engineered to combine vegetation, landscapes, and natural processes to manage water resources while also addressing urban climate issues. GRI is distinct from its grey counterpart due to its ability to adapt to changing environmental conditions and extreme precipitation events while also creating other benefits for both the environment and people, referred to as co-benefits.

As part of their Rain City Strategy, the City of Vancouver is improving rainwater management by implementing GRI around the city. These initiatives also present a chance to address other climate change concerns by building upon co-benefits. The acceleration of global warming raises concerns for water quality and quantity, air quality, rising local temperatures, and impacts on biodiversity. GRI projects can be designed to alleviate these issues and are an opportunity to create multi-faceted solutions for complex problems.

An essential consideration when implementing GRI is monitoring the co-benefits to ensure they are having the intended impact. A robust and inclusive plan is needed to communicate how effectively GRI is performing. In Vancouver, one example where this will be important is the prospective St. George Rainway, a GRI project being developed in the Mt. Pleasant community.

To this end, we are proposing a data collection, monitoring, and analysis framework for two of the co-benefits provided by the Rainway. Specifically, our plan focuses on improvements to biodiversity and the mitigation of the urban heat island (UHI) effect. Biodiversity refers to the abundance of different wildlife and vegetation present in an area. The UHI effect is when urban areas retain more heat than surrounding rural regions due to more heat absorbent surfaces. Our plan compiles the ideal methods for collecting data on biodiversity and UHI within the Rainway, determines how and when the City should conduct monitoring, and what analysis techniques could be used to assess the long-term success of the Rainway.

<u>Data Collection</u>

To collect data on the UHI effect, we propose using a combination of fixed stations and mobile transects. Both methods require sensors with meteorological capabilities, either by attaching them to stationary locations or instead to people and bikes, capable of collecting data while moving along a set route or transect. Fixed stations can continuously capture the temperature

variation in one area over a long period, while mobile transects can complement them by measuring the variations between fixed stations. Our plan also includes a comparative analysis for different sensors.

To collect biodiversity data, we highlight the use of quadrats, rapid biodiversity assessments (RBAs), and citizen science. Quadrats isolate an area of land from which estimates of percent vegetation cover can be made. RBAs involve using traps to catch arthropods, such as insects, and then counting and classifying them based on similarities in morphological traits. Lastly, citizen science relies on information collected and shared by community residents. Web applications such as iNaturalist and eBird rely on biodiversity information from citizens, which is then shared with users worldwide. Citizen science is rising in popularity due to advances in technological accessibility. It can potentially be an effective tool for collecting biodiversity data that is also cost-effective and community oriented.

Monitoring

Effective monitoring will ensure that data collection is inclusive and reliable. Our monitoring plan has two main components to ensure this for each co-benefit: location and timeline. For UHI, we recommend that sensors be placed equal distances apart along St. George Street and an adjacent street, potentially Carolina Street. To capture the most distinct changes in the UHI effect, data should be collected during the warmest months of the year, ideally from May to September. To obtain sufficient data, sensors should record measurements hourly during those months.

To ensure we create a temporally inclusive and broad dataset, quadrat and RBA data should be collected along St. George street before and after implementation of the Rainway. The specific locations of quadrats can ultimately be determined at the City's discretion, ideally in vegetated areas. We recommend quadrats be placed 50m apart along the street. For the RBAs, the pitfall traps should be set up 25m apart, while the window traps should be set up at 100m intervals. To assist with insect identification, we have curated a morphospecies evaluation chart. Furthermore, citizen science data from iNaturalist and eBird can provide a long-term source of information. Both quadrats and RBAs should be conducted once a year in July, when weather conditions are typically ideal. In the designated collection month, quadrat assessments only need to be done once, but the RBA should be performed for the whole month, with insect collection happening regularly. This should continue for five to ten years so that the yearly data trends can be statistically tested.

Analysis

Obtaining hourly temperature measurements over the space of several months will yield plenty of data. Given the wide variety of available statistical analyses, we do not suggest one specific method.

Instead, we highlight how the hourly data can be manipulated to identify variations in the hourly, daily, and monthly temperature averages. To determine if there are significant differences between the temperature data collected along the Rainway and the benchmark street, we recommend using a two-way ANOVA in conjunction with Tukey's HSD significance testing.

Both Shannon's and Simpson's Diversity Indices can be used to evaluate the quantitative biodiversity data in terms of a qualitative metric of low, medium, or high biodiversity. Testing the data with a one-way ANOVA and Tukey's HSD test will help determine if the annual variations in biodiversity are significant and which years of data collection yielded those results.

Additionally, by assessing the UHI and biodiversity, our plan will help identify the Rainway's impact on human health. Information on the long-term health of residents is difficult to obtain, especially for such a small area. Therefore, our plan only discusses possibilities for inferring the health impacts rather than measuring them directly.

Holistically, our objective is to provide the City of Vancouver with a robust directive that supports the science and justifications for GRI and its benefits. Our hope is that this framework can be used to strengthen community education and engagement regarding both the St. George Rainway and future GRI initiatives.

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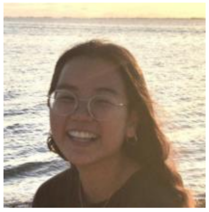
Authors



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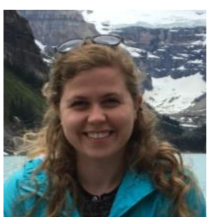

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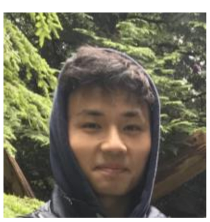

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We respectfully acknowledge that Simon Fraser University and St. George street collectively reside on traditional and unceded territories of the xʷməθkʷəy̓əm (Musqueam), Sḵwx̱wú7mesh Úxwumixw (Squamish), səl̓ilw̓ətaʔɬ (Tsleil-Waututh), q̓íc̓əy̓ (Katzie), kʷikʷəƛ̓əm (Kwikwetlem), Qayqayt, Kwantlen, Semiahmoo and, Tsawwassen Peoples.

1.0 Introduction

1.1 Rainwater Management

Many older parts of Vancouver rely on a combined drainage system that treats stormwater and sewage together before releasing them into the water bodies surrounding the city (City of Vancouver, 2019). During extreme precipitation events, incoming water can exceed these treatment systems' capacity, leading to the release of untreated sewage, a problem called combined sewer overflows (City of Vancouver, 2019). The City of Vancouver developed the Rain City Strategy to improve the city's rainwater management that includes a transition to green rainwater infrastructure (GRI) (City of Vancouver, 2019). GRI incorporates nature-based features such as vegetation and soil that allows the city to adapt to changing environmental conditions in ways that grey infrastructure cannot (City of Vancouver, 2019).

1.2 Project Site

The St. George Rainway is one of the GRI projects that Vancouver is planning on implementing throughout the city. The proposed designs for the Rainway incorporate various features such as rain gardens, rainwater tree trenches, and permeable pavement (City of Vancouver, 2021). The project, which will extend from E 5th Ave to Broadway Ave along St. George street (Figure 1), will restore some environmental benefits once provided by the historic *te Statlew* creek which now runs beneath the street (St. George Rainway Project, 2021).

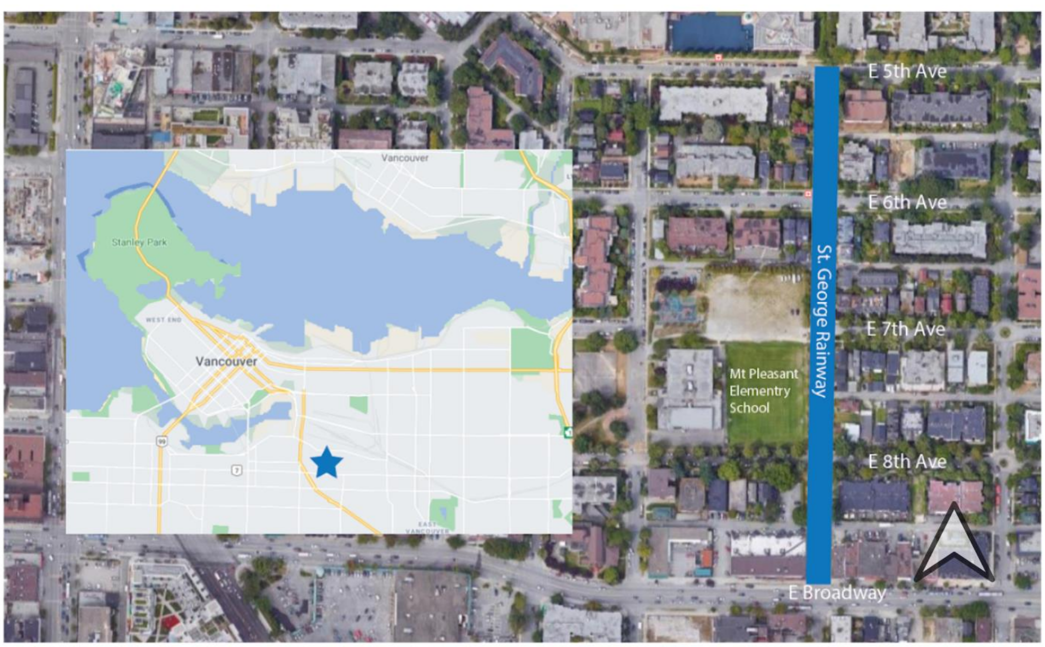

Figure 1. Map of the City of Vancouver and the St. George Rainway study site.

1.3 Co-benefits of the Rainway

In addition to improved rainwater management, GRI projects can also create various environmental, social, and economic advantages, referred to as co-benefits. These include increased biodiversity, lower urban temperatures, and improvements to human health (City of Vancouver, 2019). GRI can also introduce vegetation and wildlife to an area, contributing to overall biodiversity (US EPA, 2020a). Plants and trees sequester carbon, offer shade, and evapotranspiration, which help reduce ambient temperatures and mitigate the local urban heat island (UHI) effect (Demuzere et al., 2014). UHIs are a phenomenon where urban areas have higher temperatures compared to surrounding rural communities due to the abundance of heat absorbent surfaces (US EPA, 2020b).

These co-benefits can also improve human health. By mitigating the UHI effect, GRI can reduce the amount of heat stress and heat related illness experienced in the community (Guo et al., 2017). Additionally, biodiversity improves air quality and maintains ecosystem services that humans rely on, thus positively impacting human health (Aerts et al., 2018).

1.4 Quantifying the Co-benefits

Co-benefits can be complex to quantify and are frequently omitted from GRI assessments despite their importance to the community. Therefore, we have developed a framework to assess some of these co-benefits. Our plan focuses on the UHI mitigation and biodiversity improvements due to the Rainway. By focusing on these co-benefits we hope to create metrics by which the success of the Rainway can be measured.

We conducted an extensive literature review on methods used to monitor the UHI effect and biodiversity from various case studies and academic papers. From our research, we determined the ideal methods for evaluating the UHI effect and biodiversity within the St. George Rainway. We have compiled our research into a plan that discusses different data collection methods, the ideal locations and timelines on which to conduct those methods, and the most effective ways to analyse the data to communicate the success of the Rainway.

1.5 Objectives

1. *Curate a robust data collection methodology that will accurately track the changes in biodiversity and the local urban heat island (UHI) effect of the St. George Rainway.*
2. *Develop a monitoring plan to measure the biodiversity and UHI effect before and after implementing the Rainway.*
3. *Propose analysis techniques that assess and evaluate the effectiveness of the Rainway to provide co-benefits.*

2.0 Literature Review

2.1 Introduction

The widespread use of grey infrastructure in urban areas has made communities less resilient to flooding and more susceptible to rainwater management issues. A ramification of this in Vancouver is sewage overflows, a result of more extreme and frequent precipitation events. To mitigate this and improve water management, the City of Vancouver is developing strategies based on GRI. GRI as defined by the City of Vancouver (2019) "uses both engineered and ecosystem-based practices to protect, restore and mimic the natural water cycle". It also provides environmental, social, and economic advantages including enhanced air quality, increased biodiversity, thermal regulation, and improved human well-being, referred to as co-benefits (City of Vancouver, 2019). This literature review focuses on UHI mitigation and biodiversity. An examination of the literature has revealed key methods and trends in measuring these co-benefits, with consideration for the scope of the St. George Rainway. Common methods used to monitor the UHI effect include the use of thermal remote sensing with satellites and unmanned aerial vehicles (UAV), and in-situ measurements. As for biodiversity the most common are remote sensing, sampling surveys, and citizen science. This literature review will evaluate these common monitoring methods and discuss their strengths and weaknesses. We then frame these co-benefits in the context of human health.

