Exploring Species Distribution Modelling as a Tool to Support Knowledge of Country Food Access & Availability:
Vaccinium vitis-idaea **in the Gwich'in Settlement Area**

By
Karl Hare
BSc University of Victoria, 2023

A Thesis Submitted in Partial Fulfillment of the
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We acknowledge and respect the Ləkʼʷəŋən (Songhees and Xʷsepsəm/ Esquimalt) Peoples on whose territory the university stands, and the Ləkʼʷəŋən and W̱SÁNEĆ Peoples whose historical relationships with the land continue to this day.

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Abstract

In the Canadian North berries are essential, being used extensively as a food source, for medicines, and for dyes. In the Gwich'in Settlement Area alone, it is estimated that more than 5,000 liters of berries are harvested per year. Unfortunately, climate change poses a serious threat to berry harvests and has led to a noticeable decline in the condition and yield of harvestable berries throughout Northern Canada. Berries have been a staple food source for generations of northern residents and are equally important to northern animals, particularly birds, small mammals, bears, pollinators and caribou. This work follows my collaboration with the Gwich'in Tribal Council to work towards creating a species distribution model of *Vaccinium vitis-idaea* (mountain cranberry) with Indigenous Knowledge in the forms of participatory mapping data and quotes from interviews. During this process, I explored two separate methodological frameworks in species distribution modeling, both of which include Indigenous Knowledge in different ways. The first is a presence-only model, where harvest locations are assumed to correspond to the presence of a high abundance of berries. The second is a random forest approach which uses field data to generate an abundance model of predicted harvestable yield of mountain cranberry fruit, validated with the help of Indigenous Knowledge. This work aims to showcase methodological frameworks that could help Indigenous Governments and ecologists investigate biology throughout their land. The results of this research highlight that species distribution modeling must be navigated with caution and context, especially when applied to Indigenous Knowledge systems, as this methodology has the potential to lead to misrepresentations of this knowledge. Additionally, this research suggests that abundance predictions from random forest modeling, especially when validated with Indigenous Knowledge, offer a promising path forward for improving access to country foods.

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I would like to firstly thank my supervisor, Noémie, for the incredible opportunity to be able to work in your lab. You took a chance on me, and I will be forever thankful you did. Through your guidance, I have been able to learn so much about what it means to do good work. The perspective you bring to your research will forever inspire me to look at the world in a different way. You are an incredible leader, and I am thankful that I found a supervisor I can call my friend.

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1. Introduction

Statement of Positionality

This research was conducted in partnership with the Gwich'in Tribal Council (GTC), in full accordance with their Gwich'in Traditional Knowledge Policy (Gwich'in Tribal Council, 2004). The GTC is an Indigenous organization that represents Gwich'in Participants in the Mackenzie Delta of the Northwest Territories (NWT) and across Canada. One of the main objectives of the GTC is to "retain, preserve, and enhance the traditional and cultural values, customs, and language of the Gwich'in in a changing society" this study was developed to meet that mandate. A data release agreement, drafted by the GTC, also guided this research. Together, the GTC's Traditional Knowledge Policy and this research agreement provided the study's author with provisions to ensure the proper use of knowledge that was graciously shared with the *Indigenous Knowledge of Berries in the Northwest Territories* project. During this study, a total of 40 Gwich'in berry harvesters participated, offering to share the areas they frequently harvest. The author of this thesis, Karl Hare (University of Victoria), is not Indigenous.

Defining Indigenous Knowledge and Gwich'in Traditional Knowledge

Globally, there are many different definitions of the term "Indigenous Knowledge" (IK), none of which are universal. One definition describes IK as "interconnected and systematic knowledge about abiotic and biotic systems and the relationships of those systems with cultural and spiritual aspects of life" (Daniel, 2019). In this thesis, the term IK is used to refer broadly to the inclusion of IK in the context of species distribution modelling (SDM). Specifically, the IK that this thesis engages with is Gwich'in Traditional Knowledge. This is defined by the Gwich'in Tribal Council (GTC) as a "…body of knowledge, values, beliefs, and practices passed from one generation to another by oral means or through learned experience, observation, and spiritual teachings, and pertains to the identity, culture, and heritage of the Gwich'in. This body of knowledge reflects many millennia of living on the land. It is a system of classification, a set of empirical observations about the local environment, and a system of self-management that governs the use of resources and defines the relationship of living beings with one another and with their environment" (Gwich'in Tribal Council, 2004).

Introduction

On a global scale there has been a call to action to better recognize IK in ecological decision-making (Artelle et al., 2018). Much of this prioritization stems from an effort to dismantle colonial power structures as well as from respect for the nuances that IK can bring to understanding ecological systems (Eckert et al., 2020). The breadth of complexity, detail, and regional context that IK offers to management solutions is frequently overlooked when management officials choose to solely implement Western scientific methods (Campbell et al., 2022). Neglect of Indigenous Knowledge Systems in decision making can often result in outcomes that lack a complete understanding of the environments they aim to manage (Raymond-Yakoubian & Daniel, 2018). Further, this neglect leads to management solutions that are inherently Western and inadequate for the communities they aim to serve, inevitably leading to disappointing results (O'Faircheallaigh et al., 2017).

Indigenous scholars have emphasized that "when the rights and responsibilities of Indigenous peoples are recognized and supported, the entire planet will benefit" (Nitah, 2021). Indigenous lands are vast and provide sanctuaries for both humans and biodiversity (Nitah, 2021). Indigenous Knowledge can offer in-depth, generational understandings of these lands and has provided significant environmental and socio-cultural benefits (Campbell et al., 2022). Given the significance of these lands and the expertise of many Indigenous communities, advancing mixed-methods through a critical physical geography perspective presents one way to support ecological sustainability. These methods can be used to protect land that is crucial to safeguard during periods of extreme biodiversity loss (Campbell et al., 2022) and provide Indigenous groups with greater autonomy over the decisions made regarding their land (Baumflek et al., 2015).

As scientists and environmental planners aim to reevaluate methods which center IK in problem-solving, a necessary process that needs reevaluation is the use of species distribution modeling (SDM). In Canada, environmental modelling is a popular method for assessing critical habitat (Lefebvre et al., 2018). This type of model acts to relate "...species distribution data (occurrence or abundance at known locations) with information on the environmental and/or spatial characteristics of those locations" this can then be used to "provide understanding and/or to predict the species' distribution across a landscape" (Elith & Leathwick, 2009).

Over the past two decades, there has been a surge of interest in the ability to model and predict species distribution. This focus is the result of two significant developments in the 21st century: (1) technological advancements in Geographic Information Systems (GIS), which have provided the opportunity to analyze and model high-resolution ecological datasets, and (2) an unprecedented loss of biodiversity which has highlighted the need for biological forecasting to help in conservation efforts (Guisan et al., 2017). These two shifts have forever changed the field of spatial ecology, which is a field defined by research which "aims to understand the processes that affect species distributions and dynamics and how these processes play out across space" (Fletcher & Fortin, 2018).

Real-world circumstances, such as migration, species coexistence, deforestation, and the spread of invasive species, are inherently spatial (Tilman & Kareiva, 1997; Fletcher & Fortin, 2018). As such, models that use biological theories and consider them within a spatial context are in high demand (Kareiva, 1994). Currently, SDMs are the most widely used tools by biologists to predict species abundance across landscapes (Mateo et al., 2011). Historically, SDMs have been created using information from tracking collars, camera traps, and historic data (Misiune et al., 2022), in unison with environmental layers such as global climatic variables (Morales-Barbero & Vega-Álvarez, 2018). In addition to model inputs, there are many different types of distribution modeling techniques commonly used by ecologists, some of which include envelope models, generalized linear and additive models, regression trees and forests, and MaxEnt (Fletcher & Fortin, 2018). These models can be effective in providing ecological insight and spatial predictions, however, when they are limited by either environmental spatial data or observation data results become more uncertain (Elith & Leathwick, 2009).

One way that scientists have been reimagining species distribution modelling is by introducing IK into SDM methodology. A common way this has been done is by utilizing participatory mapping to identify the presence of certain species (Campbell et al., 2022). In a practical sense, this can act as a mechanism which helps Indigenous communities regain sovereignty over their land (Baumflek et al., 2015). Furthermore, when done well, this process can act to fill knowledge gaps, increase trust in science and management, recognize the validity of diverse knowledge in western science, advocate for rare or under-studied species, and identify areas of consensus and disagreement (Stern & Humphries, 2022). Despite the benefits of IK inclusion, some of this work has been criticized for the way in which it includes IK, as the means of inclusion can often seem supplementary as opposed to core of the process (Bélisle et al., 2018; Campbell et al., 2022). As such, exploring methods that centralize IK in context, as opposed to supplementing Western research, should be the ultimate goal of research in this mixed-methods field (Drawson et al., 2017). Some research, for example Gryba et al. (2025), has contributed to this approach; however, the continued development of IK centralized methods remains an area in needs further contribution.

In this text, I discuss my involvement with the Indigenous Knowledge of Berries in the Northwest Territories Project, which conducted interviews with 125 knowledge holders across 15 communities in the NWT. As part of this project, I had the opportunity to focus my analysis and collaborate with the GTC and knowledge holders in the Gwich'in Settlement Area (GSA). The qualitative findings from that work will be highlighted in detail in Singer et al., submitted, while this thesis predominantly used the spatial data from the interviews.

Interviews in the GSA were conducted in June and July of 2023 with all necessary permits. Knowledge holders were identified by local members of the Indigenous Knowledge of Berries in the Northwest Territories advisory committee (composed of ten Indigenous knowledge holders from across the NWT, including two knowledge holders from the GSA) as well as community organizations; all participants were residents of the GSA who had been picking berries since they were children. A total of 40 interviews were conducted in English and Gwich'in with 11, 9, 11 and 9 interview sessions in Aklavik, Inuvik, Fort McPherson and Tsiigehtchic, respectively. Knowledge holders interviewed were all adults and most typically Elders, although several younger adults were also interviewed. Most individuals interviewed were women, although several men also participated (35 women and five men).

Over two years, I worked to create an SDM analysis for *Vaccinium vitis-idaea* (mountain cranberry), a cultural keystone species that holds significant value to the Gwich'in people (Andre & Fehr, 2001). I utilized IK from interviews and maps that I was permitted to use by the GTC, along with open-source GIS data, to create this analysis.

This research holds significance to the Gwich’in Tribl Council (GTC) as they were interested in assessing the viability of incorporating participatory mapped harvest sites in an SDM process. This research also will contribute to the literature by highlighting various concepts in the field of IK inclusion in SDM. Specifically, this research will address two key questions: 1) What are some best practices to participatory mapping that can make SDM a more viable solution for Indigenous groups seeking greater representation of cultural keystone species in the decision-making process? 2) In what ways can classic techniques in SDM, which do not include IK, carry blind spots that may overlook Indigenous narratives?

Through this thesis, I examine two alternative and contrasting methodologies for conducting SDM using IK. The second chapter's conventional approach uses harvest locations as presence points in a MaxEnt model, and the resulting model was validated through a field survey. Chapter 3 employs a reversed methodology, where I create an abundance model using field-collected data and a random forest model, which was then validated through knowledge shared during interviews with knowledge holders. By conducting this research, I aim to highlight both the strengths and limitations of some current methods of fusing IK into environmental modeling. This work aims to support advances in this new field of study and provide insights that will help create more inclusive and structured methodologies for Indigenous communities seeking to pursue SDM and related ecological research.

I recognize that the use of IK in research can carry risks of harm, particularly when conducted without care. As such, this research was carried out in full partnership with the GTC, with all ethical considerations rigorously followed. Every step was made intentionally and in assurance that the process upheld principles of respect, relevance, reciprocity, responsibility and relationship building. I hope that this work can serve as a constructive example where future scientists can utilize elements of this study design in their community mapping and modeling efforts, thereby increasing Indigenous autonomy and the meaningful inclusion of diverse knowledge systems in environmental research, a field where such knowledge has often been overlooked.