2.2 UHI Monitoring Methods

2.2.1 Thermal Remote Sensing

The UHI effect occurs due to the higher prevalence of heat absorbing surfaces, such as pavement and asphalt, in urban areas which makes them noticeably warmer than surrounding rural ones. These increased temperatures can impact the health and quality of life of urban communities. Thermal remote sensing is commonly used to measure the UHI effect because of its ability to collect land surface temperature (LST) data over large areas simultaneously (Estoque & Murayama, 2017; Weng, 2009). LST data is traditionally estimated from infrared images captured by Earth-orbiting satellites and is accessible to the public at little to no cost (Voogt & Oke, 2003; Zhou et al., 2019). Since satellites have a large range, they are excellent resources for measuring mesoscale UHI changes; however, this results in a low spatial resolution that makes them ineffective for local- and micro-scale studies (Zhou et al., 2019). Their temporal coverage is also relatively low since images are taken on fixed schedules, often weeks apart (Ruiz-Aviles et al., 2020). Additionally, satellite imaging is impeded by variable weather conditions such as cloud cover and consequently, LST data can have discontinuities (Estoque & Murayama, 2017). Some studies have opted to use aircrafts as an alternative to improve the spatial resolution and flexibility of measurements, but this is quite expensive thus limiting its feasibility (Bartesaghi-Koc et al., 2020).

The use of unmanned aerial vehicles (UAVs) could provide a more localized alternative for monitoring the UHI effect. UAV use is becoming more common in research because they are lightweight, low maintenance, and provide high spatial and spectral resolutions (Anweiler et al., 2017; Sagan et al., 2019). UAVs can be fitted with both a standard and thermal camera to provide coloured images of study sites and their corresponding LST (Anweiler et al., 2017). The thermal cameras are useful because they use non-uniformity correction (NUC) to account for the UAVs self-generated heat to ensure thermal image accuracy, and flat-field correction to improve digital image quality (Sagan et al., 2019). Technological advances in camera quality, the precision of measurements, mobility in urban environments, and cost-effectiveness compared to satellites are clear advantages (McDonald & Naughton, 2019; Sagan et al., 2017). However, LST values tend to trend higher than air temperature because many surfaces release heat slowly, thus requiring LST data to be corrected to measure the UHI effect accurately (Malik, 2018). While remote sensing techniques can only collect LST data (Malik, 2018), in-situ measurements can be used to obtain air temperature data.

2.2.2 In-Situ Measurements and Mobile Transects

In-situ measurements are taken at the location of interest rather than from a distance like remote sensing (Sun et al., 2019). One in-situ method uses fixed stations where sensors are set up to take regular measurements of variables like air temperature, humidity, or air pressure (Sun et al., 2019; Vant-Hull et al., 2014). A stationary setup is ideal for obtaining temperature data for one location over a long period (Sun et al., 2019). However, the resulting spatial resolution of UHI distributions in an area can be low if not enough fixed stations are used (Sun et al., 2019; Tian et al., 2021). Additionally, the cost to install and maintain a large number of fixed stations is high, since the devices must be properly installed to minimize skewed readings due to factors like direct sunlight or hot surfaces (Sun et al., 2019). Moreover, remotely accessing the data is not possible for sensors that require a USB connection (Sun et al., 2019).

One way that researchers have overcome this is through the use of personal weather stations (PWSs) to measure UHIs in urban environments (de Vos et al., 2020; Varentsov et al., 2019). PWSs can take temperature, rainfall, and other weather readings much like sensors, but are designated for personal use rather than for traditional research. Many companies that sell PWSs have an associated network or map where the data from all their devices are collated, which can be accessed remotely, at no cost via the internet (de Vos et al., 2020). Since these devices are not explicitly designed for research purposes, their accuracy in comparison to sensors or established meteorological networks is variable (de Vos et al., 2020; Varentsov et al., 2019). When citizens install PWSs without consideration for confounding factors, Varentsov et al. (2019) and de Vos et al. (2020) found that resulting temperature measurements were prone to error and bias. Regardless, researchers have explored their uses in quantifying UHI changes and when used in combination with established meteorological stations, PWSs can produce supplementary data that contributes to higher resolutions of localized UHIs (de Vos et al., 2020; Varentsov et al., 2019).

Mobile transects can be used in tandem with fixed stations to offset the limitations they have in measuring the spatial variation of UHIs (Sun et al., 2019; Vant-Hull et al., 2014). Mobile transects require attaching sensors to vehicles, bikes, or people and collecting temperature readings at regular intervals along planned routes (Sun et al., 2019). The transient nature of mobile transects yields difficulties for collecting long term UHI data but they can provide snapshots of how temperature varies spatially in urban areas (Sun et al., 2019; Vant-Hull et al., 2014).

2.2.3 UHI and Human Health

For humans, prolonged exposure to extreme temperatures can cause heat stress resulting in serious health impacts and has been linked to increased cardiovascular and respiratory mortality and morbidity (Kenney et al., 2014; Zhao et al., 2015). While some studies have measured the direct health impacts of extreme temperatures and UHI, they relied on decades-long medical information (Tan et al., 2009). Other studies have attempted to simply infer health impacts from temperature data; however, there is no standard method for assessing the impacts of extreme heat (Zhao et al., 2015).

Many studies on the health impacts of heat have relied on heat indexes such as 'apparent temperature' or' humidex' which consider humidity and wind speed, along with air temperature to better represent the perceived temperature (Sun et al., 2019). These heat indexes are useful because they account for thermoregulation through sweating which air temperature does not (Sun et al., 2019). Nevertheless, Anderson et al. (2013) found that for moderate climates there is no significant difference between air temperature and heat index measurements.

There is also disagreement on the use of relative temperature or absolute temperature. Absolute temperature defines thresholds that classify health risk categories, allowing for more straightforward comparisons between disparate communities (Sun et al., 2019). However, Zhao et al. (2019) found that the ability to acclimate to ambient conditions means that people living in regions with high ambient temperatures are less impacted by heat compared to those in moderate and cold regions. Relative temperature thresholds adjust for this by assessing the health impacts for temperatures at community-specific distribution percentiles (Guo et al., 2017).

2.3 Biodiversity Monitoring Methods

2.3.1 Remote Sensing

Beyond its applications for UHI, remote sensing has been used to evaluate the effects GRI has on habitat creation and the ecological connectivity of urban landscapes (Liquete et al., 2015), both of which are positively correlated with biodiversity (Hill, 2005). Remote sensing can be used directly to measure habitat vegetation through the combination of colour and infrared photography (Brunbjerg et al, 2018; Grafius et al., 2019; Marulli & Mallarach, 2005). High resolution photos can be used to identify vegetation type through visual analysis or use of "spectral signatures" (Hill, 2005). However, identifying specific plant species can be difficult, and this data is more often used to infer biodiversity from the relationship between vegetation type and a particular species (Grafius et al., 2019; Hill, 2005; Liquete et al., 2015). These types of associations do not always translate well in environments as complex as urban areas (Brunbjerg et al., 2018; Grafius et al., 2019). To incorporate this complexity, LiDAR data can be used to quantify the varying heights and areas of vegetation cover while excluding interference from buildings (Brunbjerg et al., 2018). These vegetation characteristics are an important metric and can be associated with species richness (Brunbjerg et al., 2018; Filazzola et al., 2019).

To assess ecological connectivity in an urban environment, aerial photography can produce raster data that shows cell connectivity (Marulli & Mallarach, 2005; Wickham et al., 2010). This was done in the Barcelona Metropolitan area using a modified Ecological Connectivity Index (Marulli & Mallarach, 2005). A similar approach that has been applied to GRI specifically is classifying GRI corridors as "links" and larger habitats as "hubs", which may be useful for future GRI planning if raster data on the surrounding area is available (Wickham et al., 2010).

2.3.2 Wildlife and Vegetation Sampling Surveys

Sampling surveys are an effective way to measure the species richness and abundance of an area (Buckland et al., 2005). This technique is ideal for monitoring stationary biodiversity such as plants and other vegetation within a small spatial context (Fasham & Mustoe, 2005). Survey data can help determine rates of change in populations (Buckland et al., 2005), which indicates whether biodiversity is increasing or decreasing. Sampling surveys can be performed in different ways. Some common approaches are quadrats or rapid biodiversity assessments. Quadrats can be used to estimate plant density and canopy cover, providing a percent estimate of overall coverage (Fasham & Mustoe, 2005). Rapid biodiversity assessments involve counting and classifying organisms according to their morphological traits (Obrist & Duelli, 2010). Small species like arthropods are typically used for rapid biodiversity assessments. They are an excellent indicator of overall biodiversity because they make up the largest proportion of species richness at any population scale (Obrist and Duelli, 2010). However, sampling surveys have limitations. Biases in the data arise due to variation in observer's skills as well as differences in species detectability, which depends on colour, size and mobility (Buckland et al., 2005). Therefore, data from sampling surveys should be considered minimum population estimates (Fasham & Mustoe, 2005). Citizen science may be an alternative method of monitoring biodiversity that addresses these concerns.

2.3.3 Citizen Science

To get a more comprehensive view of species biodiversity and abundance in an area, employing citizen science is not only cost-effective but has the capacity to produce long-term, high quality data (Biggs et al., 2015; Swanson et al., 2016; Theobald et al., 2015). It can also address educational and public outreach goals (Kelemen-Finan et al., 2018; Theobald et al., 2018). Contributory citizen science has been used for peer-reviewed research (Biggs et al., 2015), while collaborative projects have been used for more practical purposes, such as quantifying urban encroachment effects on biodiversity (Cooper et al., 2007; Dickinson et al., 2012). Despite these applications there are some concerns about the shortcomings of citizen science, namely bias and unreliable data entry (Boakes et al. 2016; Dickinson et al. 2012). However, further research has shown that it is possible to address and adjust for these issues (Boakes et al., 2016; Krabbenhoft & Kashian 2020; Swanson et al., 2016).

In addition, a multitude of citizen science phone applications have been developed to measure biodiversity. Smartphone technology is now able to provide intuitive applications that incorporate GIS software, the internet, access to expert opinions, and ecological databases (Dickinson et al., 2012). Some applications such as iNaturalist, measure all taxa, while others, such as Ebird, focus on certain taxonomic groups. These apps can be used worldwide while others such as BC's Central Coast Biodiversity App and North America's HERP have been developed for specific geographic locations.

2.3.4 Biodiversity and Human Health

Biodiversity can have direct and indirect effects on human health. The direct effects are not well recorded, but many links have been made between the indirect impacts biodiversity has on human health. As a main driver of the ecosystem services that humans rely on, biodiversity is essential to human well-being (Aerts et al., 2018; Sala et al., 2009). Ecosystem services include preventing disease spread and improving air quality, allergies, asthma, and cardiovascular diseases (Aerts et al., 2018). The biodiversity hypothesis suggests that being exposed to a diverse microbiota environment early in life can result in improved immunity against inflammatory disorders (Ruokolainen et al., 2016). It is also hypothesized that disease pathogens can be diluted in the environment when species richness is high, decreasing the possibility of human infection (Aerts et al., 2018; Sala et al., 2009). Studies have also found that immersing in nature can instill calm and relaxation in individuals, decrease stress and anxiety and create a stimulating environment that promotes physical activity (Kellert, 2009). Most health and well-being research has been conducted through surveys, though some research has examined blood pressure and other physiological indicators (Kellert, 2009). By monitoring biodiversity, we can infer how the biodiversity present in the community will impact human health.

2.4 Conclusion

There are extensive methods to measure both UHI and biodiversity, however due to spatial, temporal, and financial constraints not all of them are effective for the St. George Rainway. Viable monitoring methods must be able to collect data that can be used to accurately quantify the co-benefits and evaluate the success of the Rainway. There is no ideal method for measuring either UHI or biodiversity, but a combined approach at varying spatial and temporal scales that incorporate public participation could mitigate the drawbacks of the individual methods. The data collected with these monitoring techniques could also prove useful for identifying other GRI co-benefits such as improving human health. However, the relationship between human health and the monitored co-benefits is complex and difficult to quantify. While inferences on the health co-benefits can be made, they should not be perceived as absolute. Monitoring methods that produce metrics for success are essential to create a cost-effective data collection, monitoring, and analysis framework for the St. George Rainway. This framework and its results are not only important in the context of the Rainway but also for the implementation of future GRI projects.