2. Fusing Indigenous Knowledge with Species Distribution Modelling in the Gwich'in Settlement Area

2.1 Introduction

In Gwich'in, Natł'at is the word for Vaccinium vitis-idaea (Mountain cranberry) (Andre & Fehr, 2001). This berry is recognized throughout the circumpolar Arctic for its traditional value (Hjalmarsson & Ortiz, 2001; Fediuk et al. 2002; Andre & Fehr, 2001; Boulanger-Lapointe et al., 2019; Andre & Fehr, 2001). In the Northwest Territories (NWT), the Gwich'in use mountain cranberry for food, medicine, and dyes, making the fruit an important part of local culture (Parlee et al., 2005; Andre & Fehr, 2001; Singer et al., submitted). The leaves and stems are commonly brewed into tea, while the fruits are eaten in jams, pies, muffins, and it'suh, a traditional dessert made from pounded dried fish (Andre & Fehr, 2001). Knowledge holders mentioned that cranberry is also important to small mammals, large mammals and birds, which contribute to Gwich'in tradition (Singer et al., submitted). In Fort McPherson, it was estimated that approximately 10 % of community members harvest berries, yielding an estimated total of 5,000 liters in the year 2003 (Parlee et al., 2005). For many Gwich'in people, cranberries are significant to well-being, specifically contributing as a food source that often lasts throughout the winter (Parlee et al., 2005; Singer et al., submitted).

There are several barriers that currently prevent people living in the Gwich'in Settlement Area (GSA) from continuing to participate in berry harvest, including changes in cost, safety, access, competing economic demands, and land related knowledge lost in generational shifts (Singer et al., submitted). These challenges are compounded by the growing impact of climate change, which many knowledge holders and researchers identify as a significant factor that makes berry harvest in northern Canada more difficult (Downing & Cuerrier, 2011). Increasing temperatures are projected to continue to influence the seasonality and location of berry patches (Hirabayashi et al., 2022; Souliere et al., 2020) and have been observed to influence the size, quality, and harvestable yield of the berries themselves (Singer & Lee, 2021; Mucioki, 2024). Furthermore, the accessibility of this important resource is likely to continue to deteriorate with unpredictable fruiting times (Mucioki, 2024) and other climate related factors such as increases in wildfire smoke (Dodd et al., 2018; Singer et al., submitted), the drying of rivers that Gwich'in people use to access their harvesting sites (Singer et al., submitted), and increases in shrub cover making it increasingly difficult to move across the land (Tremblay et al. 2012; Myers-Smith et al. 2015).

While studies have projected the potential range shift of mountain cranberry across parts of North America (Hirabayashi et al., 2022; Hamilton et al., 2024; Seider et al., 2022), current literature suggests that there is a wide range of environmental issues causing the decline of harvestable berries in the Canadian North (Mucioki, 2024). These climatic and environmental variables have a poorly understood correlation to plant productivity with fruit abundance varying greatly across geographic locations (Boulanger-Lapointe, 2020; Tirmenstein, 1991). The cumulative impact of multiple different changing environmental and human factors makes creating mitigation solutions difficult, highlighting the need for detailed and localized solutions. Including IK in Geographic Information Systems (GIS) analysis is one such way that mapping solutions can become community specific (Campbell et al., 2022). This type of collaboration can produce geo-spatial tools and analysis that are directly relevant to the local landscapes, micro-climates, and resources of northern communities.

A classic option for tracking and predicting changes in species range is through the employment of species distribution modeling (SDM). These models analyze an organism's known presence and relate distribution data to environmental layers, from which mapped inferences about suitable habitat and species occurrence can be generated (Mateo et al., 2011). These models are often paired with projections (ex. Climate change simulations 2020-2100) of what a future environment may look like, making them extremely powerful environmental information for management. SDMs which include IK, presents a unique methodology that differs in many ways from species models based on large-scale citizen science or discrete tracking data. This methodology focuses on the co-creation of SDMs alongside knowledge holders who are familiar with their local environment, addressing resources important to Indigenous communities. By linking IK with participatory mapping, information from interview sessions can be extrapolated to solve land use planning and ecological issues (Baumflek et al., 2015; Campbell et al., 2022; Gryba et al., 2025). When implemented properly, IK and SDM composites can empower Indigenous communities to assert sovereignty over their land, helping protect or increase access to species that are underrepresented in Western Science (Baumflek et al., 2015; Campbell et al., 2022).

The co-learning process exhibited in many collaborative partnerships between Indigenous groups and researchers can allow for parties involved to come to a holistic picture of very complex ecological systems (Reid et al., 2020). Using research paradigms that promote Indigenous voices can deepen the understanding of physiology, applied ecology, evolution and ecology. When commonalities are found, they can be the starting point of shared understandings and mutually beneficial collaborations (Jessen et al., 2022). These collaborations have been beneficial for creating historical ecological datasets, conserving exceedingly rare species, distinguishing among similar but distinct evolutionary taxonomic groups, and quantifying species morphology change (Lee et al., 2019; Wehi et al., 2009; Santos & Antonini, 2008; Eckert et al., 2018; Jessen et al., 2022). These examples involve long-term observations that have contributed to enhanced monitoring of species and ecosystems health (Jessen et al., 2022). Although there is growing literature on best practice approaches to cross-cultural knowledge sharing (Drawson et al., 2017), there are few case studies that center IK in the discipline of species distribution modelling (Campbell et al., 2022; Ogar et al., 2020; Sterling et al., 2017).

In the past, projects have used IK in their SDMs to fill gaps that were unachievable utilizing other methods (Campbell et al., 2022). This means that the use of IK was additional as opposed to central (Campbell et al., 2022; Bélisle et al., 2018). When studies neglect the socio-cultural context of the information they are utilizing, it perpetuates neocolonial values that are extractive in nature (Drawson et al., 2017; Campbell et al., 2022). Therefore, when conducting this type of analysis, it is very important to understand the power dynamic that is generated when mapping. To support indigenous voices, SDM creation that utilizes IK needs to be iterative and engaging, aiming to create analyses that respond to community identified issues (Baumflek et al., 2015).

It is important to be critical of new methods in analysis to ensure that the products they generate are accurate and contextual. By including IK in modeling efforts, this study simultaneously explored best practices in fusing SDM processes with IK while learning more about berries in tundra and taiga. Although berries are cultural and ecological staples, there is a lot that is still unclear regarding their habitat preference. Further, the studies that have assessed mountain cranberry species distribution have been dependent on historic archive information (Hirabayashi et al., 2022) and observations from government agencies (Hamilton et al., 2024), neglecting the value that IK can bring to this question. Although these studies have proven useful, observations are limited in northern Canada. Increased observation data is essential to improve the accuracy of an SDMs (Hernandez et al., 2006). By attempting to create a distribution model with an increased number of observations in this region, at a unique scale, with region specific environmental intel this study aimed to create a GIS tool valuable to the Gwich'in people.

The results from interviews suggested that berry harvest is becoming increasingly inaccessible in the GSA. Considering this, the GTC was interested in exploring methods that predict suitable habitat for mountain cranberry. Inspired by methodologies that fuse IK and SDM, this chapter focuses on berry harvest locations, from community mapping sessions, and their employment in a MaxEnt model. Importantly, the mapped points were not simply presence locations, but they represented high quality harvest sites that were identified as being used year after year. It was hypothesized that these points could act as a reliable proxy for ecosystems where mountain cranberry fruit is highly abundant. Using the harvest location data, this chapter aimed to predict relative index of occurrence (RIO) of mountain cranberry within the GSA to produce a continuous map predicting areas with high fruit availability. The GTC believed that this would be of significant value, having expressed a desire for GIS tools relating to berry harvest. Such a tool could guide local mitigation and management strategies to improve harvest access and strengthen Gwich'in autonomy, particularly by recognizing culturally significant spaces and anticipating how future developments may affect them.

2.2 Materials & Methods

Study Area

Over thousands of years, the Gwich'in people living in the Northwest Territories have become highly skilled at utilizing the biological resources provided by the ecosystems around them for food, medicine, and tools (Andre & Fehr, 2001). The Gwich'in Settlement Area (GSA) is located in the northwest corner of the NWT. Covering approximately 59,000 km² of area, this space is home to 4 major Gwich'in communities including Inuvik, Aklavik, Fort McPherson, and

Tsiigehtchic (Kritsch & Andre, 1997; Smith, 2005). Together, these communities support a total population of approximately 4,500 residents (Statistics Canada, 2021). While the GSA is formally Gwich'in territory, other Indigenous peoples who are not Gwich'in share parts of this space (Government of Northwest Territories, n.d.).

This large area also boasts incredible biodiversity, being home to 3 different Level II ecoregions: the taiga cordillera, located to the south, the taiga plains, in the center, north, and east, and the tundra cordillera located in the west (Figure 1) (Ecosystem Classification Group, 2007; Ecosystem Classification Group, 2010). Of the land within the boundaries of the GSA, approximately 40 % is Gwich'in private land, while the rest consists of public land where the Gwich'in have land use rights (GTC, 2020).

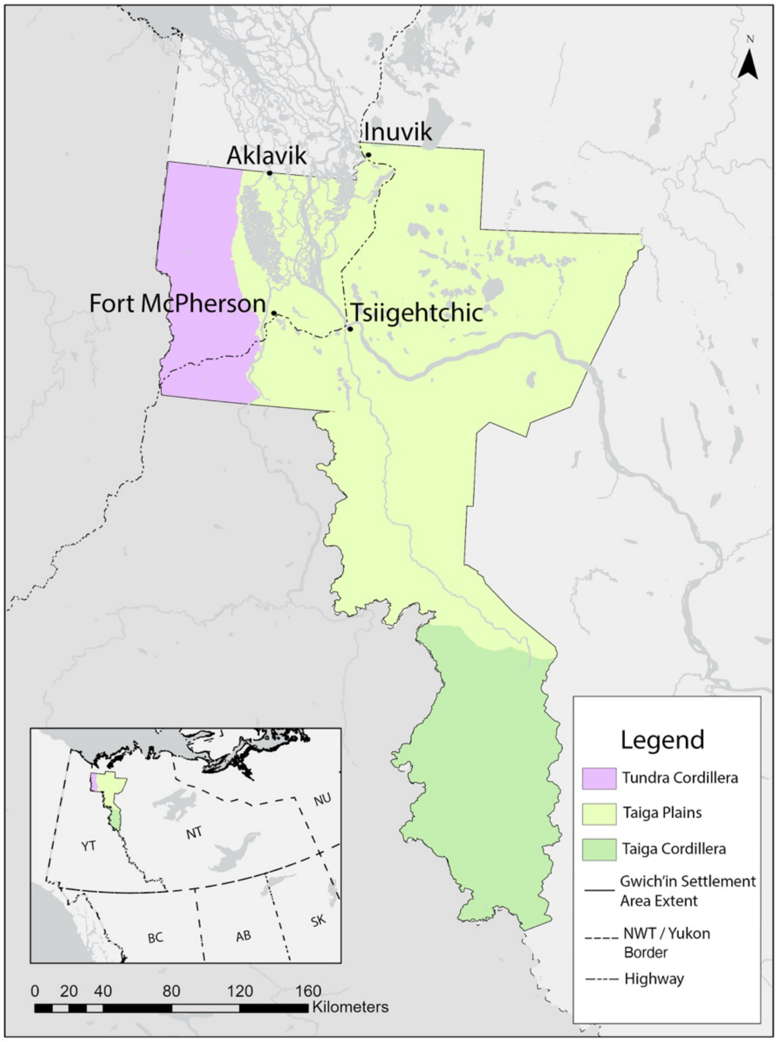

Figure 1. Communities in the Gwich'in Settlement Area (GSA) and level II ecoregions within the area

The taiga plains are home to all four major NWT Gwich'in communities (Figure 1). In this ecoregion, the predominant vegetation is stands of black and white spruce (Andre & Fehr, 2001; Ecological Stratification Working Group, 1996). These trees are mostly stunted because the soil in the area is frozen for much of the year, shortening the duration of the growing season (Ecosystem Classification Group, 2007). Understory vegetation in these stands typically consists of willows, lichens, dwarf birch, northern labrador tea, and arctic bearberry (Andre & Fehr, 2001; Ecosystem Classification Group, 2007). Poorly drained sites generally consist of tussocks of sedge, cottongrass, and sphagnum moss (Ecological Stratification Working Group, 1996). The taiga plains are also home to the Mackenzie River Basin, which is the largest river basin in Canada (Canada Water Agency, 2025). This basin includes large rivers, such as the Nagwichoonjik (Mackenzie), Teetł’it Gwinjik (Peel), and Tsiigehnjik (Arctic Red) (Proverbs et al., 2020). These bodies of water, along with their accompanying lakes and channels, are used by Gwich’in people to access their lands, fostering mobility that is incredibly important to individual and community well-being (Proverbs et al., 2020).