3.0 Proposed Plan

Our proposed plan presents a compilation of data collection methods for the UHI effect and biodiversity, shown below in Figure 2.

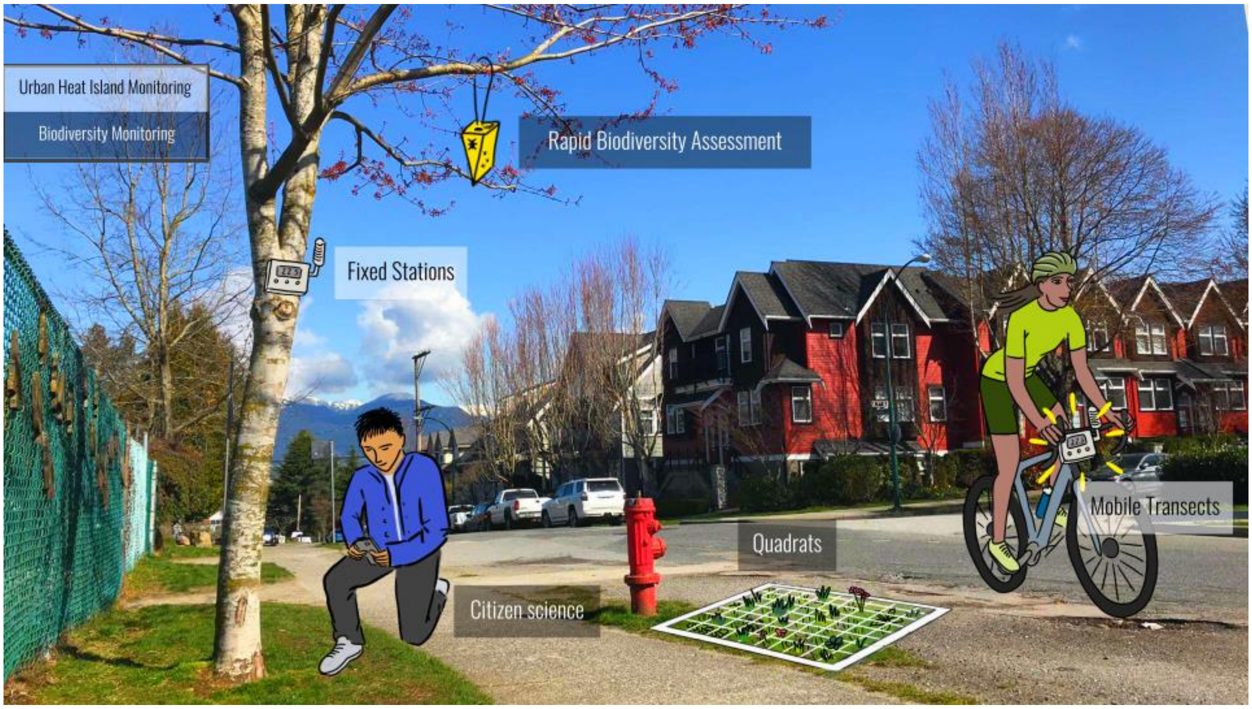

Figure 2. Visual representation of data collection methods for monitoring UHI and biodiversity changes on the Rainway. White boxes represent UHI monitoring methods, black boxes represent biodiversity monitoring methods.

3.1 UHI

To monitor the change in the UHI effect, we are proposing two methods for data collection. Our plan includes recommendations for when this data should be collected, what devices should be used, and where they should be placed. We also provide some suggestions on how this data can be analyzed to show if the Rainway is successful in mitigating the effect.

3.1.1 Data Collection

Given the size of the Rainway and our review of the literature, we propose using a combination of fixed stations and mobile transects to measure air temperature. Both methods require temperature sensors to collect data, either by attaching them to stationary locations such as electrical poles or trees or attaching them to bikes or people capable of collecting data while moving. Fixed stations allow for long-term continuous data collection but require numerous devices to be installed to accurately capture the spatial distribution of temperatures. Using mobile transects would compensate for this by measuring the temperature variation between the fixed stations and measuring the spatial heterogeneity of the Rainway. Using these two methods together increases the probability of obtaining temperature data that is accurately represented over both time and space.

Device Comparison

There are a variety of sensors on the market with a wide range in prices and features. We have included a comparison of some of the devices available (Table 1) that could work for our plan; however, this is not an exhaustive list, and there may be other options available. Our main requirements for sensors are that they must be waterproof and can record air temperature. Some sensors included in our comparison can measure other variables such as humidity or precipitation, which are not essential to our plan; however, they may be useful for monitoring other co-benefits of interest.

Other considerations that should be made when choosing a device include the potential for vandalism, the type of power source, and data accessibility. Ideally, the device should be mounted high and out of easy reach. The power source is another important consideration since some devices are battery-powered while others require a wired connection, thus limiting placement options. Furthermore, some devices require manual data retrieval, whereas others rely on cloud storage and can be accessed remotely.

3.1.2 Data Monitoring

Our team has considered two aspects that are significant to data monitoring. The locations of fixed stations and mobile transect routes are important for establishing benchmarks to compare the difference in the UHI effect. Additionally, we suggest how often data collection should take place.

<u>Locations</u>

In order to effectively monitor and assess the UHI effect over the entire length of the St. George Rainway, we propose that fixed stations are installed at set intervals (eg. every 100m) along the Rainway between East 5th street and East Broadway. Similarly, fixed stations should be set up along the neighbouring Carolina street at similar intervals for benchmark measurements. For mobile transects, we propose two sampling routes that are paralleled along St. George street and Carolina street. However, since the effects of the Rainway may extend beyond Carolina street, we recommend the City use its discretion to choose an appropriate benchmark that has similar urban features to St. George street. Temperature sensors will be used to collect measurements at set intervals (eg. every 10 seconds) along each transect route, and will

Table 1. A comparison of some of the available temperature sensors that could be used to monitor the UHI effect.

Device	Cost per Unit	Resolution	Accuracy	Battery Life	Storage Space	Operating Temperature	Additional Measures	Pros	Cons
Acurite Notos	$130 USD	Unknown	1.11°C	Unknown	Wireless 433Mhz	-40 to 70°C	Humidity Wind Speed	Wireless Battery-Powered Cost	Pole Mounted
Comptus A70H-HT-S	$294 USD	0.1°C	±0.5°C	Wired	Wired	-40°C-60°C	Humidity	Radiation Shield Cost	Wired Power Source
Comptus A70H-T-S	$178 USD	0.1°C	±0.5°C	Wired	Wired	-40°C-60°C	N/A	Cost Radiation Shield	Wired Power Source
Dyacon Modbus	$534	0.01°C	± 0.2 C	Wired	Wired	-40 to 80°C	Humidity Pressure		Wired Power Source
Intellisense MWS-C400	$6000 USD	0.1°C	±1.0°C	Solar Powered	Wireless Satellite or Cellular Connection	-40°C-60°C	Pressure Humidity Precipitation Wind Speed/Direction Angular Tilt Lightning Distance	Solar Powered Cloud-Based Data Storage	Cost Extraneous Data
Omega OM-CP-ETR101A-KIT	$480	0.1°C	±0.25°C	10yr	500,000 Readings	-40 to 80°C	N/A	Long Battery Life	USB Data Retrieval
T&D TR-51i	$169	0.1 °C	± 0.5 °C	4 yr	16,000 Readings	-40 to 80°C	N/A	Battery-Powered Cost	USB Data Retrieval

be conducted during the same time, allowing us to accurately compare temperatures along each street.

<u>Timeline</u>

Monitoring along the St. George Rainway and neighbouring communities should occur from May till the end of September. We have chosen these parameters because research suggests that the UHI effect will be the most significant during the warmest months of the year (Malik, 2017). The fixed stations should be set up to take hourly measurements, in order to account for the daily temperature variation. Mobile transect data collection will be conducted twice a month, once at the beginning and once in the middle. Although we would like for more frequent measurements with mobile transects, we recognize that cost, among other factors, may limit the ability to do so.

3.1.3 Data Analysis

There are numerous ways that temperature data can be assessed, the usefulness of which depends on what information is desired. Therefore, we do not suggest any one analytical method is better than another. Instead, we have compiled different options that present a variety of ways to assess the Rainway's impact on the surrounding UHI effect. The variation in data can be examined based on the location relative to the Rainway, the location along the Rainway, and through time.

<u>Variation in Time</u>

Essential to our analysis is understanding the temporal variation of the UHI effect. Questions that should be considered are: 1) *Is the UHI effect more pronounced at a certain time of day, or during a particular month?* 2) *Is the mitigation effect created by the Rainway more pronounced at different times?* To assess the variations in time, the data will need to be condensed to a more manageable size. Starting with hourly data recorded over several months offers a few different ways to assess the data.

Hourly Average

This method would allow for a comparison of the average daily variation in temperature. Averaging the temperature readings for each hour over the course of a month could help identify during what time the temperatures are typically highest and if mitigation of the UHI effect is more pronounced at a specific time of day. While the data could be averaged over an entire collection period, seasonal variability may skew the average, so we suggest each month be assessed separately (Figure B1).

Daily Average

The hourly data can also be averaged for each day to find the mean daily temperature. Comparing the mean daily temperatures recorded at each station can show the variability for an entire month. As with the hourly variation, we suggest that daily mean comparisons are made for each month individually to reduce confounding factors from seasonal variability (Figure B2). Alternatively, comparisons can be done with the daily maximum temperature rather than the mean to assess the temperature extremes recorded at each station.

Monthly Average

This method could be used to assess the seasonal variability of temperatures around the Rainway. Averaging the daily mean temperature data for each month would allow for an examination of longer-term trends (Figure B3).

<u>*Variation in Space*</u>

The temperature measurements will also be affected by the placement of the sensors. The main difference will likely be between the sensors set up along the Rainway and those along the benchmark street. However, another critical variable to consider is the location along those streets and the proximity to major infrastructures such as intersections, buildings, or green space.

Proximity to the Rainway

A simple comparison between the temperature measurements between the Rainway and benchmarks sensors would be the most direct way of assessing the effects of the Rainway. Data collected from all the sensors on the Rainway could be averaged over the desired period and compared to the average temperature collected at the benchmark stations. However, this method on its own cannot be adjusted for confounding factors or biases that arise from device placement.

Position Along Rainway

The proximity of sensors to urban infrastructure has the potential to affect the data. This could be accounted for by identifying each sensor based on its location and noting the features adjacent to it. The analysis could then be done to compare the variation between each individual sensor.

Mobile Transects

The temperature readings from the mobile transects can be plotted against time to compare the variability between the Rainway and the benchmark. Plotting transects run on multiple days will allow for further temporal variation comparisons. Although this will require transects to be run at the same time of day to eliminate any differences due to daily variations (Figure B4).

Significance Testing

Plotting the variations in temperature is helpful for visually comparing the differences in time and location. Although to properly assess the success of the Rainway, the significance of these variations needs to be tested. We suggest the City use two-way analysis of variance (ANOVA) tests and Tukey multiple comparison tests. A two-way ANOVA conveys significant variation in the temperatures recorded at the different stations based on specific values such as location or time of day. A two-way ANOVA can also indicate if there is significant variation due to the interactions between those variables. Unfortunately, ANOVA does not explain how the data varies or which variables are causing the differences. To account for this we suggest using the Tukey test. An example of both these tests is shown in Figure B5 and a plot of the Tukey test is shown in Figure B6. For both tests we suggest using a significance of 95%, if the p-value for a test is less than 0.05 then the variation can be considered significant.

Health benefits

Inferring direct health benefits from UHI mitigation is difficult without long-term health data. Even with this data, the citizens living adjacent to the Rainway would likely be too small of a sample size to form any concrete conclusions. Therefore, we propose that the health impacts are assessed indirectly based on temperature reductions. Health impacts occur primarily during heat waves where the air temperature remains above the 95th percentile for an extended period of time (at least two days) (Guo et al. 2017).