West of Fort McPherson and Aklavik, is a tundra cordillera ecoregion which differentiates from the taiga plains in both its ecology and geomorphology. This area is largely considered arctic-alpine tundra, and its ecological communities are mainly composed of dwarf birch, willow and arctic bearberry (Andre & Fehr, 2001; Ecosystem Classification Group, 2020). In this ecoregion lower elevations, there is a transition zone between tundra and taiga environments. Here, open sedge-cotton grass meadows and spruce forest stands intermix (Andre & Fehr, 2001; Ecosystem Classification Group, 2020; Ecological Stratification Working Group, 1996). Other species that are predominant in the region are cranberry, blueberry, blackberry, along with various lichens (Andre & Fehr, 2001).

In this text, I refer to the terms habitat, ecosystem, and ecoregion. I use “ecoregions” to describe delineated areas that are classified into different types of ecological space. I use “ecosystems” when referring to ecological interactions and energy flows. I use “habitats” to describe the preferred areas where a species can fulfill its realized niche.

Study Species

Although there are a variety of berries that grow throughout the GSA, mountain cranberry (Figure 2) is recognized as one of the most important species for harvest (Singer et al., submitted; Parlee, 2005; Andre & Fehr, 2001). Mountain cranberry belongs to the Ericaceae family and is a low-growing, evergreen shrub with creeping stems (Tirmenstein, 1991). This species is found throughout the circumpolar north and is known for its resilience to low temperatures, unfavorable soil conditions and drought (Ştefănescu et al., 2020; Vilkickyte et al., 2022; Tirmenstein, 1991). Typically, mountain cranberries prefer sites with low pH soils, low base saturation, and low calcium (Zheng et al., 2019; Holloway, 1982) as well as low competition (Tirmenstein et al, 1991).

Figure 2. Mountain Cranberry shoots, leaves and fruit set in the wild,, September 2024, Fort Mcpherson.

Mountain cranberry has small shiny oval-shaped leaves (approximately 1-3cm) that sometimes turn purple in autumn (Hall & Shay, 1981). In the summer the plant can be recognized by its small pink flowers, and in the fall by its small red globular berries (approximately 6-10 mm diameter) (Tirmenstein et al, 1991; Andre & Fehr 2001). The roots of the plant have been noted to range in depth (observed maximum of 5 to 28 cm), which is a factor influenced by environmental conditions and soil composition (Roland & Smith, 1969; Tirmenstein, 1991). Underground, rhizomes expand horizontally, creating interconnected mat-like colonies, that expand well in peat soils, but can also be found in mineral soil (Tirmenstein, 1991).

2.3 Data Collection & Analysis

Interviews, Map Digitization & Validation sessions

The Indigenous Knowledge of Berries in the NWT project was a multi-year project that spanned the spatial entirety of the NWT. This project sought to examine changes in berry condition, size, and yield in berries in the NWT, from a framework defined by Indigenous knowledge holders. Its goal was to document Indigenous knowledge of berries throughout the NWT to describe the extent of the declines, and whether they constitute a response to recent ecological changes in the region or remain within the scope of normal interannual variability. It also sought to understand the evolving relationship of peoples and animals to berries in order to support access to country food and the health of the land. This was done using multiple methods, including interviews and participatory mapping. Although this work was conducted in communities outside of the GSA, I only refer to information gathered within the GSA. The analysis of this information was conducted in accordance with the University of Victoria Human Ethics permit #23-0188. Guided by this permit, along with the previously mentioned Gwich'in Tribal Council Traditional Knowledge Policy (Gwich'in Tribal Council, 2004) and data release approval, this research obtained free, prior, and informed consent from participants, as well as permission to publish their information.

In the summer of 2023, 40 interviews were conducted across four communities in the GSA: Aklavik, Inuvik, Tsiigehtchic, and Fort McPherson. Interviews were conducted by Annie Buckle (Aklavik) and Alestine Andre (Tsiigehtchic/Whitehorse), who both played major roles in the Indigenous Knowledge of Berries in the NWT project as parts of the advisory committee. The pair are community role models, knowledge holders, fluent speakers of local language, who grew up in the area harvesting berries.

During these interviews, participants were asked about their experiences and knowledge related to berry harvest. This project had a guiding set of interview questions which made interviews consistent throughout the NWT (Singer et al., submitted). The questions touched on subject matter regarding berry harvest such as typical harvest locations, type of berries harvested, uses of these berries, preferred habitat of these berries, noticeable changes in the environment and barriers to berry harvest. During interviews, knowledge holders were encouraged to mark any location they associate with as traditional berry harvest areas, on paper maps (Gwich'in Social and Cultural Institute, 2015, Map Sheets 85I/12, 85J/9, 85J). Participants were financially compensated following guidelines from the GTC's Traditional Knowledge Policy (Gwich'in Tribal Council, 2004).

The paper maps which were annotated by berry harvesters were digitized using ArcGIS Desktop 10.6 (ESRI, 2025), using the rubber sheeting tool, creating a third-order transformation. Once georeferenced, all annotations were transformed into shapefiles. These annotations took on three different vector forms: points depicting common harvesting locations, polygons outlining general harvest areas, and lines illustrating trails along which knowledge holders harvest berries. All mapping data related to these interviews, and additional material including audio recordings, transcripts, and photos, is owned by the Gwich'in Tribal Council, Department of Culture and Heritage, and their consent is required for any use beyond what is specified in the data sharing and research agreements established for this study.

The Indigenous Knowledge of Berries in the NWT team, now including myself, returned to the GSA in June 2024, to further assess the accuracy of the GIS process. This group revisited each community and shared the digitization we had done since our last visit in 2023. Led by Claire Singer, Annie Buckle, Alestine Andre, Giannina Karki, and myself, these sessions provided interviewees with an opportunity to review the digitized mapping data and correct draft results prior to publication.

Environmental Layers

Most of the environmental layers used in this study were the same as those used by Hamilton et al. (2024) and Hirabayashi et al. (2022), who produced SDMs for mountain cranberry in Alaska and Canada, respectively. Based on these studies, I selected 21 open-source layers that were usable in the GSA, adding an additional 10 layers based on academic knowledge of the environmental requirements of mountain cranberry. The cumulative layers consisted of five different categories of variables including: climate (10 layers), soil (8 layers), topography (4 layers), land cover (7 layers), and habitat heterogeneity (2 layers) (Table 1).

The layers that were adopted from Hamilton et al. (2024) and Hirabayashi et al. (2022) are described here. A digital elevation model with a 2 m resolution was downloaded from the ArcticDEM project on the Polar Geospatial Center website (Porter et al., 2018). Soil data and edaphic properties were retrieved from SoilGrids2, with mean values at a depth of 5–15 cm (Poggio et al., 2021). These layers included bulk density of the fine earth fraction, proportion of clay particles, volumetric fraction of coarse fragments, total nitrogen, organic carbon density, soil pH, proportion of sand particles, and cation exchange capacity of the soil. Consensus land cover and habitat heterogeneity variables were obtained from EarthEnv at a resolution of 30 arc seconds (Amatulli et al., 2018). Historic bioclimatic variables, including mean temperature, maximum temperature of the warmest month, minimum temperature of the coldest month, mean temperature of the wettest quarter, mean temperature of the driest quarter, annual precipitation, precipitation of the wettest quarter, precipitation of the driest quarter, precipitation of the warmest quarter, and precipitation of the coldest quarter, were downloaded from WorldClim version 2.1 at a 30 arc-second resolution (Fick & Hijmans, 2017).

The additional 10 layers relevant to the GSA are described here. I chose to include NDVI layers as it was likely to serve as a good proxy for canopy cover, which is known to influence the fruit production of mountain cranberry (Lussier et al., 2025). Using NASA Earthdata in ArcGIS (ESRI, 2025), I created two Normalized Difference Vegetation Index (NDVI) layers for the typical GSA harvest season of mountain cranberry. Together, these two layers represented the period from August 13, 2023, to September 13, 2023 (Didan et al., 2015). I also incorporated 2020 land cover data from the Government of Canada, which is available nationwide at a 30 m spatial resolution. From this dataset, still using ArcGIS, I extracted binary layers for water cover, wetland, shrubland, lichen, and tree dominated areas (Natural Resources Canada, 2022). The water cover and wetland maps served as substitutes for the "regularly flooded vegetation" layer used in Hirabayashi (2022), as the original resolution was too high for this purpose. Using the ArcticDEM data and ArcGIS, I also created three additional layers for factors that are influential to the growth of mountain cranberry including: aspect, roughness, and slope (Porter et al., 2018). These layers were generated at a 2 m resolution. I also explored the use of permafrost layers; however, I found that none were likely to produce satisfactory results.

To test multicollinearity in all 31 raster files, I used the R (R Core Team, 2024) programming package caret version 6.0-94 (Kuhn, 2008). There was no significant correlation between layers, as none showed a value above 0.75. Collectively this resulted in 31 layers used in the model. Finally, I standardized all spatial predictor layers to a uniform resolution of 30 m, aligned them to a common grid, and reprojected them to the NAD83(CSRS) / UTM zone 8N coordinate reference system. This resampling was done using the terra package version 1.7-29 (Hijmans, 2024)

Table 1. List of the 31 layers used to model the likelihood of occurrence of mountain cranberry in the Gwich'in Settlement Area and their source

Category	**Code**	**Layer**	**Source**
Climate			
	Bio 1	Annual Mean Temperature	WorldClim
	Bio 5	Max Temperature of Warmest Month	WorldClim
	Bio 6	Min Temperature of Coldest Month	WorldClim
	Bio 8	Mean Temperature of Wettest Quarter	WorldClim
	Bio 9	Mean Temperature of Driest Quarter	WorldClim
	Bio 12	Annual Precipitation	WorldClim
	Bio 16	Precipitation of Wettest Quarter	WorldClim
	Bio 17	Precipitation of Driest Quarter	WorldClim
	Bio 18	Precipitation of Warmest Quarter	WorldClim
	Bio 19	Precipitation of Coldest Quarter	WorldClim
Soil			
	BD	Organic Bulk Density	Soil Grids
	CC	Clay Content	Soil Grids
	CF	Coarse Fragments	Soil Grids
	N	Nitrogen	Soil Grids
	OCD	Organic Carbon Density	Soil Grids
	PHW	pH water	Soil Grids
	SA	Sand	Soil Grids
	CEC	Cation Exchange Capacity (at pH 7)	Soil Grids
Topography			
	DEM	Digital Elevation Model	Arctic DEM
	AS	Aspect	Arctic DEM (Edited)
	RO	Roughness	Arctic DEM (Edited)
	SL	Slope	Arctic DEM (Edited)
Land Cover			
	NDVI 1	MODIS/Terra Vegetation Indices 16-Day L3 Global	NASA Earthdata
	NDVI 2	MODIS/Terra Vegetation Indices 16-Day L3 Global	NASA Earthdata
	Trees	Trees	Gov Canada

	Lichen	Lichen	Gov Canada
	Water	Water	Gov Canada
	Wetland	Wetland	Gov Canada
	Shrubland	Shrubland	Gov Canada
Habitat Heterogeneity			
	DIS	Dissimilarity	EarthEnv
	HO	Homogeneity	EarthEnv

Data Analysis & Model Development

Since line and polygon data needed to be converted to point data to be used in the model, a methodology was adapted from other studies which convert polygons & lines to points. The methodology I followed associated a different number of random points to a polygon based on the size of that polygon (Skroblin et al., 2021). This is opposed to other methodologies, such as Konowalik & Nosol (2021), which use the points generated in the centroid of polygons. I chose the random sampling method as this would better emulate the size of a single polygon, while not confining my interpretation to solely one point. The generated points were randomly spread across the space within each usable polygon, and along each line, creating a cumulative point dataset of harvesting locations. Polygons smaller than 1 km^2 and lines shorter than 1 km received one random point, for every additional 1 km^2 or 1 km, an extra random point was created, up to a maximum of 10 points. Polygons and lines that surpassed 10 km^2 or 10 km were too ambiguous and had to be discarded. This was considered the threshold because including 10 points for a single polygon would be a disproportionate amount of the entire dataset (115) and would likely contribute to noise in the model.