For Vancouver, the 95th percentile for the mean daily temperature is approximately 19.4°C. Then, if the number of days with temperatures exceeding this threshold is fewer on the Rainway than the benchmark street, we can infer the Rainway is mitigating the heat-related health impacts felt by the St. George street residents. If the City is also collecting humidity data, using perceived temperature instead of air temperature could potentially provide a more accurate inference of the human health impacts, but because Vancouver has a temperate climate this is not a requirement (Anderson et al. 2013).

3.2 Biodiversity

To assess changes in biodiversity along the Rainway, we propose data is collected with the combined use of quadrats, RBAs, and citizen science. This approach will encompass data on a range of taxa over short and long time scales, while also engaging the community with the ecological changes taking place in the St. George neighbourhood. With this data, we propose using simple diversity calculations and indices to determine biodiversity and statistical analysis for comparison over several years.

3.2.1 Data Collection

Quadrats

Quadrats can be used to sample specific areas and provide measurements of overall percent frequency, density, and plant cover (Fasham & Mustoe, 2005). Quadrats are best suited for stationary species, making them ideal for sampling the Rainway's vegetation. We suggest using standard 1m x 1m quadrats to avoid extreme percentages of individual species which can lead to over-or underrepresentation of certain species (Fasham & Mustoe, 2005). We also recommend a couple of trial surveys, so that the estimates can be calibrated between surveyors. This would give surveyors a chance to establish similar estimation methods, creating consistency for subsequent quadrat surveys.

Rapid Biodiversity Assessment

Rapid biodiversity assessments would be used to collect data on arthropods, specifically insect species. Insects are extremely abundant, making them a good indicator of overall biodiversity and therefore a desirable species to monitor in the Rainway. Terrestrial insects have two main modes of transportation; flying and crawling. Therefore, we suggest using two different traps to enhance the number and variety of species caught. Pitfall traps (Figure 3a) can capture invertebrates that live in the soil and on plants (Dennis et al, 2005). These traps are commonly used, cost-effective, and low maintenance (Dennis et al, 2005) The containers would have a solution (2% formaldehyde) to euthanize the insects that fall into the trap, ensuring they do not escape and are not double-counted. To collect flying arthropods, we suggest window trapping (Figure 3b). Window traps are similar to pitfall traps in that they use containers, but they are instead placed on stakes and have colourful plastic to attract the insects (Dennis et al, 2005). With both these traps, we can determine population sizes (Dennis et al, 2005).

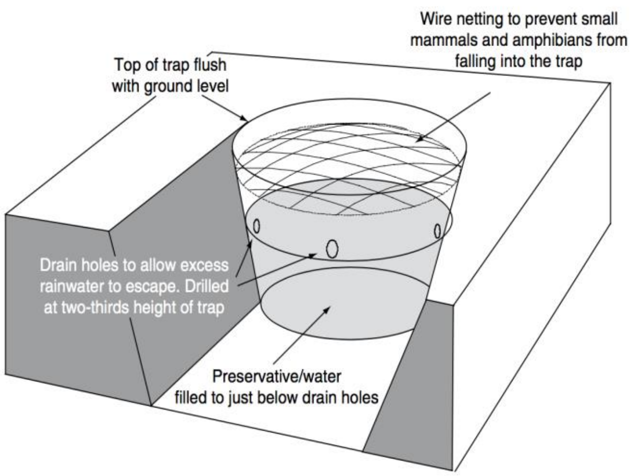

Figure 3a. A depiction of a pitfall trap. The container could be as simple as a yogurt container, and is placed in the ground so that it is flush with the ground surface. The netting size allows only insects to fall through. Holes can be punctured two-thirds from the top of the container to let rainwater drain out.

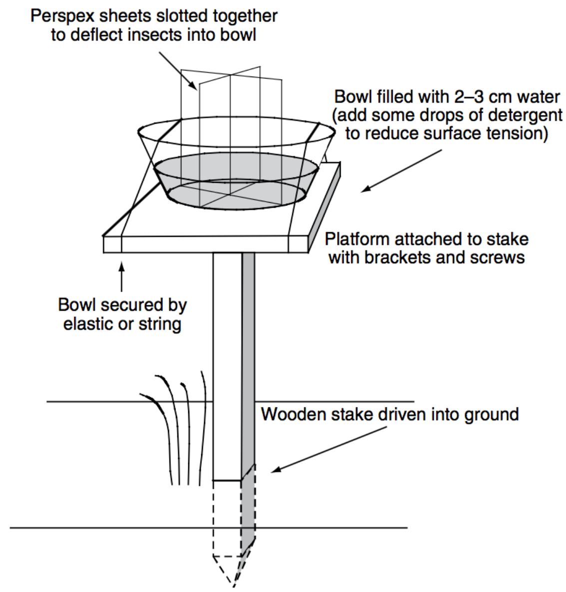

Figure 3b. A depiction of a window trap. A stake is driven in the ground with a platform on top that a bowl-like container can sit on. The container holds plastics sheets of different colours to attract specific species. Holes can be punctured two-thirds from the top of the container to let rainwater drain out.

<u>Citizen Science</u>

Citizen science is used by many web platforms to track biodiversity (Table 2). Some of these specialize in particular taxonomic groups while others collect observations from all taxa. It is important to note that certain platforms are created for specific geographic locations, and not all are compatible with our project objectives. Also, reviews of some newer and less developed apps have reported user-interface issues. Regardless, citizen science is an avenue of data collection we are exploring because of its potential to foster education and community engagement with GRI. Furthermore, most of these platforms have developed corresponding smartphone applications that make data collection accessible to researchers and community residents alike.

Table 2. Comparison of citizen science biodiversity tracking platforms. Some data is "unknown" when the platform does not openly advertise the number of records or users.

Name	Geographic Distribution	Taxonomic Focus	Smartphone Application	Average App Rating (# of reviewers)	Number of Records	Number of Users
BugGuide	North America	Arthropods	No	N/A	Unknown	5600
Central Coast Biodiversity	BC, Canada	All	Yes	3.8 (4)	Unknown	Unknown
eBird	Global	Birds	Yes	4.1 (2183)	7 370 000	500 000
HERP	North America	Amphibians and Reptiles	Yes	3.8 (33)	235 792	3099
iNaturalist Canada	Canada	All	Yes	4.3 (8269)	71 200	2475
iGoTerra	Global	All	Yes	3.9 (27)	Unknown	1807

After considering user-base, accessibility, and app development, we suggest that both iNaturalist and eBird be used to help track biodiversity in the St. George Rainway. Using an app that encompasses all taxa like iNaturalist will give a larger picture of the different types of species present in the Rainway. The use of eBird may help garner more attention due to the popularity of birding worldwide. Since birds are mobile species and are not confined to the barriers of the Rainway, changes to their presence may be more pronounced within a short time frame.

Within the iNaturalist platform, there is an option to create individual citizen science projects. We propose creating a project specifically for the Rainway so that biodiversity observations in the area can be located and accessed from one place within the platform (Figure 4). Alternatively, iNaturalist can also be used to compare data in the St. George area from different timescales using the 'map' feature (Figure 4) in tandem with the 'filter' feature for selected dates (Figure 5). Both methods support long-term data collection and allow users to track both biodiversity and other online visits to the platform.

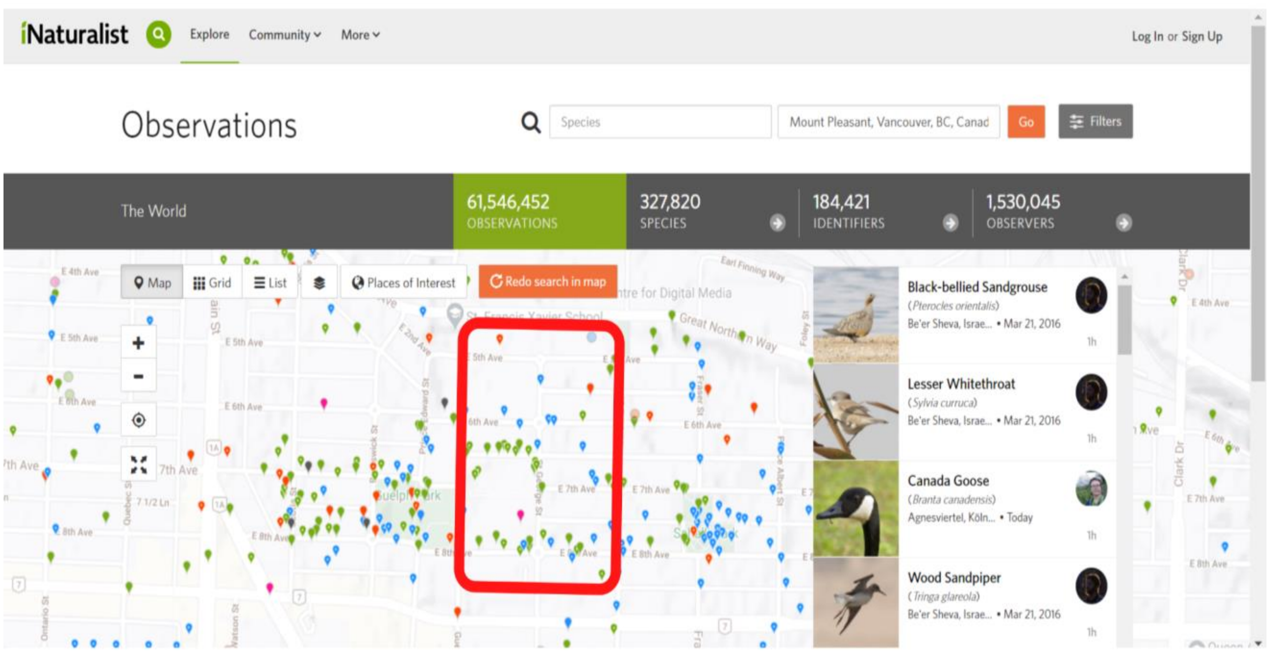

Figure 4. iNaturalist's "Map" feature overview of current observation data on St.George Street in iNaturalist, proposed project area within red box.

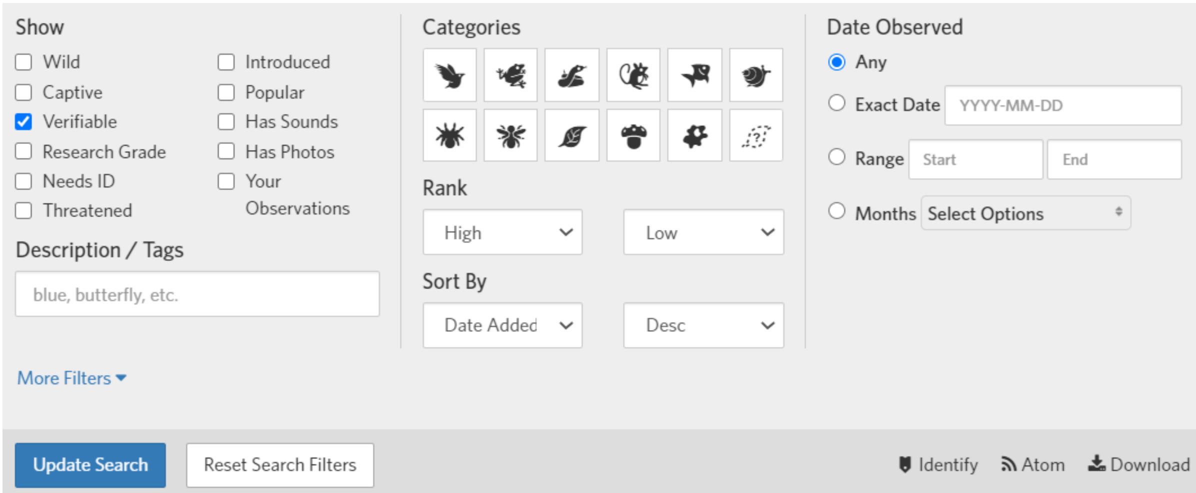

Figure 5. iNaturalist's filter options on the observations "Explore" map.