The harvesting data was presence-only, meaning the model selection was restricted. Following the approach of Hirabayashi et al. (2022), I created a model for the GSA for mountain cranberry using a MaxEnt modelling algorithm. MaxEnt is a very common approach to species distribution modelling, as it was specifically designed for presence-only data (Phillips et al. 2006). The MaxEnt model was developed using the R software package Maxnet version 0.1.4 (Phillips et al., 2017) and 1000 random background points.

The extent of the map encompassed all points used to create the model. We evaluated that it would not have been appropriate to model the entire GSA, as harvest locations did not fall within the bounds of the taiga cordillera ecoregion (Figure 1). Therefore, we included only ecoregions surrounding the GSA which had accompanying data points: the tundra cordillera, taiga plains, and tundra plains. A buffer was applied around the GSA to ensure the extent of the area was fully recognized. Additionally, the modeling extent also extended northward beyond the northernmost boundary of the GSA, to allow for the complete inclusion of all annotated harvesting locations.

The model's discrimination capacity to distinguish presence from absence was evaluated twice using an area under the curve (AUC) value based on the model's receiver-operating characteristic. The first evaluation used a reserve of 25 % of the training points, the second time used an independent dataset (field data described in the next section). In this second analysis, I used areas of low occurrence as absences. The threshold value was set to the median value (55.39 g) of harvestable yield. These values were calculated using the dismo package version 1.3-9 (Hijmans et al., 2021). The interpretation of all AUC values was guided by Hosmer and Lemeshow (2000) where values below 0.5 indicate no discrimination and AUCs above 0.9 are outstanding. The values used in this assessment were calculated using the evaluate function in the dismo package version 1.3-9 (Hijmans et al., 2021).

Field Measurements

In September 2024, a field technician and I sampled 60 sites in the GSA. Samples from these sites were used to evaluate the accuracy of the model created. Using the raster output from the MaxEnt model, the relative indices of occurrence (RIO) were used to select the study sites. RIO values depict the relative probability distribution of habitat suitability within the study area, where higher values represent a prediction of better environmental conditions (Phillips et al., 2006). A random stratified sampling method using the model's predictions was used to ensure that the predicted occurrence was equally represented throughout the dataset. Of the total 60 sites, 20 sites were selected within each of the following categories: low predicted RIO (0.00–0.33), medium predicted RIO (0.34–0.63), and high predicted RIO (0.64–1.00) (Figure 3). This three-scale approach offered a useful and easy to interpret tool for community members. Additionally, the random stratified method offered a means to ensure that the entire range of the model was represented, because there were disproportionate amounts of values within our potential sampling area. To accommodate field constraints, sites were limited to a maximum distance of 500 m from the roadside, excluding areas of open water and locations within a 10-kilometer radius of communities. A 500 m buffer was selected because, during validation sessions (discussed later), knowledge holders explained that they typically travel up to 1 km from the road. Others, however, reported harvesting only a few meters from the road. As a compromise between these ranges, 500 m was selected. The choice to exclude locations outside a 10 km buffer from communities was taken because during interviews, numerous participants expressed that local berries should be reserved for those who have difficulty accessing land further away from community centers (Singer et al., submitted).

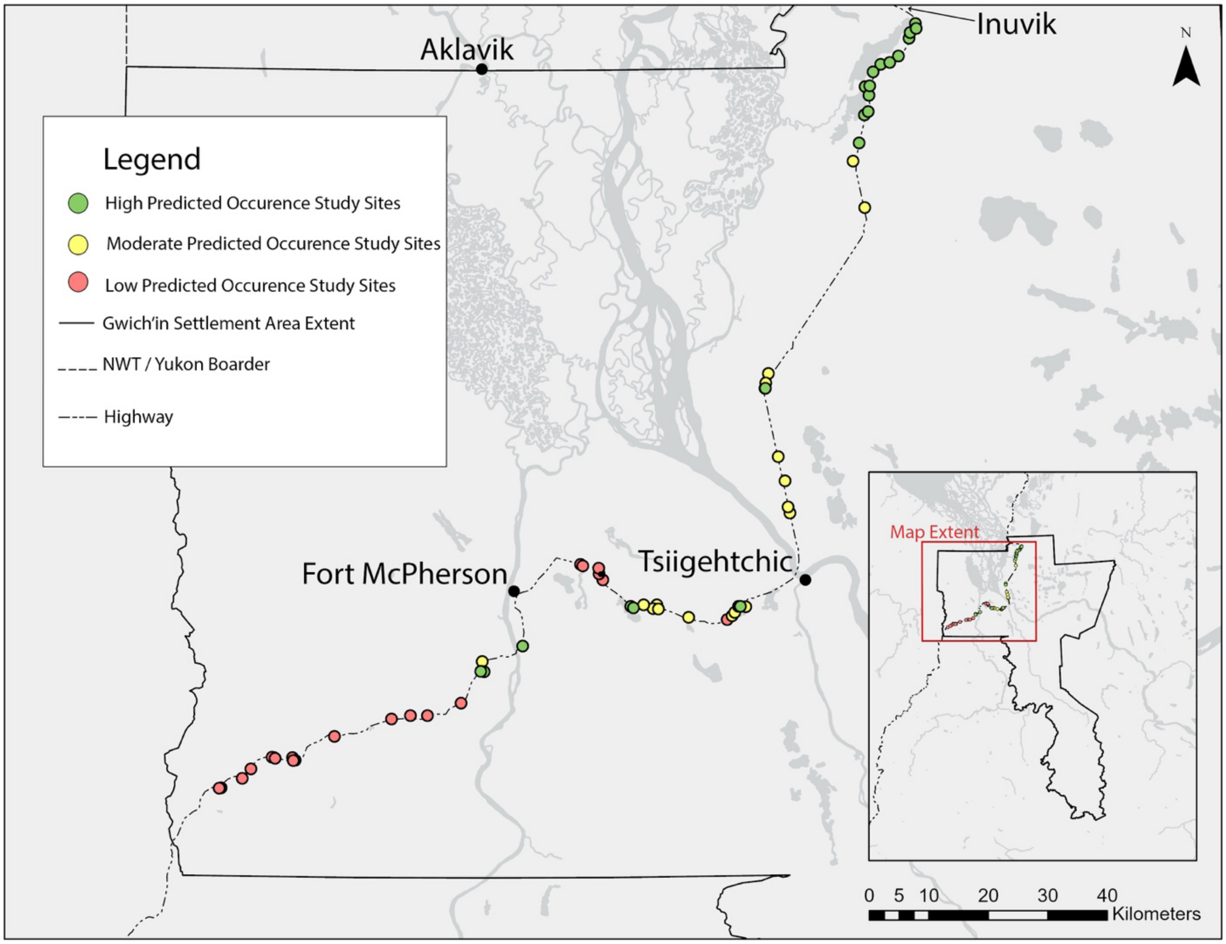

Figure 3. Visualization of the random stratified sampling technique and the resulting 60 field sites selected along the Dempster Highway

After arriving at each site, a field technician and I dedicated 10 minutes to harvesting at the location, within a 15 m radius. At the end of the session, the collected fruit was weighed by gram to two decimal points. This value was labelled "Harvestable Yield". This surveying methodology was inspired by Madsen (1999), who used a similar meandering technique to assess flower abundance. Although this technique is not widely used and has the potential to introduce bias, it offered this study some practical advantages. This technique allowed us to assess a greater number of sites in less time and with fewer resources than traditional methods such as transects or quadrats. Potential disadvantages of this surveying technique are, inconsistencies in harvesting techniques, which could have influenced the quantity we collected compared to more experienced pickers; fatigue and weather conditions influencing harvest speed; and differences in perceptions of what constituted "harvestable" fruit. To address this potential lack of consistency, everything that was not rotten or excessively dry was collected. Additionally, consistency was maintained by the same two harvesters sampling at all 60 sites. It is important to note that future results could differ depending on the surveyors involved. Despite this survey methodology being less common, this technique allowed for a greater number of sites to be sampled in less time and with fewer resources, which was important to this study.

2.3 Results

During interviews knowledge holders from the GSA explained in detail subject matter regarding the berry species' they prefer to harvest, locations and ecology of harvesting sites, changes in availability, changes in abundance, changes in phenology, and potential ways to increase access to harvest. Some participants expressed serious concerns about the changing abundance of species, while others mentioned that they had not noticed any difference. However, across communities, there seemed to be spaces that were reliable for harvest, typically those considered "cooler." For instance, in Aklavik and Inuvik, these areas were north of the drier areas around these communities and closer to the Arctic Ocean. While in Fort McPherson, interviewees considered the mountains in the west to be the cooler refuge for berries. Roads and rivers were essential features that allowed locals to access their lands. However, knowledge holders mentioned that they have experienced increases in accessibility issues, such as rivers drying up early, reducing opportunities to revisit sites used in the past, increased transportation costs, and increases in wildfire smoke and health limitations. These results are by far not a complete evaluation of what people said during interviews, for a more robust look please look to Singer et al. (submitted).

Approximately one year after the first round of interviews took place, I participated in group validation sessions. These sessions were held in community centers in each of the four communities. Group sessions may be criticized for catering to dominant voices, however there were many pros including taking less time, increased cross checking and the ability validate annotations of those who were absent. There were four validation sessions in total, one taking place in each of the four Gwich'in communities in the GSA. These validation sessions were incredibly beneficial, specifically for bringing clarity to the georeferenced dataset. The in-person validation interviews allowed me to include an additional 55 mountain cranberry harvesting locations, increasing the number of original point annotations from 60 to 115. These additional points were primarily observations that had been annotated but not labeled during the first round of community mapping. The rest were entirely new annotations that were later digitized. Of the total 115 points described, 15 % were within a 10 km radius of the four major communities, 30 % were within a 20 km radius of community, and 60 % were within a 30 km radius of community (Table 2). Additionally, 65 % of the 115 points occurred within an ecoregion classified as taiga plains, while 24 % occurred within tundra cordillera ecoregion and 10 % occurred within tundra plain ecoregion, highlighting that most observations were within the taiga (Table 3).