Unlike iNaturalist, the eBird platform does not have the same capacity for projects. Species data cannot be viewed collectively, only within hotspots or shared locations (Figure B7). However, it is possible to create a shared location as well as suggest an area become a hotspot (Figure B8). Once this location is shared, observations that are added to it make up a birding "checklist" of an area. An example of this is shown in Figure B9, with an observation of Anna's hummingbird. This way all sightings in the area will show up in the hotspot or shared location. Currently, the closest hotspot to St. George Street is at Guelph Park (Figure B7). This hotspot includes 55 species listed on a checklist within the eBird platform to assist birdwatchers (Figure B10). This checklist could be a useful handout to provide information about possible bird species that will inhabit the area. This handout in tandem with bird size, range, and call info provided on Cornell Lab's website "Birds of the World" and smartphone app "Merlin" will be a useful tool for residents who may be interested or already participating in birding and adding to the biodiversity data of the area.

3.2.2 Data Monitoring

<u>*Locations*</u>

For benchmark measurements, quadrats should be placed along St. George street prior to installation on vegetated spaces (e.g. grass on side of the road). Once the Rainway is implemented, the quadrats should be placed in the Rainway's vegetated areas. The City should determine the specific location of each quadrat based on where vegetated spaces are located. An ideal sampling area would include small grasses, flowers, and other low-lying plants. To increase measurement accuracy and fully represent the Rainway, we suggest placing quadrats approximately 50m apart, starting the first quadrat 50m from the edge of the Rainway. All locations should be recorded using GPS coordinates as well with reference photos to help ensure consistent sampling locations.

To collect benchmark insect data before the St. George Rainway is implemented, we suggest putting window traps along the sidewalk where the Rainway would be. Pitfall traps can be placed in grassy areas around St. George Street. Once the Rainway is constructed, we suggest placing 15 pitfall traps 25m apart, starting the first trap 25m from the edge of the Rainway. Ideally, they should not be placed in rocky, shallow or water-logged soils (Dennis et al, 2005). Different colours and reflections attract different invertebrates, and window traps can be displayed with different colours and at varying heights to optimize insect collection (Dennis et al, 2005). Window traps should be placed approximately 100m from each end of the Rainway, and one evenly spaced in the center between the two. We recommend using our morphospecies chart (Table B1) to record and identify the arthropods collected by the pitfall and window traps.

Due to the nature of the observations, citizen science will be conducted within and around the Rainway with no specific sampling locations. The iNaturalist project should focus on the length of the street plus one block in each direction (Figure 4). However, additional data outside of the area may also be useful to track the movement of more mobile species. The eBird observations will be submitted to a shared location created within the center of the Rainway (Figure B8), or if approved, a hotspot at this location.

Timeline

A study done by Oberist and Duelli (2010) in Switzerland, determined that the best time of the year to collect data using RBAs was early to mid-June. Ideal weather conditions would be a rainless day with minimal cloud cover and at minimum 13°C (Dennis et al, 2005). However, in Vancouver the weather in July and August align more with these conditions. Therefore we suggest RBAs be done in July. This is also the ideal time to perform quadrat sampling because floral and leafy plants are easier to ID once they have bloomed.

To get baseline biodiversity data for comparisons, it is important to begin the data collection process before the implementation of the GRI. This is most critical for quadrat sampling and RBAs since they will be used as quantitative assessments of biodiversity changes. Once the Rainway is installed, we suggest collecting data every year, for at least 5 years, preferably 10. This yields enough data to reveal statistical differences between the years and indicates if there is a significant increase in biodiversity. We suggest performing one quadrat survey per year, and not per month, since the percent coverage is not likely to change within a month. For RBA, we suggest having the traps out for at least one month, and collect the arthropods regularly to count them, once a day or as appropriate. Having the traps out for one month can alleviate any influence weather may have on the data (Dennis et al, 2005).

Although less critical, engaging the public with citizen science early on would help increase the accuracy of this supplemental data as there are currently only a few observations in iNaturalist that are directly on St. George street (Figure 4). To kickstart community awareness, social media would be beneficial to promote the use of iNaturalist and eBird, as well as adding QR codes linking to the apps to any informative signage that is installed about the Rainway. Flyer handouts with these QR codes and a bird-watching list (Figure B10) is another option to encourage residents of the community to participate and start looking out for current species of their area. After the installation of the Rainway, community events hosted at the Rainway could have a booth introducing people to the apps and the information they provide. This citizen science monitoring is especially advantageous once there is a reliable member base in an area adding to their observations. Therefore, this aspect of the monitoring plan has no end date and can provide data long-term.

3.2.3 Data Analysis

Biodiversity data can be analyzed in a variety of ways, although depending on data collection restrictions, some analysis might not be applicable. Therefore, we will suggest a couple of options which could be useful and the City can decide which ones would be most suitable.

Diversity Index

For both quadrat and RBA data, both species abundance and richness can be easily calculated from the raw data. Abundance is calculated by summing the total number of individuals found, while richness is calculated by summing the number of species. This data can also be used to calculate diversity indices. We suggest using both Shannon's and Simpson's Diversity indices to estimate the biodiversity of the Rainway each year. Both indices give a value to infer population diversity. Shannon's diversity index uses the overall percent distributions. While the quadrat data is recorded as percentages, the RBA data will need to be converted, although this can be done easily by dividing the individual species totals by the overall total. To obtain a complete estimate of the species diversity in the Rainway, the quadrat and arthropod data can be combined to calculate the indexes. The index infers low, medium or high diversity; $H' < 1.5$, $1.5 \leq H' \leq 2.5$, $H' > 2.5$. This index is calculated with Equation 1 below, and example calculations can be found in Figure B11.

$$H' = -\sum_{i=1}^{S} p_i \ln p_i$$

Equation 1. S is the total number of species in the community, and p_i is the percentage of species from the total number of individuals within each ith species.

Simpson's Diversity Index (SDI) can be calculated to provide the percent probability of two randomly selected individuals being different. SDI considers species richness, and evenness, to calculate its percentage. A higher probability infers a more diverse population. This index is calculated with Equation 2 below, and example calculations can be found in Figure B12.

$$D = \frac{N(N-1)}{\sum n(n-1)}$$

Equation 2. D is the diversity index, N is the total population sample size, n is the total number of each individual species.

<u>*Simple Linear Regression*</u>

Once data has been collected for a few consecutive years, a simple linear regression model can be used to determine any trends. For example, a regression line of the index values calculated for several years with a positive slope indicates that the diversity is increasing over time. We suggest performing a simple linear regression (Figure B13) for both Shannon's and Simpson's diversity index. If the data shows a positive trend, we can communicate that the Rainway is successfully improving biodiversity. Linear regression can also be done on the total number of individuals to see how much the Rainway population is growing.

<u>*Significance Testing*</u>

Furthermore, data analysis can determine if the differences between years are statistically significant. We recommend doing a one-way ANOVA and a Tukey HSD test using the raw data collected. Both can be done by focusing on a specific species, and comparing its total count for each subsequent year, or comparing the cumulative number of individuals of all species counted each year. The ANOVA would reveal if there are significant differences between the total counts of each year, while Tukey's test distinguishes which years are statistically different and how they differ. An example is shown in Figure B14. For both tests we suggest using a significance of 95%, if the p-value for a test is less than 0.05 then the variation can be considered significant.

Human Health

Quantifying human health impacts from biodiversity data is currently limited due to a lack of accessibility to health records for small, local areas. However, there are several studies showing biodiversity has both direct and indirect positive human health impacts (Aerts et al., 2018; Kellert, 2009; Sala et al., 2009). Therefore, it can be inferred that increases in biodiversity will lead to overall increased human health through improved air quality, disease prevention, and increased mental well-being (Aerts et al., 2018; Kellert, 2009; Sala et al., 2009).

4.0 Limitations

Although our plan attempts to assess the biodiversity and UHI impacts of the Rainway as accurately and efficiently as possible, no plan is perfect. To measure the UHI effect we suggest the use of temperature sensors; however, the accuracy of these measurements will depend on the placement and precision of the sensors used. Increasing the number of devices used will improve the reliability, however, these devices are not cheap. The City will need to determine the optimal number to purchase that balances data accuracy and cost.

The biodiversity aspect of our plan is similarly constrained by placement and cost. The more RBA traps installed and quadrats sampled along the Rainway, the more accurate the data will be, however collecting the data requires employees or volunteers to manually count species which limits how many traps and quadrats can be used due to financial constraints. Data collection is also subject to error from misidentification or incomplete sampling. Unlike the other monitoring strategies we are proposing, citizen science will be dependent on community engagement. Without interest from the local residents, data collection using citizen science will not be effective.

Additionally, environmental factors can complicate UHI and biodiversity data collection. Factors such as time of day, daily variation of air temperature, weather conditions, seasonality, migration patterns of species, and existing urban infrastructure can result in data uncertainties. It is critical that these uncertainties and potential sources of error are kept in mind when analyzing the data. Although the St George Rainway will have numerous co-benefits, we were not able to include them all in our plan. Several important co-benefits such as water quantity and quality were intentionally omitted while other co-benefits such as human health were included. However, due to the lack of healthcare data at such a small scale, quantifying the direct impacts is difficult.

5.0 Next Steps

We hope our monitoring plan can demonstrate the St. George Rainway's success in providing co-benefits to the community. We are confident that our monitoring plan will accurately measure the changes to the UHI effect and biodiversity within St. George Street. We hope these results can be used to communicate the benefits provided by the Rainway to the public. Moreover, we hope our work can also provide guidance for developing and monitoring future green rainwater infrastructure projects.

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APPENDIX A

Glossary

Absolute temperature A measure of extreme temperatures based on specific temperature ranges.

ANOVA Analysis of Variance, A statistical test for comparing variation between means.

Apparent temperature A heat index based on the combined effect of temperature, wind speed, and humidity. *See* Heat index

Cover of plants A measurement of the area of substrate covered by a perpendicular projection of foliage and stems.

Ecological connectivity A measure of the ability of species and resources to flow between habitats and ecosystems.

Heat index An index that combines air temperature and other climatic variables including humidity and wind speed that represents perceived temperature.

Humidex A heat index based on the combined effect of temperature and humidity. *See* apparent temperature.

Infrared photography Photography which captures the infrared radiation that is emitted by surfaces.

LiDAR Light Detection and Ranging, a remote sensing technique that uses laser scanning to examine the surface of the Earth.

Relative temperature A measure of extreme temperature based on a long-term normal distribution of regional min., mean, or max. temperatures.

Shannon's Diversity Index An information statistic index, which assumes all species are represented in a sample and that they are randomly sampled.

Simpson's Diversity Index A dominance index that gives more weight to common or dominant species.

Species abundance The amount of individuals per species in a given area.

Species richness The number of different species in a given area.

Spectral signature The unique wavelength that each vegetation type transmits.

Transect A continuous line or route along which measurements are taken at regular intervals.

Tukey Test A statistical test for determining significance of relationship between two sets of data.

APPENDIX B

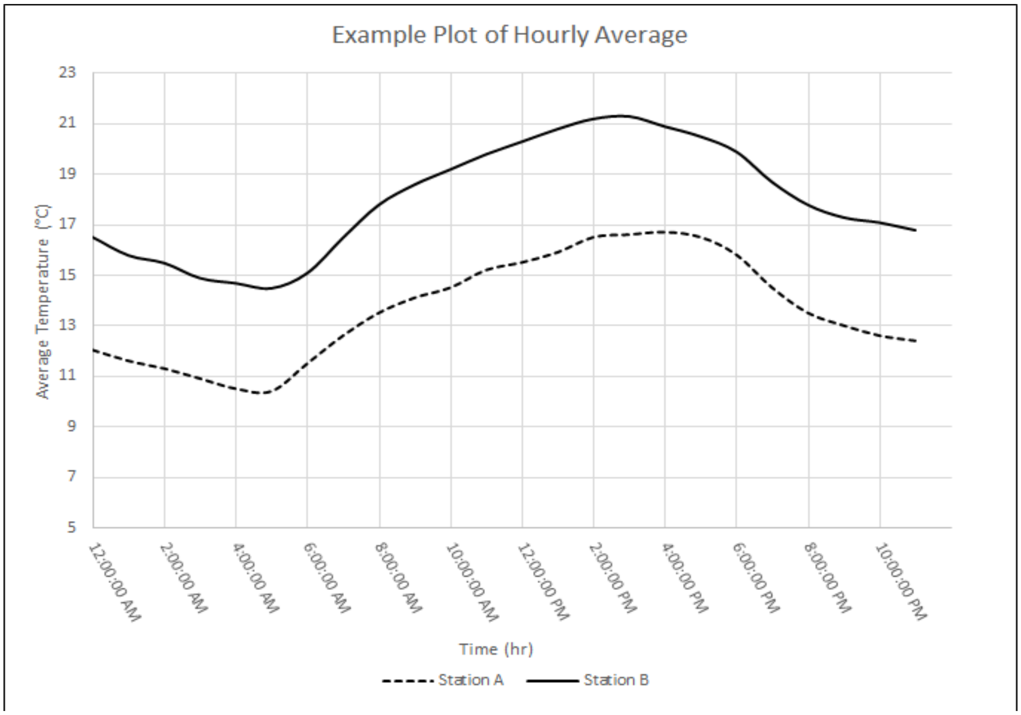


Figure B1. Example plot of the mean hourly temperature averaged over an entire month for two stations. Data from multiple sensors could be plotted as separate lines or as an average from all the Rainway sensors and the benchmark sensors.

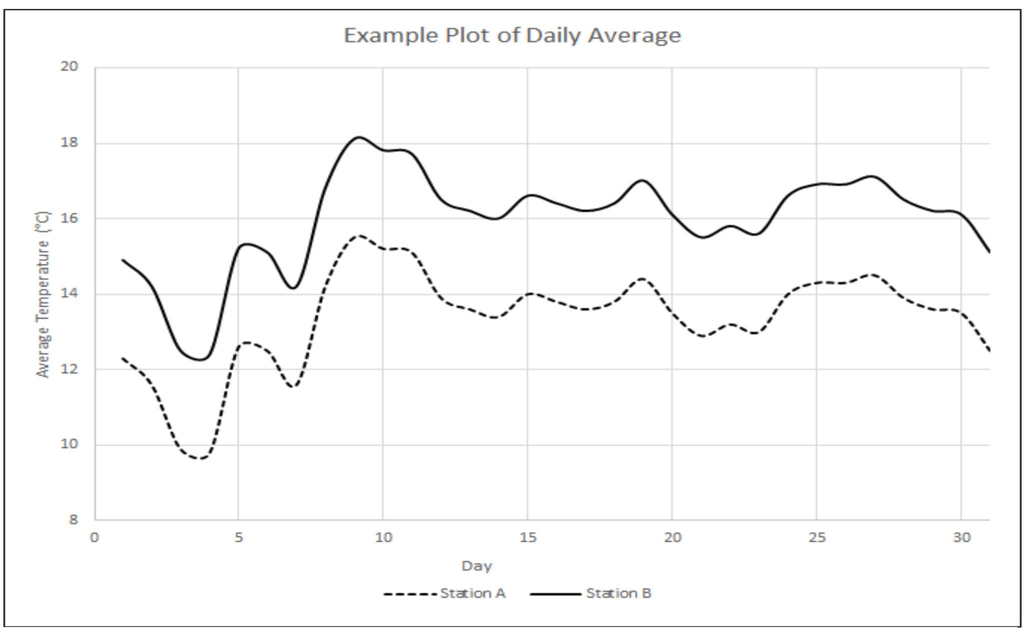


Figure B2. Example plot of the variation in daily mean temperature between two stations over the course of a month. Data from multiple sensors could be plotted as separate lines or as an average from all the Rainway sensors and the benchmark sensors.

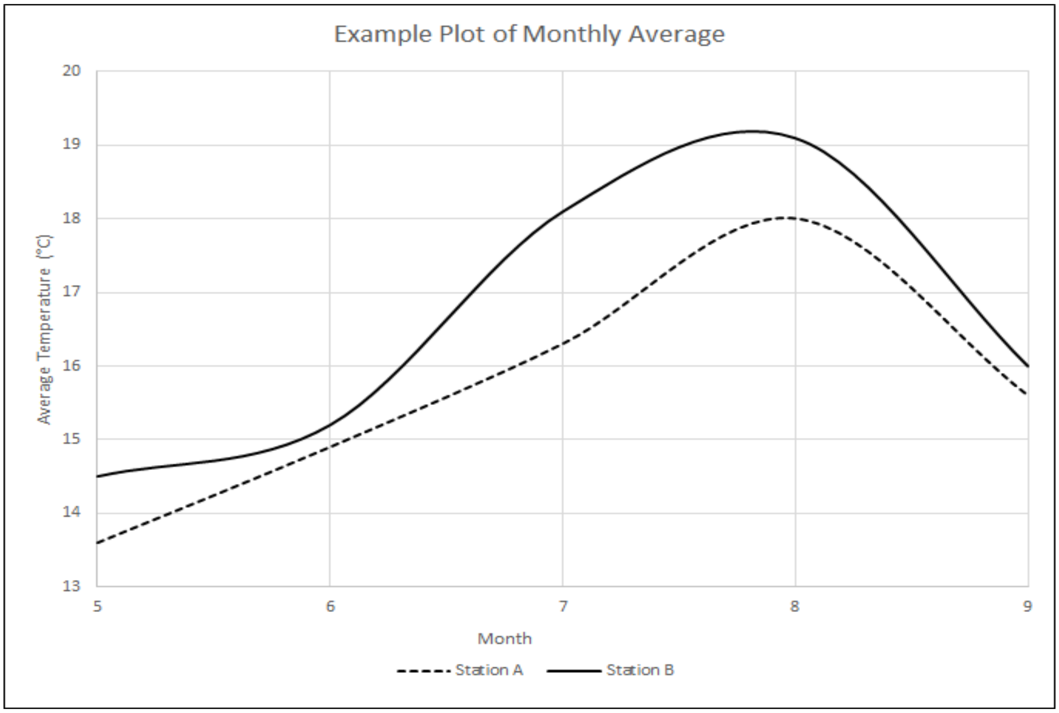


Figure B3. Example plot of mean daily temperature averaged over each month for two stations. Data from multiple sensors could be plotted as separate lines or as an average from all the Rainway sensors and the benchmark sensors.

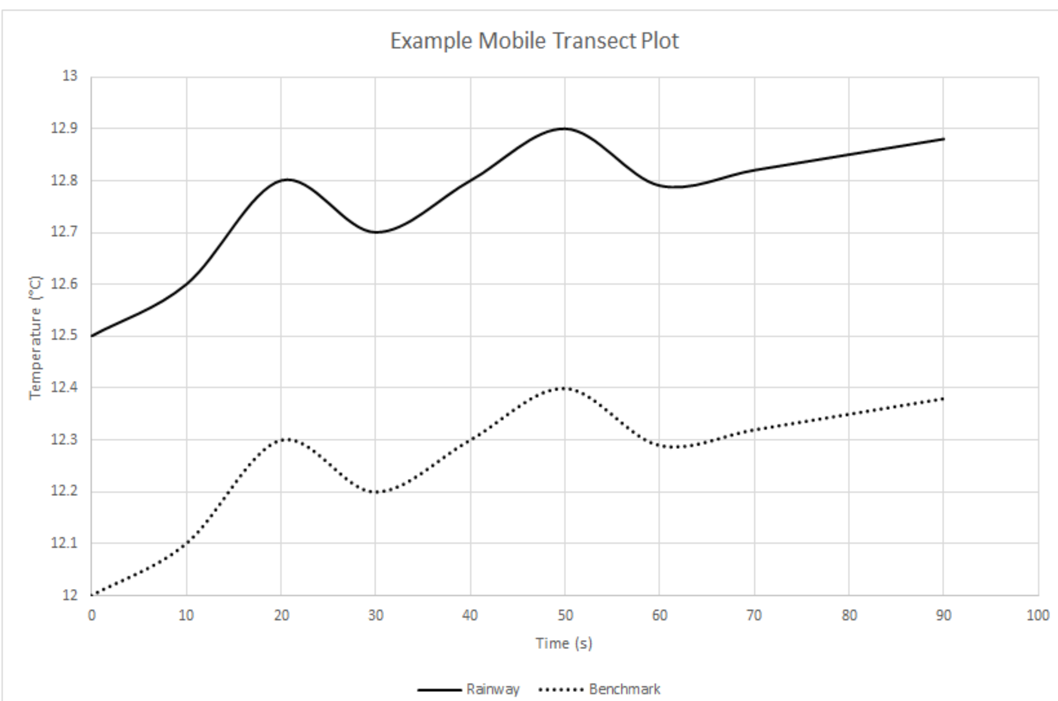


Figure B4. Example plot of temperature variation over the duration of the mobile transects.

```
> summary(anova_2way)
                  Df Sum Sq Mean Sq F value   Pr(>F)    
Location           1 22.894  22.894  282.25 1.06e-09 ***
Distance           2  1.763   0.882   10.87  0.00202 ** 
Location:Distance  2  6.914   3.457   42.62 3.53e-06 ***
Residuals         12  0.973   0.081                     
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> plot(TukeyHSD(anova_2way))
> (TukeyHSD(anova_2way))
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Average_Temp ~ Location + Distance + Location * Distance, data = Temp_avg)

$Location
                       diff       lwr       upr p adj
Rainway-Benchmark -2.255556 -2.548074 -1.963037     0

$Distance
          diff         lwr         upr     p adj
Y-X  0.3833333 -0.05534196  0.82200863 0.0894957
Z-X -0.3833333 -0.82200863  0.05534196 0.0894957
Z-Y -0.7666667 -1.20534196 -0.32799137 0.0014691

$`Location:Distance`
                             diff        lwr        upr     p adj
Rainway:X-Benchmark:X   -1.2333333 -2.0144112 -0.4522555 0.0019913
Benchmark:Y-Benchmark:X  1.7666667  0.9855888  2.5477445 0.0000726
Rainway:Y-Benchmark:X   -2.2333333 -3.0144112 -1.4522555 0.0000065
Benchmark:Z-Benchmark:X -0.2333333 -1.0144112  0.5477445 0.9081167
Rainway:Z-Benchmark:X   -1.7666667 -2.5477445 -0.9855888 0.0000726
Benchmark:Y-Rainway:X    3.0000000  2.2189222  3.7810778 0.0000003
Rainway:Y-Rainway:X     -1.0000000 -1.7810778 -0.2189222 0.0102333
Benchmark:Z-Rainway:X    1.0000000  0.2189222  1.7810778 0.0102333
Rainway:Z-Rainway:X     -0.5333333 -1.3144112  0.2477445 0.2678314
Rainway:Y-Benchmark:Y   -4.0000000 -4.7810778 -3.2189222 0.0000000
Benchmark:Z-Benchmark:Y -2.0000000 -2.7810778 -1.2189222 0.0000206
Rainway:Z-Benchmark:Y   -3.5333333 -4.3144112 -2.7522555 0.0000000
Benchmark:Z-Rainway:Y    2.0000000  1.2189222  2.7810778 0.0000206
Rainway:Z-Rainway:Y      0.4666667 -0.3144112  1.2477445 0.3921400
Rainway:Z-Benchmark:Z   -1.5333333 -2.3144112 -0.7522555 0.0002860
```

Figure B5. Example code for calculating two-way ANOVA and Tukey multiple comparison. Created using Rstudio. In this example we can see the variation in temperatures between the Rainway and Benchmark stations is significant (p-value < 0.05). The variation between distances Y-X and Z-X are not significant, but the variation between stations at Z and at Y are significant. For the interaction effects only three stations are not significant, all three of which are ones with the same location but different distances.