Table 2. Proportions of harvest sites which occurred within 10 km, 20 km and 30 km radiuses of community centers

	Tsiigehtchic	**Aklavik**	**Inuvik**	**Fort McPherson**	**Total**	**% of observations within this radius**
Within 10 km	15	1	0	1	17	15
Within 20 km	17	3	3	11	34	30
Within 30 km	18	6	21	24	69	60

Table 3. Proportions of harvest sites which occurred within specific ecoregion types

	# of points	% of points
Tundra Cordillera	12	10.43
Tundra Plains	28	24.35
Taiga Plains	75	65.22

Field Data

Mountain cranberry fruit was present at 55 out of 60 randomly sampled sites (92 %). The occurrence of the plant itself was seen at 57 out of 60 sites (95 %). The sites where fruit was present had different ecological conditions ranging from scree slopes to sedge-grass plains and spruce and birch forest stands. The harvestable yield at these sites ranged from 0.19 g to 359.84 g. All sites that were predicted to have a high RIO value (0.64-0.1) had the occurrence of mountain cranberry fruit. Of the five sites that did not have the occurrence of fruit two were predicted as low RIO (0.00-0.33) and 3 were considered moderate (0.34-0.63, Figure 4).

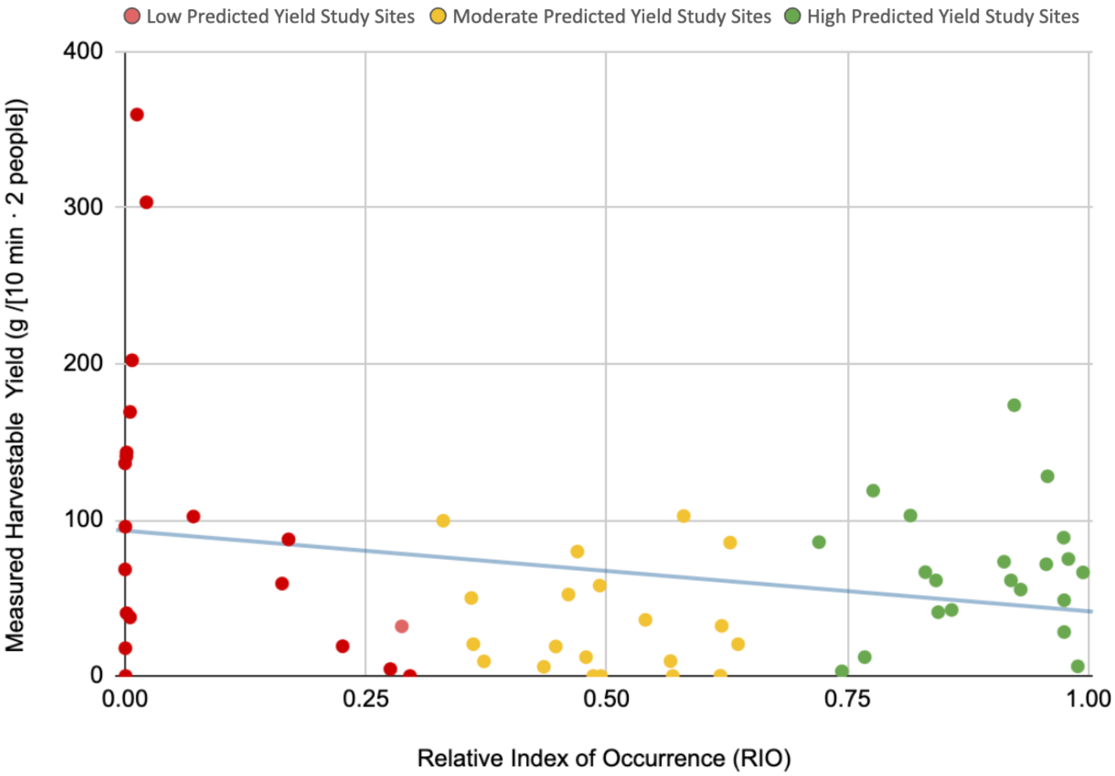

*Figure 4 Measured harvestable yield (grams/10min*2 people) plotted against predicted RIO values at each site sampled in the GSA region*

Model Results

By working with harvest locations, I was able to develop and evaluate a 30 m model that aimed to predict the presence of good harvesting sites for mountain cranberry within the upper portion of the GSA (Figure 5). When tested against a reserve 25 % of Gwich'in observation points, the model resulted in an AUC of 0.93 with a correlation of 0.73. No additional tests were run prior to field work. When the model was tested against the median value of harvestable yield (55.39 g) which was deemed to be a standard for a quality harvesting site, the model resulted in an AUC of 0.53. When harvestable yield was tested against predicted RIO, this resulted in a correlation of -0.24 (Figure 4).

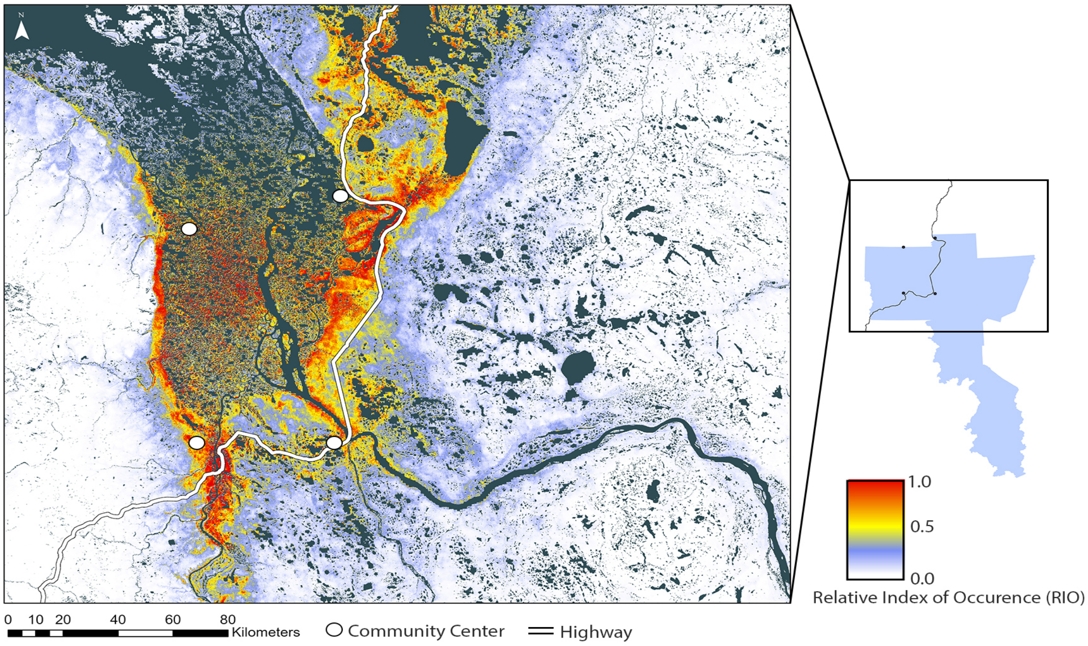

Figure 5. MaxEnt model depicting the relative index of occurrence (RIO) of mountain cranberry created with traditional harvest locations in the Gwich'in Settlement Area

Using climatological, biological, and topographic data, this model suggests that approximately 4.5 % of the study area was considered good harvesting sites suitable for mountain cranberry, 7.9 % was predicted as moderate harvesting sites potential and 87.6 % was predicted as low quality for site suitability. These pixel distributions varied but were similar in both tundra and taiga ecoregions (see Appendix A). Within tundra ecoregions 83.3 % of the total area was considered low, 12.2 % was considered moderate and 4.5 % were considered high RIO. In the taiga ecoregion, 88.8 % considered low, 6.7 % considered moderate, and 4.5 % was considered high RIO (Figure 6). Throughout the projected raster, the data had a minimum value of 0.00 RIO, a maximum value of 1.00 RIO, mean value of 0.11 and median value of 0.017, which had different but similar distributions across taiga and tundra ecoregion (Figure 6).

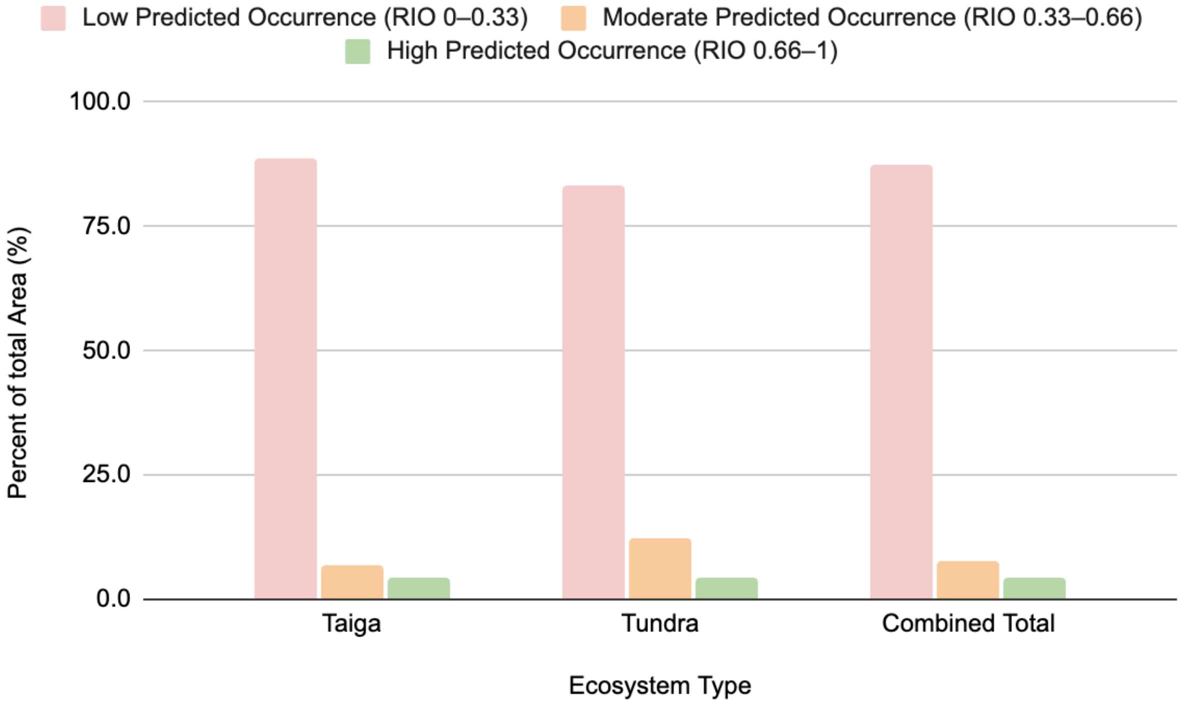

Figure 5. Distribution of pixels produced within MaxEnt raster in high, medium, and low RIO value categories for the three ecoregion types of the GSA region

2.4 Discussion

The primary goal of this study was to assess the possibility of understanding mountain cranberry distribution in poorly documented areas of the GSA. With a habitat suitability model, the GTC could gain more insight into whether future developments would impede critical mountain cranberry habitat. However, it was found that modelling effort did not address presence of quality harvesting sites. The assessment indicates that factors of accessibility influence harvesting locations more than previously anticipated, resulting in an SDM that does not critically assess fruit abundance.

During validation sessions, I had heard from knowledge holders in Fort McPherson that the area towards the Yukon/NWT border is a prime ecosystem for harvest, yet annotated harvesting locations in this region were limited. Participants mentioned that barriers to access dramatically increased when picking far from home, and the border is nearly a two-hour drive from Fort McPherson. Additionally, Elders expressed fear of the roads due to harsh unpaved conditions, bad drivers, and concerns about bears in the area. Moreover, this area is remote and has limited opportunity to camp or stay, so harvesting would likely need to take place in one day.

Taking these factors into account, a reasonable interpretation is that the model created reflects the influence of accessibility. When tested against its own dataset, the model achieved an AUC of 0.93, indicating strong performance in relation to the points annotated by participants. However, when tested against field data, the map proved to be less accurate, with an AUC of 0.53. From this, along with rationale heard in validation sessions, it is hypothesized that the data annotated on the maps represented features more related to accessibility than harvestable yield. Furthermore, it is hypothesized that this compounds with the widespread distribution of mountain cranberry in the area, as only 3 out of the 60 sites visited showed no occurrence of mountain cranberry. This epitomizes the idea that harvest is more than subsistence and revolves around more than simply harvestable yields (Parlee et al., 2005; Singer et al., submitted). Instead, choices of harvesting locations are likely less prioritized by fruit abundance and more prioritized around convenience – although fruit abundance still likely has some roll in locations participants chose to harvest.