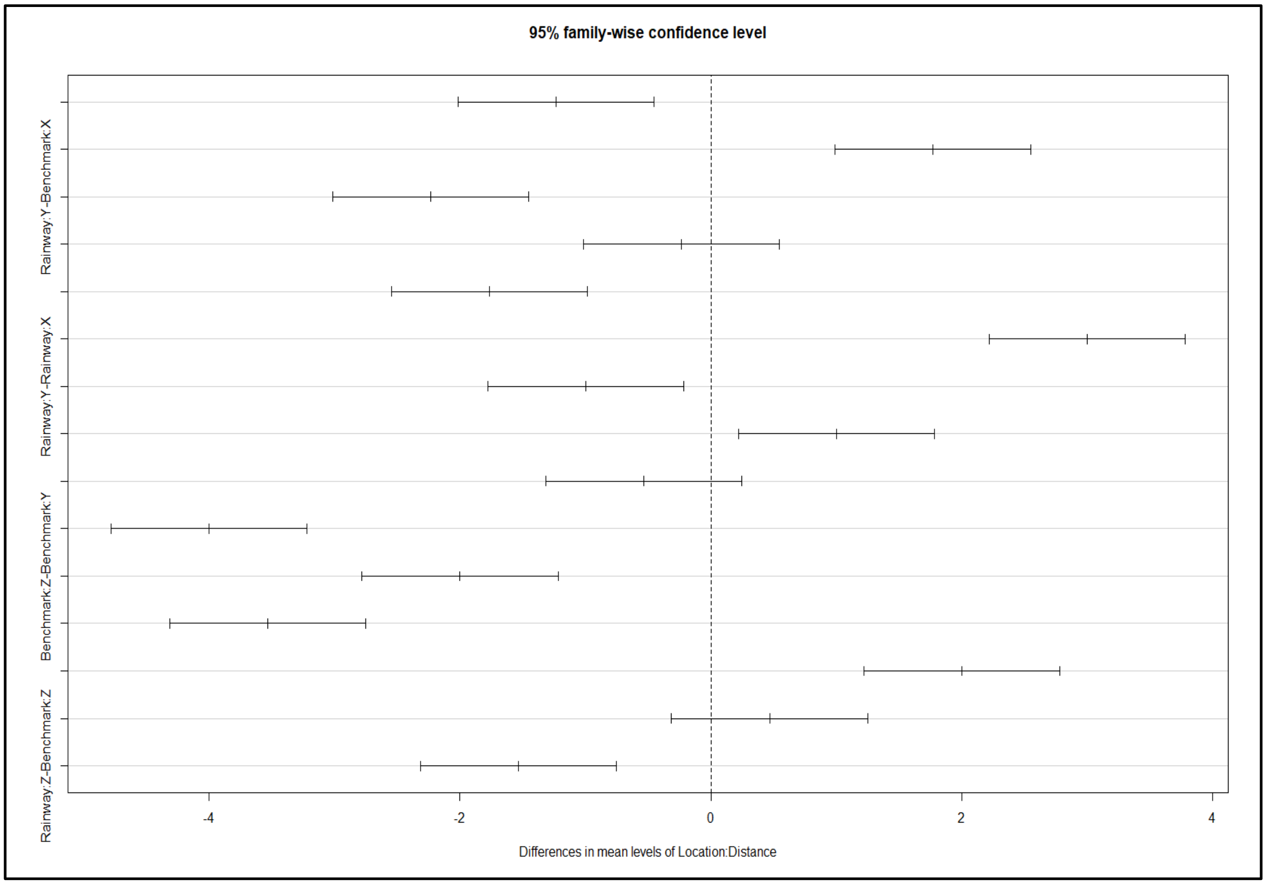


Figure B6. An example plot of a Tukey confidence test. Variations are based on the location relative to the Rainway (Benchmark or Rainway) and based on the position along the streets (X,Y, Z). In this example there is no significant difference between the temperatures recorded on the Rainway, but there is significant variation between the benchmark stations and between the benchmark and Rainway stations.

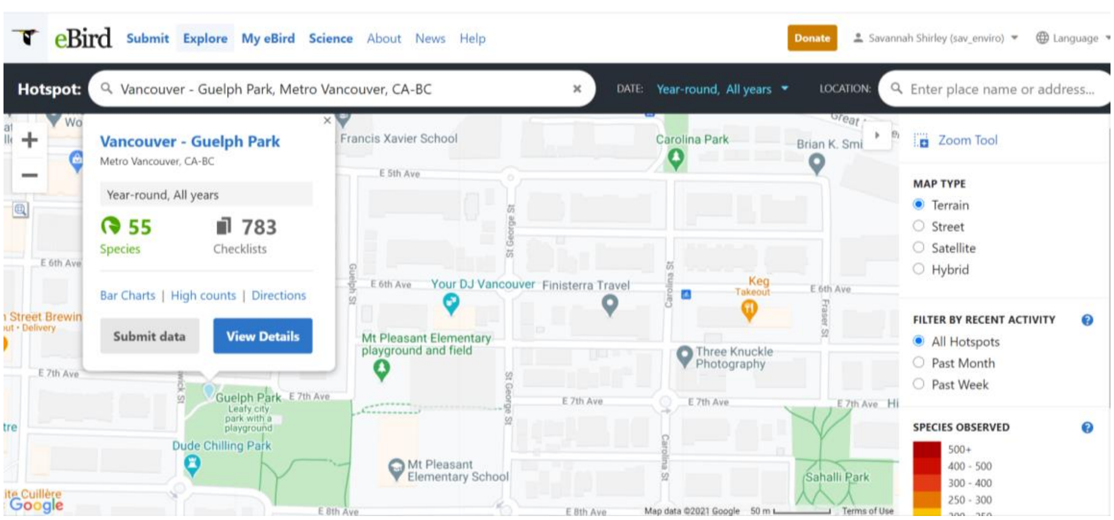


Figure B7. Example of a hotspot in eBird. The Birding checklist for this hotspot can be found in Figure 10.

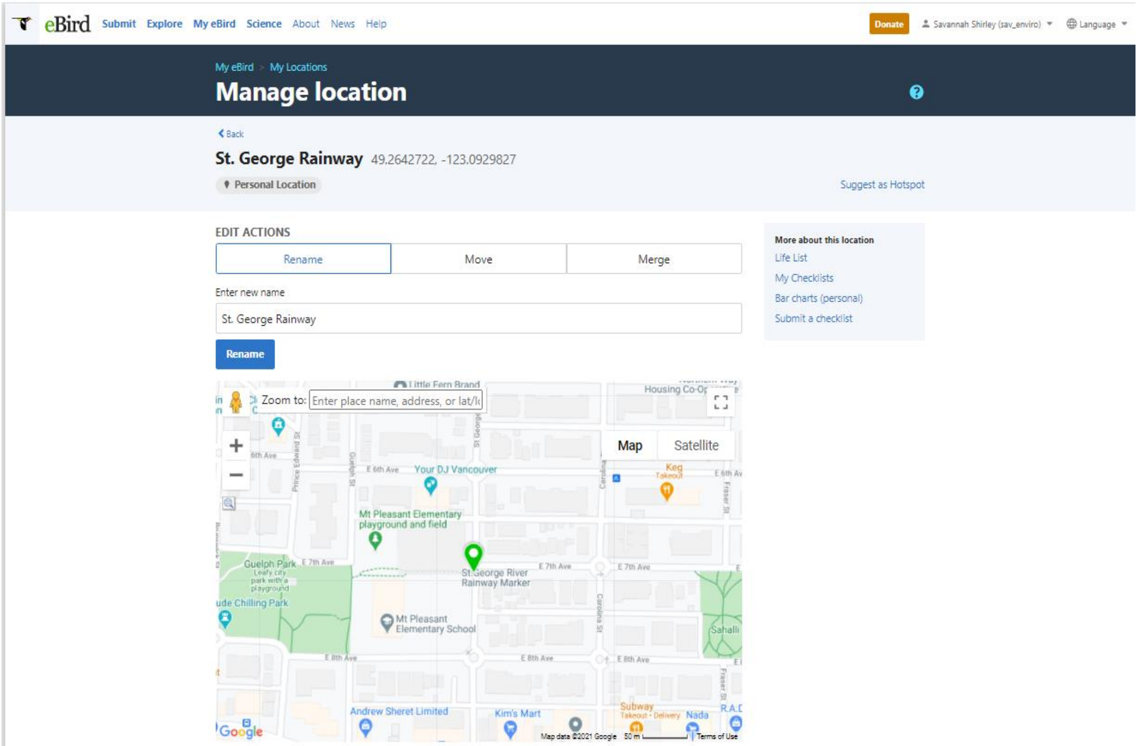


Figure B8. eBird location used for example observation. This location can be suggested as a hotspot in the top right.

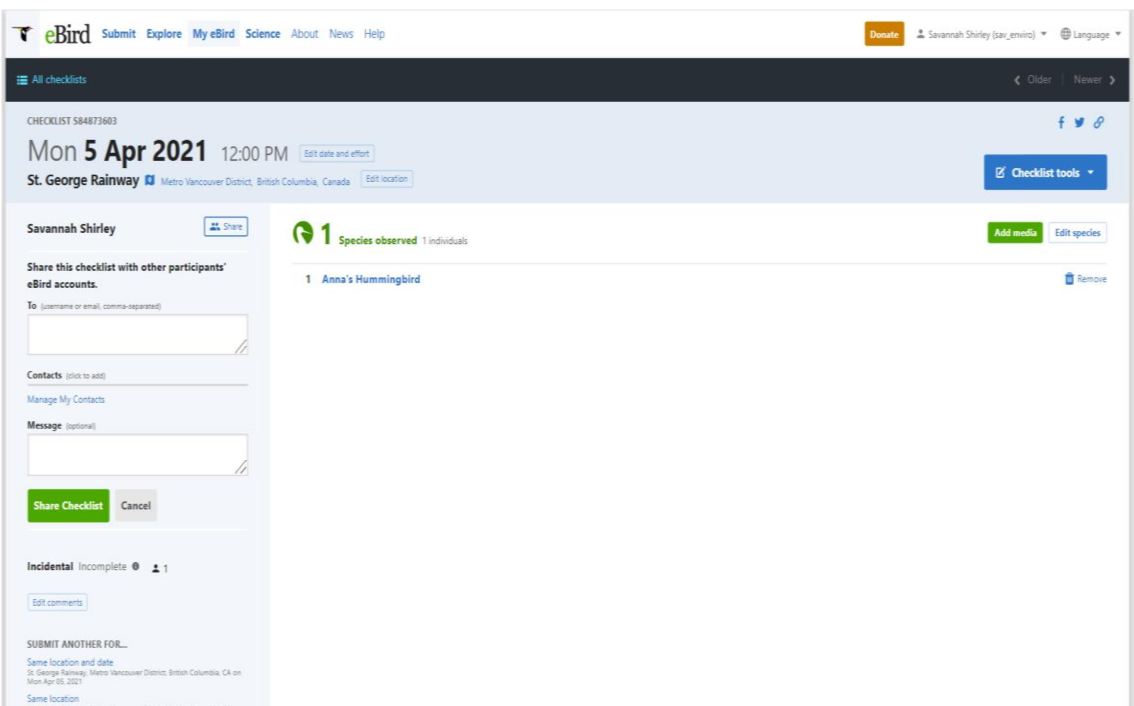
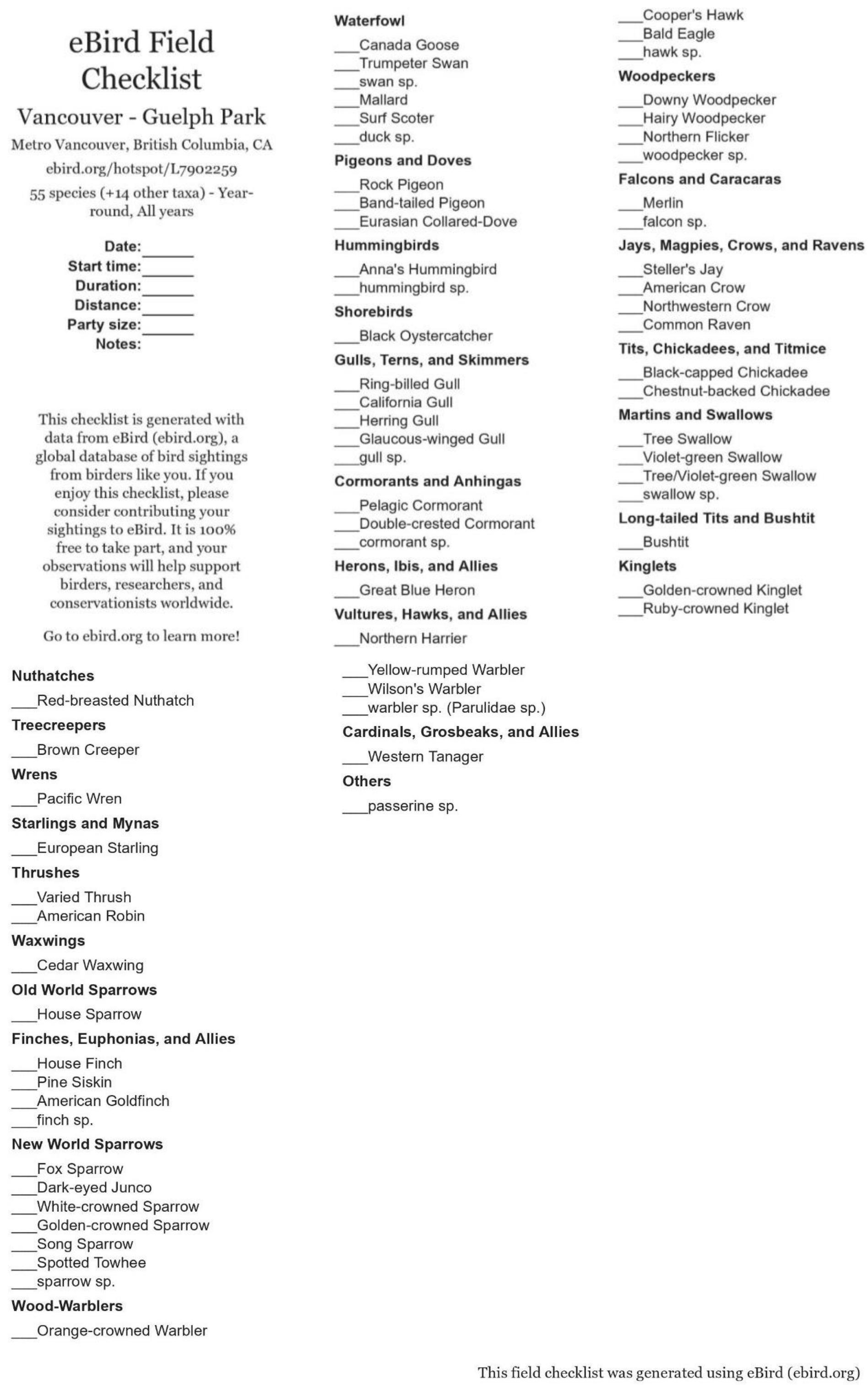