Since cranberries are widespread throughout the GSA, in this case, using points that represent traditional harvest sites may not have provided the most efficient data for modelling habitat suitability. The observation points are located disproportionally in areas closer to community centers, underrepresenting locations outside of a 30 km radius from community centers. According to the data, 60 % occurred within 30 km of community centers and 65 % occurred within taiga plains classified ecosystems (Table 2 & 3) (Government of Northwest Territories, 2025). This inevitably caused bias in the modelling process resulting in values that were disproportionately representative of areas with less berries but high accessibility. Furthermore, MaxEnt modeling exacerbates this error since it is a presence-only modeling technique that treats random points as pseudo-absences. If cranberries are widespread throughout the area, these pseudo-absences are easily misidentified, resulting in increased false negatives (Fletcher & Fortin, 2018).

Although this methodology did not produce a physical product that was identical to the goals expressed at the beginning of this chapter, the GTC was pleased with results and expressed that findings were still beneficial for management purposes. Additionally, the research has advanced knowledge of including IK in the species distribution modelling process. One positive is that the collected data can be utilized to create a species abundance model for the GTC, as discussed in Chapter 3. The weak results of this method were influenced by a few specific flaws in this chapter's methodological process. In this discussion, I will explain some of the shortcomings in detail and provide recommendations for future communities who are interested in this type of analysis regarding the following topics, community mapping sessions, meaning of polygon data, meaning of point data, ability to communicate consultation efforts.

Meaning of point data

Prior to going into the field, the model tested at an AUC of 0.93 which is considered excellent. However, when I tested the field data against the same model, it obtained an AUC value of 0.53 which is very poor (Hosmer & Lemeshow, 2000). There are two main points which influenced the accuracy of the modelling, underrepresentation of key ecosystem types in the observation data and the widespread distribution of the mountain cranberry in the GSA.

Sample selection bias is a common problem for presence-only datasets such as the one used in this study (Fletcher & Fortin, 2018). Usually, these types of datasets have inherent bias as the observation points can be commonly documented near easily accessible areas, such as near roads or urban areas (Fletcher & Fortin, 2018; Kadmon et al. 2004; Loiselle et al. 2003; Phillips et al. 2009). As the points represent harvest data points, which are the nexus of socio-ecological relations, human-bias were inherent in the dataset. This bias may have resulted in the identification of inaccurate environmental relationships, which further provided predictions of sampling bias rather than underlying distributions.

A primary assumption that was made at the beginning of the research was that traditional harvest sites would typically have the highest abundance of berries, since these are locations that people visit year after year. I later concluded that the traditional harvest sites may have been less correlated to harvestable yield than previously thought, as it is common to harvest during other traditional activities such as fishing or hunting or near cabins (Singer et al., submitted). This indicates that many of the annotated harvest sites may be more correlated to convenience as opposed to pure fruit abundance. I found that many of the locations were spatially correlated to community centers (Table 2). Additionally, Inuvik, Aklavik, Tsiigehtchic, and Fort Mcpherson all occur within a similar taiga plains ecosystem that is abundant but not homogenous across the entire GSA. This could mean that the model may be overfitted in relation to taiga plains ecosystems and lacks transferability to other ecosystems such as tundra cordillera or plains (Qiao et al., 2019; Roberts et al., 2017). Of the 115 points used to develop the model, only 10 % occurred within tundra cordillera ecosystems (Table 3), which field data indicated as the highest producing ecosystem.

Despite the tundra having a low proportion of data points, during interviews, validation sessions and field surveying it was highlighted as ideal picking terrain. Some participants would make the trip out to the tundra "whenever they got the chance". This was, of course, if the conditions were right. Conditions included having a large enough group to split the price of gas, weather and road conditions being favorable, and having somebody willing to use a gun to protect the group from bears.

Because mountain cranberries have a wide spanning realized niche relative to the GSA, this led us to the conclusion that abundance was not the most influential factor contributing to the location of traditional harvest sites. Although taiga plains sites typically produced less than tundra cordillera sites, they were always closer to communities. The barriers to harvest, such as the price of gas, limited time, etc. are decreased by staying close to home. When time is limited, participants may be able to achieve similar or higher yields at moderately productive sites located nearby, rather than spending extra time driving to further harvesting locations.

Community mapping

The emerging body of research examining best practices to decolonize participatory mapping often points to language and place names as a key starting point for leveling power dynamics between participants and researchers (Tuhiwai-Smith, 2012; Johnson et al., 2016). Studies have been critical of the lack of meaning associated with Indigenous toponyms in bureaucratic maps, which often desaturate the meaning of place names by presenting them as static, inanimate objects void of meaning (Palmer & Korson, 2020). Nonetheless, currently in resource mapping exercises, best methods are likely hybrid options which can offer both Indigenous toponyms and standardized spatial base maps which can attempt to simultaneously provide material that can be both georeferenced and representative of place names important to participants.

In this project, paper topographic maps from the "Place Names of the Gwich'in of the Northwest Territories Map Series 2015" were used as the best available hybrid option. These were used during the first round of community mapping, which took place in June 2023. Participants hand drew points, polygons and lines, onto these maps. These data points later needed to be digitized into shape files and then validated in a second round of interviews that took place in 2024. The long process of participatory mapping, digitizing, validation and making corrections, likely introduced unnecessary errors into the dataset, simply via the multiple steps needed to translate these annotations to digital form by a non-local technician. The scale of the maps was 1:250,000, which likely limited participant specificity during the participatory mapping process. This traditional method of digitizing annotations from paper maps has been criticized for being slow and subject to the influence of positionality on the part of the researcher, leading to misinterpretations of annotations and dilution of important knowledge (Brown & Kyttä 2018; Ramirez-Gomez et al. 2015). Validation sessions are often used as the solution to the misinterpretations caused by this process, however, if the mapping was done accurately in the first place, less corrections would be necessary during these sessions. This is not to suggest that paper maps should be excluded from the participatory mapping process, particularly in the context of species distribution modelling using IK, as they have been successfully incorporated elsewhere (Campbell et al., 2022). Rather, academics should be mindful that choosing between digital or paper based participatory mapping can have consequences and should be done in respect of the preference of the Indigenous participant.

Other considerations need to be made when selecting base maps. In particular, the physical size, scale, and basemap type can influence the resulting dataset (Curtis et al. 2014; Yabiku et al. 2017; Denwood et al., 2023). During validation sessions, I found that participants reacted well to paper maps with satellite imagery bases with limited toponyms. Although the paper maps from the original mapping sessions had traditional names, which was the rationale for originally being chosen, the satellite imagery offered a new opportunity for participants to engage with visual space. This gave participants the ability to discern ecosystem features such as spruce forests, birch forests, riverbanks, and marshes, something that was not possible with the paper topographic maps. Despite the positive aspects of this method, during validation sessions, a limiting factor of these maps was that they were still confined to a single scale, chosen at my discretion, which inevitably would have been biased by positionality. Although the size and scale of paper maps in participatory mapping sessions, has been highlighted to not have a major consequence on data quality if they are selected at the correct scale (Denwood et al., 2023).

Oftentimes, participants are seen by researchers as "novice GIS users" and "inexperienced" in their use of digital spatial data making the participatory mapping process challenging (Elwood, 2006). Although it is true that participants are likely less skilled in terms of GIS compared to the GIS technician, the accessibility of GIS systems has significantly improved over the last two decades. Paper maps are often seen as a more accessible option that is better for people with physical challenges such as visual impairments or reduced fine motor skills, as well as more psychological barriers such as technological self-efficacy (Denwood et al., 2023). Additionally, paper maps play a role in scenarios where locations are remote, Wi-Fi/power is limited, and for participants who prefer using analogue tools. However, there are tradeoffs that come with solely utilizing paper-based methods. I believe that a mapping process that uses a hybridization of paper-based and digital methodology may have been better representative of the IK in this study, by limiting the amount of interpretation needed in post-processing. This would limit researcher bias and error by removing the need for the multiple steps in digitizing paper maps, including georeferencing original maps, re-drawing the annotations as spatial features and interpreting words depicted on maps, all of which introduce possibility for inclusion of positionality or mistakes. Tools such as tablets and phones have been used for digital participatory mapping in ecological projects, with promising results (Altmann et al., 2018; Hahn, 2016; Polas et al., 2025).

Had straight-to-digital mapping been used during the original interview sessions, with tools such as tablets and accompanying GIS software, there would have been the possibility to 1) toggle between map overlays such as satellite and topographic maps; 2) have participants annotate digitally, eliminating the need for georeferencing in the post process; 3) have infinite range of scale, not limiting participants to areas that are uniquely displayed on the extent of the paper maps chosen by the technician; 4) potential to introduce base maps and toponyms simultaneously; 5) decrease expenditure on technicians tasked with georeferencing the data. These were dilemmas that were discovered independently but backed by past research which has reviewed similar incompatibilities in paper-based participatory mapping and the positives regarding straight to digital approaches (Denwood et al., 2023). This is not to say that paper maps are obsolete, they served the needs of this study and many others. However, as public familiarity with digital technology increases, digital participatory mapping will become a more feasible, accurate, and representative method for documenting IK. Indigenous nations are not static and do not need to follow old customs, they live by any technology or materials they want (Lucchesi, 2018). As such, choosing which base map to use should be thoughtfully deliberated, and never assumed. This will lead to results that better reflect the voices of participants (Denwood et al., 2022).

Meaning of polygon data

Through this research I found the importance of grounding analysis in the social context. This is exemplified by how interpretations of mapped features, such as a point or polygon, may be viewed differently by an ecologist or a participant. During sessions, participants drew polygons which needed to be simplified to point data to be used in the model. In some regards, this is controversial since point-based data methods have been criticized for oversimplifying human experience (Denwood et al. 2020; Huck et al. 2014; Evans & Waters 2007; Denwood et al., 2023). Additionally, during digitization, GIS technicians can inadvertently cause misinterpretation (Denwood et al., 2023; Brown & Kyttä 2018)

This case study exhibits how polygons have the potential to process different meanings as opposed to point data, and likely are a more accurate representation of harvest since harvest does not strictly occur as one specific coordinate on a map. If a participant wanted to demonstrate a location that they frequent but this area may vary seasonally, the participant might draw a polygon as opposed to a point, insinuating that year to year or season to season they pick in different spots within this area. Additionally, participants could have been protective of harvesting locations and as such use polygons as a form of censoring their information. However, this was likely not the case during this study since, since during validation sessions many participants were adamant about knowledge sharing, quoting the belief that food and the land should be for everyone.

As mentioned, I adapted practice from Skroblin et al. (2021) to convert polygon to point data. However, the randomization of points introduced potential errors into the methodology for a few reasons. Primarily, when randomly generating points across a polygon, this meant that points could be created in areas where berries could not grow or are very unlikely to grow. This is specifically controversial for species distribution modelling where the model needs to pick up on ecosystem similarities to create accurate results. This problem was evident when polygons encompassed non-homogeneous spaces (Figure 7), for example polygons that included swamp, estuary, river, and forest. Polygons have been noted to be problematic in mapping cultural practices, in Ramirez Arandra et al. (2021) polygons drawn by participants repeatedly included water sections, even when their cultural practices were not related to water. In this scenario, where some polygons encompassed non-suitable habitat, points could be randomly generated in different ecosystems, when participants only meant points to be interpreted in a single ecosystem type. This is especially true with the employment of maps that have no indication of ecological features. This problem could be minimized if satellite imagery was used during the participatory mapping process. This way, participants could visibly discern the areas that clearly did not fit the description of a good harvest site. Limiting the inaccuracies that come with annotating on non-specific map features. This is opposed to paper maps, where topographic and large hydraulic elements are the only visible ecological borders. Although this does not completely solve the issue, having participant choice would likely lead to more accurate and precise annotations.

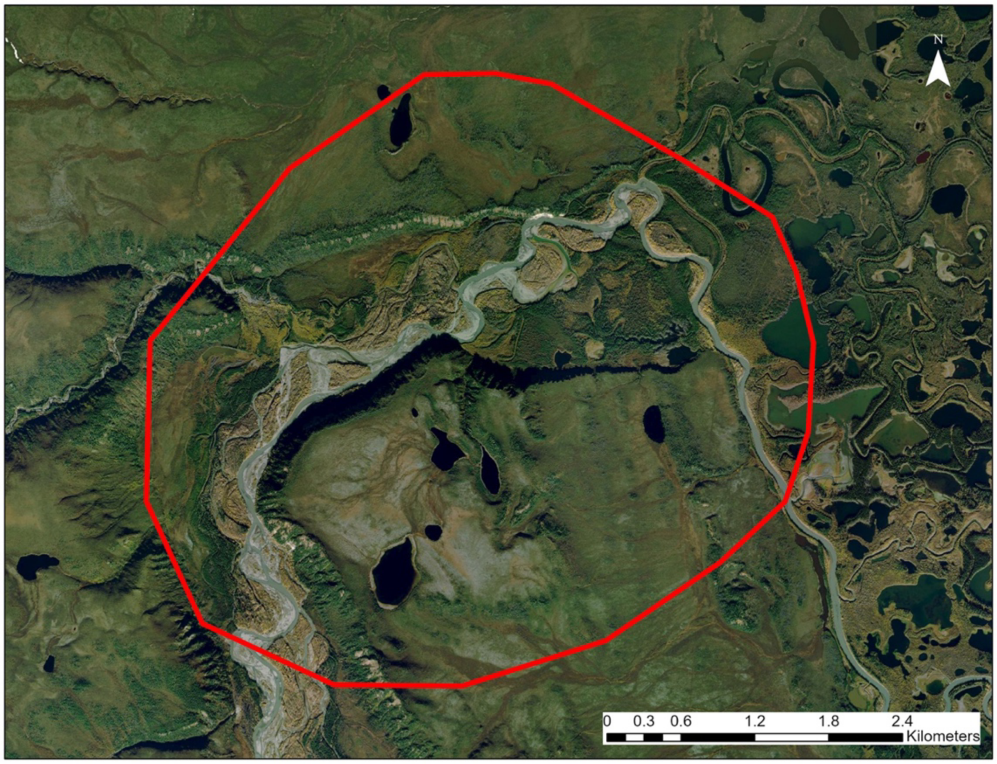

Figure 6. Example of a polygon drawn in mapping session that encompasses multiple different landcover types, which could lead to possible misclassification in modelling efforts

In a similar context, some polygons were too large and therefore not ideal for modeling (Figure 8). This is an example of how choices made in postprocessing can lead to dismissal of knowledge. This issue could be even more prominent in a modelling scenario with limited points, as the technicians would have to decide between including undescriptive polygons or using fewer occurrence points. Although large polygons worked for the function of the larger project, they conflicted with SDM methodology. These incompatibilities could have been avoided by understanding the limitations of SDM methodology prior to conducting the mapping sessions. Although less restrictions during participatory mapping can give freedom to the participant to express themselves through annotation, the employment of clear scheme of notation is important to produce comparable and homogenous results (Klonner et al. 2018; Denwood et al., 2023). Along with that, for mapping to be meaningful, participants should have a clear understanding of what different annotation types such as, polygons, points and lines, may represent in the context of the study (Denwood et al., 2023).

Figure 7. Example of a large polygon drawn in mapping session which is non-specific to ideal harvesting locations, possibly leading to misclassification in modelling efforts

The problem of non-homogenous and oversized polygons may be avoided by the technician structuring the session to include a clear scheme of notation and clear communication (Klonner et al. 2018; Denwood et al., 2023). A structured and clear approach would lend itself well to uniformity in the dataset, which can then be better used in processes such as SDM. One way that participatory mapping technicians could achieve both information retention from polygons and versatility in modelling with unedited point data, is by asking how participants would interpret their drawn polygons as specific points. In this way, the polygon a participant annotated could be retained, saving the complexity included in the spatial feature, which can be used in forward facing cartography, while the point data offered could be reserved for use in point-dependent processes such as SDM, or other methods the Indigenous group aims to pursue.

2.5 Conclusion

A major takeaway from this process is that there should be no "one size fits all" methodology for working with IK in species distribution modelling. Methodologies should, instead, always be tailored to the needs and capacity of communities. Although there are some foundational parts to the methodology that should be held as standard, especially those regarding respectful practice. Relationship building and iterative approaches are key to the success of co-created projects. Therefore, the pursuit of streamlined methodologies should be grounded in community needs (Drawson et al., 2017).

The main suggestion made in this text is that each choice starting from the participatory mapping to validation should be made with intention. In participatory mapping, when selecting appropriate methods, the study area, nature of the question and characteristics of the target population must be uniquely taken into consideration (Denwood et al., 2022). Equally, the needs of community and ethical nature of research should be considered when expanding this to SDM techniques (Baumflek et al., 2015). Through critical analysis this thesis refers to how participatory mapping can be done in a way that minimizes the involvement and interpretation needed by the GIS technician, while aiming to maintain the complexity of the IK displayed via annotations. Some items that may decrease the need for interpretation included the use of harmonized straight to digital and paper mapping techniques, choice of regionally appropriate base maps, and structured mapping session with clear expectations from participants, that do not limit their expression.

Although these choices may seem minor, they have implications that extend to the analysis, if the community decides to utilize these datasets for further analysis.

During validation sessions, it was expressed that modelling habitat suitability should not replace consultation. Thus, the maps generated do not indicate where land use should and should not occur, instead provide a preliminary option for Indigenous governance agencies to use as a guide. This statement is further exacerbated by the fact that harvest locations did not necessarily line up well with true habitat suitability, indicating that habitat suitability may be a less important factor to consider than previously thought. Instead, accessible areas should be prioritized for conservation, as this was the more important factor influencing the location of harvesting patches. Further, studies such as these have limitations, for example sampling methods and practicality of modelling a ubiquitous species such as mountain cranberry, these highlight how over saturated dependability of GIS analysis may lead to mismanagement.

Some Indigenous groups experience fatigue from being asked to consistently participate in consultation and research efforts, while often not seeing the results of the research firsthand (Goodman et al., 2018). As such, scientists, when given the opportunity to conduct research on Indigenous land with knowledge holders bear the responsibility of conducting research that is robust and applicable for use beyond the purposes of their study, keeping in mind that IK would need future consent beyond the original study. Species distribution modeling is one of the most popular spatial analytic tools used by biological researchers (Valavi et al., 2022). Given participatory mapping has been usefully applied in SDM process (Baumflek et al., 2015; Campbell et al., 2022), participatory mapping projects should hold quantitative applicability as an additional goal of their research. This is important for Indigenous governing bodies who may want to utilize this information for SDM purposes in the future. Additionally, some groups may have other plans for the participatory mapping which are not analytical, but rather as knowledge transfer tools. Either way, reusability must be a priority when conducting participatory mapping, to make certain that the GIS resource is more valuable and versatile for communities.

3.0 Rooted in Data: Modeling Berry Abundance with Random Forest Modelling to Strategize Indigenous Land Management

3.1 Introduction

Over past years, temperatures in the highest northern latitudes have shifted dramatically, with some locations experiencing warming at a rate four times the global average (Rantanen et al., 2022). Northern areas are also experiencing increases in extreme weather events (Walsh et al., 2020). As such, it should come as no surprise that these changes in climate and weather have been linked to significant landscape changes in northern environments (Henry et al., 2022). Landscape changes can vary from alterations in erosional processes to shifts in vegetation cover (Henry & Molau, 1997). These changes to the land ultimately impact northerners who call the north home, changing the ways they engage with the land.

Berry harvest, specifically regarding mountain cranberry, is one such way tradition has been impacted by climate change. Considered a cultural keystone species, this fruit offers a wide variety of benefits to the people who consume it. Medicinal values include preventative medicine against colds, bladder infections, and intestinal problems (Parlee et al., 2005) and some of the traditional values include use in dyes and traditional meals (Singer et al., submitted). Unfortunately, this fruit has become increasingly hard to access, as illustrated by studies such as Parlee et al. (2005), Singer et al. (2025) & Parkinson et al. (2024). Specifically, climate change has been highlighted by knowledge holders as one of the main barriers that is exacerbating this lack of access, both physically through examples such as low access due to wildfire smoke and climatic repercussions such as less fruitful yields (Parlee et al. 2005; Singer et al. 2025; Parkinson et al. 2025). Throughout the Canadian North and Alaska there is understanding that berry harvest is variable year to year, but a consistent fear remains that mountain cranberries may become a thing of the past with increasingly limited access and lower harvestable yields. As such this study aims to take a contextual approach to abundance modelling, where the aim is to predict harvestable yields (in grams) as opposed to purely species range.

Berry harvest is a practice that has significant economic and environmental value (Parlee et al., 2005). Food prices in the Canadian North are known to be some of the country's most expensive, sometimes reaching above three times the national average (Kenny et al., 2018). Country foods, defined as foods that inherently come from the land, such as berries, offer an alternative to market foods, which can often be an unhealthy and expensive source of nutrition (Kuhnlein, 2014; Usher, 1976). Additionally, mountain cranberries provide key subsistence to animals such as bears, caribou, birds, and small mammals (Singer & Lee, 2021). Although berry harvest is economically and environmentally important, it should be noted that, solely looking at berry harvest through these lenses greatly undervalues the importance of the tradition, with many more values, such as stewardship, knowledge transfer, and community unity, to name a few (Parlee et al., 2005).

There is a need to increase access to mountain cranberry because barriers to harvest are increasing. One example of strategies employed to increase the viability of access to country food is through species distribution modelling, which can indicate suitable habitats for cultural keystone species (Baumflek et al., 2015; Campbell et al., 2022). These models can be an effective tool for estimating areas that communities may want to choose to preserve or seek harvesting opportunities in. Knowing where a species is likely to occur, through binary or continuous rasters, may be beneficial for studies focused on the harvest of entire plants; however, by employing the use of abundance modelling, studies can gain specificity by predicting fruiting weights as opposed to plant habitat suitability. Two different variables that are not always interchangeable.

In this chapter, I specifically focus on modelling fruit abundance, thus simultaneously focusing on issues of increased barriers to berry harvest highlighted by Gwich'in knowledge holders while developing an understanding of environmental drivers of change in fruit production. I used data, collected in Chapter 2, to explore how well random forest modelling can model mountain cranberry fruit abundance. Additionally, I make the case that the use of similar methodologies can be easily adopted by communities looking to use Geographic Information Systems (GIS) to assess the fruit abundance of local plant populations, and more specifically of mountain cranberry.

3.2 Materials & Methods

Study Area

See "Materials & Methods 2.2"

Study Species

See "Materials & Methods 2.2"

Data Collection

See "Data Collection and Analysis 2.3"

Environmental Layers

A noteworthy change that was made between the climate layers used in Chapter 2 and Chapter 3 is rather than using WorldClim v2.1 (Fick & Hijmans, 2017), I opted to use "Climatologies at High Resolution for the Earth's Land Surface Areas" (CHELSA) dataset (Karger et al., 2017) in Chapter 3. Although the layer variables are the same (Table 4 & 1) CHELSA has been proven to perform at a higher standard in complex arctic and alpine environments (Karger et al., 2017; Bobrowski et al., 2021; Rammig et al., 2020). Additionally, landcover layers, including lichen, water, trees, and shrubs, were all converted in ArcGIS into distance-from variables, as the random forest tool in ArcGIS could not process binary layers.