Figure B9. Example of observation added at the "St. George Rainway" location in eBird. This location was suggested as a hotspot and can be shared manually using the share option on the right-hand side of the page.


eBird Field Checklist

Vancouver - Guelph Park

Metro Vancouver, British Columbia, CA

ebird.org/hotspot/L7902259

55 species (+14 other taxa) - Year-round, All years

Date:______
Start time:______
Duration:______
Distance:______
Party size:______
Notes:

This checklist is generated with data from eBird (ebird.org), a global database of bird sightings from birders like you. If you enjoy this checklist, please consider contributing your sightings to eBird. It is 100% free to take part, and your observations will help support birders, researchers, and conservationists worldwide.

Go to ebird.org to learn more!

Waterfowl

___Canada Goose
___Trumpeter Swan
___swan sp.
___Mallard
___Surf Scoter
___duck sp.

Pigeons and Doves

___Rock Pigeon
___Band-tailed Pigeon
___Eurasian Collared-Dove

Hummingbirds

___Anna's Hummingbird
___hummingbird sp.

Shorebirds

___Black Oystercatcher

Gulls, Terns, and Skimmers

___Ring-billed Gull
___California Gull
___Herring Gull
___Glaucous-winged Gull
___gull sp.

Cormorants and Anhingas

___Pelagic Cormorant
___Double-crested Cormorant
___cormorant sp.

Herons, Ibis, and Allies

___Great Blue Heron

Vultures, Hawks, and Allies

___Northern Harrier
___Cooper's Hawk
___Bald Eagle
___hawk sp.

Woodpeckers

___Downy Woodpecker
___Hairy Woodpecker
___Northern Flicker
___woodpecker sp.

Falcons and Caracaras

___Merlin
___falcon sp.

Jays, Magpies, Crows, and Ravens

___Steller's Jay
___American Crow
___Northwestern Crow
___Common Raven

Tits, Chickadees, and Titmice

___Black-capped Chickadee
___Chestnut-backed Chickadee

Martins and Swallows

___Tree Swallow
___Violet-green Swallow
___Tree/Violet-green Swallow
___swallow sp.

Long-tailed Tits and Bushtit

___Bushtit

Kinglets

___Golden-crowned Kinglet
___Ruby-crowned Kinglet

Nuthatches

___Red-breasted Nuthatch

Treecreepers

___Brown Creeper

Wrens

___Pacific Wren

Starlings and Mynas

___European Starling

Thrushes

___Varied Thrush
___American Robin

Waxwings

___Cedar Waxwing

Old World Sparrows

___House Sparrow

Finches, Euphonias, and Allies

___House Finch
___Pine Siskin
___American Goldfinch
___finch sp.

New World Sparrows

___Fox Sparrow
___Dark-eyed Junco
___White-crowned Sparrow
___Golden-crowned Sparrow
___Song Sparrow
___Spotted Towhee
___sparrow sp.

Wood-Warblers

___Orange-crowned Warbler
___Yellow-rumped Warbler
___Wilson's Warbler
___warbler sp. (Parulidae sp.)

Cardinals, Grosbeaks, and Allies

___Western Tanager

Others

___passerine sp.

This field checklist was generated using eBird (ebird.org)

Figure B10. Birding checklist for hotspot adjacent to St. George Street.

Table B1. Morphospecies checklist.

Morphospecies	Body	Wings	Example
Araneae	❑ cephalothorax (fusion of head and thorax) ❑ abdomen ❑ 8 legs ❑ no antennae	0	Spiders
Blattodea	❑ abdomen has 10 segments ❑ similar hind and middle	0 or 4	Cockroaches & Termites
Coleoptera	❑ separate head, thorax and abdomen ❑ hard elytra (forewings) ❑ one pair of legs is anchored in the pro-, meta- and mesothorax	4	Ladybugs & Lightning Bugs
Dermaptera	❑ projecting lower jaw ❑ cerci modified into forceps	0 or 4 First pair short Second pair large	Earwigs
Diptera	❑ head ❑ compound eyes ❑ mesothorax ❑ abdomen ❑ antennae	2	Flies & mosquitoes
Diplopods	❑ long/multiple body segments ❑ two pairs of legs on each body segment		Millipede
Hemiptera	❑ large compound eyes ❑ piercing mouth part ❑ antennae have 4-5 segments ❑ thorax divided into 3 segments each with a leg ❑ abdomen has 9-10 segments	0 or 4	Stink bug
Hymenoptera	❑ constriction between the first two body segments ❑ chewing mandible	4 -forewings larger than hind wings	Bees, Wasps, Ants
Lepidoptera	❑ various wing patterns	4	Butterflies/

	❏ 3 segments: prothorax, mesothorax, and metathorax, connecting to the abdomen. Forewings attach to the mesothorax, hindwings attach to the metathorax. Each thoracic segment has one pair of legs.		Caterpillars & Moths
Odonata	❏ minute antennae ❏ large eyes ❏ long slender abdomen	4 or 2	Dragonflies
Orthoptera	❏ large head ❏ pronotum is saddle shaped ❏ hind legs elongated for jumping ❏ wings held overlapping the abdomen ❏ short antennae (grasshopper) ❏ long antennae (cricket)	0 or 4	Grasshoppers & Crickets
Psocoptera	❏ prominent head ❏ narrow "neck" ❏ wings "tented" over body	0 or 4	Book lice
Thysanoptera	❏ short antennae ❏ head narrows anteriorly ❏ body cylindrical shape ❏ wings are slender, with dense fringe of hairs	0 or 4	Thrips
Trichoptera	❏ resembles moths ❏ wings rest folded along the body ❏ wings with hair	4	Caddisflies

Raw Data	Species A	Species B	Species C
1	5	6	7
2	1	2	3
3	4	5	6
4	3	4	5
5	2	4	6
Species Totals (n)=	15	21	27
Overall Total (N)=	63		

Shannon's Diversity Index				
Species	n	Pi (n/N)	ln(pi)	pi*ln(pi)
A	15	0.238	-1.435	-0.342
B	21	0.333	-1.099	-0.366
C	27	0.429	-0.847	-0.363
Overall Total (N)=	63		Sum=	-1.071
			H= Sum*(-1) =>	**1.071**

Figure B11. Sample calculation of Shannon's Diversity Index performed in EXCEL. The index infers low, medium or high diversity, if "H" is less than 1.5, between 1.5 and 2.5, or greater than 2.5 respectively.

Raw Data	Species A	Species B	Species C
1	5	6	7
2	1	2	3
3	4	5	6
4	3	4	5
5	2	4	6
Species Totals (n)=	15	21	27
Overall Total (N)=	63		

Simpson's Diversity Index					
Species	n	n-1	n*(n-1)	N*(N-1)	**SDI= n*(n-1)/(N*(N-1)**
A	15	14	210	3906	SDI=1332/3906
B	21	20	420		**0.658986175**
C	27	26	702		
Totals=	63		1332		

Figure B12. Sample calculation of Simpson's Diversity Index performed in EXCEL. An SDI of 0.66 infers, a 65% chance that if two individuals were selected at random, they would be different species.

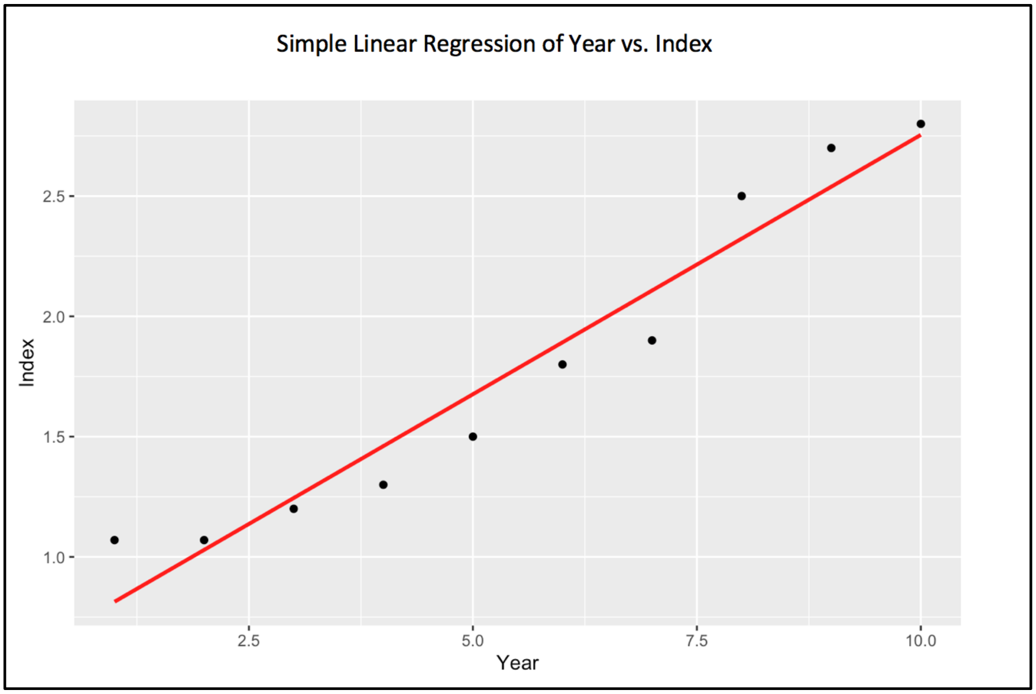


Figure B13. A simple linear regression comparing Shannon's Diversity Index to Year, performed in R. The positive slope indicates a positive relationship between index value and year.

```
Analysis of Variance Table

Response: values
          Df  Sum Sq Mean Sq F value    Pr(>F)
ind        4 1596.94  399.24  107.49 < 2.2e-16 ***
Residuals 95  352.85    3.71
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = values ~ ind, data = SpeciesA)

$ind
             diff        lwr       upr     p adj
year2-year1  0.15 -1.5447791  1.844779 0.9991757
year3-year1  0.95 -0.7447791  2.644779 0.5273318
year4-year1  2.80  1.1052209  4.494779 0.0001280
year5-year1 10.65  8.9552209 12.344779 0.0000000
year3-year2  0.80 -0.8947791  2.494779 0.6840499
year4-year2  2.65  0.9552209  4.344779 0.0003271
year5-year2 10.50  8.8052209 12.194779 0.0000000
year4-year3  1.85  0.1552209  3.544779 0.0251746
year5-year3  9.70  8.0052209 11.394779 0.0000000
year5-year4  7.85  6.1552209  9.544779 0.0000000
```

Figure B14. Example calculations of ANOVA and Tukey's HSD. The ANOVA p-value is less than 0.05, this suggests there is a significant difference between the two variables being tested. For Tukey's HSD any p adj value that is less than 0.05 indicates that the two years specified are significantly different.