All other layers remained the same as Chapter 2. Collectively, this resulted in 31 layers used in the model (Table 5). I standardized all spatial predictor layers to a uniform resolution of 30 m, aligned them to a common grid, and reprojected them to the NAD83(CSRS) / UTM zone 8N coordinate reference system. This resampling was done using the R (R Core Team, 2024) package Terra version 1.7-29 in R (Hijmans, 2024). All layers were tested for multicollinearity in raster files using the cor function from the caret package version 6.0-94 (Kuhn, 2008). There was no significant correlation between layers (Kuhn, 2008).

Table 4. List of the 31 layers used to model the likelihood of occurrence of mountain cranberry in the Gwich'in Settlement Area and their source

Category	**Code**	**Layer**	**Source**
Climate			
	Bio 1	Annual Mean Temperature	CHELSA
	Bio 5	Max Temperature of Warmest Month	CHELSA
	Bio 6	Min Temperature of Coldest Month	CHELSA
	Bio 8	Mean Temperature of Wettest Quarter	CHELSA
	Bio 9	Mean Temperature of Driest Quarter	CHELSA
	Bio 12	Annual Precipitation	CHELSA
	Bio 16	Precipitation of Wettest Quarter	CHELSA
	Bio 17	Precipitation of Driest Quarter	CHELSA
	Bio 18	Precipitation of Warmest Quarter	CHELSA
	Bio 19	Precipitation of Coldest Quarter	CHELSA
Soil			
	BD	Organic Bulk Density	Soil Grids
	CC	Clay Content	Soil Grids
	CF	Coarse Fragments	Soil Grids

	N	Nitrogen	Soil Grids
	OCD	Organic Carbon Density	Soil Grids
	PHW	pH water	Soil Grids
	SA	Sand	Soil Grids
	CEC	Cation Exchange Capacity (at pH 7)	Soil Grids
Topography			
	DEM	Digital Elevation Model	Arctic DEM
	AS	Aspect	Arctic DEM (Edited)
	RO	Roughness	Arctic DEM (Edited)
	SL	Slope	Arctic DEM (Edited)
Land Cover			
	NDVI 1	MODIS/Terra Vegetation Indices 16-Day L3 Global	NASA Earthdata
	NDVI 2	MODIS/Terra Vegetation Indices 16-Day L3 Global	NASA Earthdata
	Distance to Trees	Trees	Gov Canada
	Distance to Lichen	Lichen	Gov Canada
	Distance to Water	Water	Gov Canada
	Distance to Wetland	Wetland	Gov Canada
	Distance to Shrubland	Shrubland	Gov Canada
Habitat Heterogeneity			
	DIS	Dissimilarity	EarthEnv
	HO	Homogeneity	EarthEnv

Data Analysis & Model Development

Using ArcGIS Pro (ESRI, 2025) I was able to create multiple variations of random forest models to eventually select the best version that explains the data, choosing the final model based on its accompanying R-squared and MSE values. In the field of habitat modelling, random forests are known for their predictive accuracy and ability to handle many explanatory variables and potential interactions (Fletcher & Fortin, 2018). This modelling algorithm uses multiple decision trees, each giving a classification resulting in the classification having the most votes being the outcome (Fletcher & Fortin, 2018). An important distinguishment between this model and the model in Chapter 2 is that the inclusion of relative units (grams) makes this model an "abundance model" as opposed to a "suitability model". Using the Random Forest Tool, the harvest data, and the open-sourced environmental layers, I was able to create the final model at 30 m spatial resolution.

The first step in the modelling process was selecting which variables to include in the final iteration of the model. The aim was to achieve maximum variation explained, while minimizing the amount of noise created by source layers. To select the top performing model, a standard set of model characteristics was chosen (Table 5), and each model iteration was tested 10 times with 10 different seeds to ensure fairness and accuracy across the model iterations. During this process, 20 % of the dataset (12 data points) was reserved for validation data. This reserved validation data was randomly selected at each iteration.

Table 5. Random Forest Model Characteristics

Model Characteristics	
Number of Trees	100
Leaf Size	5
Tree Depth Range	5-12
Mean Tree Depth	7
% of Training Data Available per Tree	80
Number of Randomly Sampled Variables	2
% of Training Data Excluded for Validation	20

Once a standard set of model characteristics was chosen, I proceeded with a stepwise analysis. Here, I tested a total of 11 different model iterations, each with a different number of predicted variables. Starting with a total of 31 environmental layers, I ran the model 9 times, each time eliminating the three least contributing variables, based on their % contribution value. I then chose the highest performing iteration (Iteration 9, 6 variables), and created two more iterations, one where I removed the least performing variable from iteration 9, and one where I added an additional variable (Table 6). The preferred model was selected based on testing criteria highlighted in Fletcher and Fortin 2018, for assessing the quality of abundance models, namely MSE and R-Squared values.

Table 6. Stepwise methodology, results of MSE, percent of variation explained, R-Squared value, p-value, standard error

Model #	# of Variables	MSE	% of variation explained	R-Squared	p-value	Standard Error
1	31	3633.49	12.36	0.42	0.0569	0.14
2	24	3917.23	17.50	0.44	0.0559	0.12
3	21	3669.20	15.69	0.45	0.0517	0.14
4	18	3853.51	17.50	0.44	0.0343	0.15
5	15	3507.25	20.32	0.44	0.0381	0.14
6	12	3752.53	19.90	0.45	0.0331	0.15
7	9	3615.83	20.88	0.41	0.0408	0.16
8	7	3360.88	21.78	0.47	0.0375	0.15
9	6	3541.27	21.00	0.50	0.0282	0.15
10	5	3428.17	17.60	0.46	0.0427	0.17
11	3	3894.72	13.80	0.39	0.1025	0.17

The model was extrapolated to a slightly different extent than in Chapter 2, as a reduced extent would be more likely to provide a more accurate product for the Gwich'in Tribal Council (GTC). The new model used a distance of 30 km from the furthest north, west, south, and east harvesting locations annotated by knowledge holders to select this study area extent. This ensured that no unreasonable extrapolation was made, while ensuring that predictions still included areas identified as common harvesting locations.

3.3 Results

Model iteration #8 was chosen as the best model, as it provided the most consistent and best relative test scores among all model iterations. This iteration had the lowest MSE value (3360.88) and second highest R-squared value (0.47), both of which are key for assessing the quality of abundance models (Fletcher and Fortin 2018). In addition to these variables, the model also performed well by other standards, with the highest amount of variance (21.78 %) explained and fourth lowest p-value (0.0375). While this was the best performing variation of the model, the statistical results demonstrate room for increased detail.

Model #8 had a total of 7 variables with different contributions, which herein will be referred to as mean temperature of the wettest quarter (21.2%), nitrogen content (18.6%), distance to tree dominated landcover (16.3%), mean temperature of the driest quarter (12.5%), cation exchange capacity of the soil (12.3%), distance to water dominated landcover (10.1%), and Soil pH (pH) (9.3%) (Table 7). Because each model iteration was tested 10 times, the iteration with the highest R squared value, from iteration #8, was the model selected for visualization and further testing (Figure 9).

Table 7. Contribution of Each variable in chosen model variation (Model #8)

Variable	**% contribution**
Mean Temperature of the Wettest Quarter (BIO 8)	21.2
Total nitrogen (cg/kg)	18.6
Distance to Trees (m)	16.3
Mean Temperature of the Driest Quarter (BIO 9)	12.5
Cation Exchange Capacity of the soil (mmol(c)/kg)	12.3
Distance to Water (m)	10.1
Soil pH (pH)	9.3

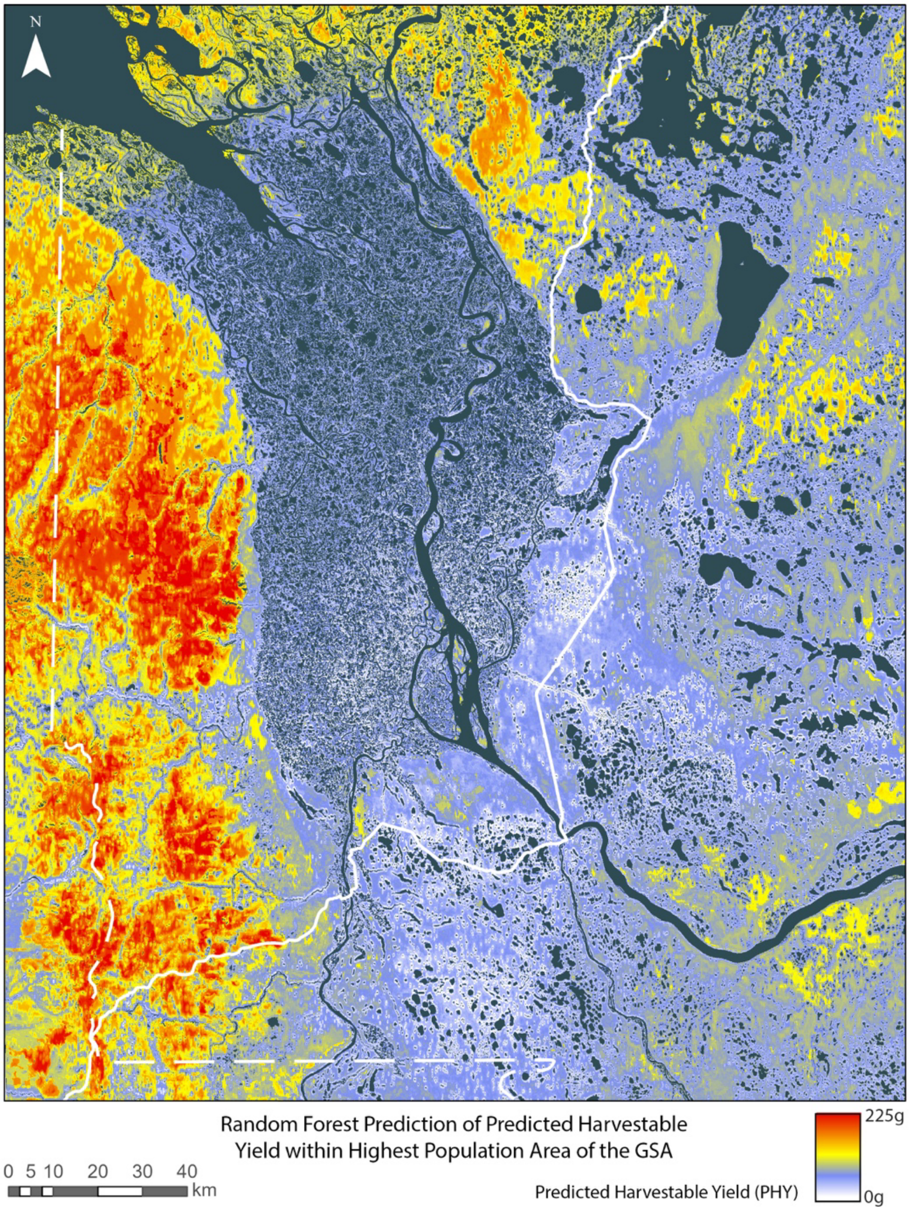

Figure 8. Random forest model predicting the likelihood of mountain cranberry abundance (in grams) across traditionally harvested areas. Predictor variables include cation exchange capacity at pH 7, nitrogen content, soil pH, distance to water and distance to tree dominated ecosystem

Spatial Analysis & Trends

From the outputs given by the ArcGIS (ESRI, 2025) random forest tool, the best performing version of model iteration #8 achieved an average testing R-Squared value of 0.74, doing a reasonable job predicting harvestable yield in grams. This model showed similar correlations to the trends between measured harvestable yields (MHY) and predicted harvestable yields (PHY) for the training and testing datasets (Figure 10). This correlation reflects that in scenarios where measured harvestable was high, predicted harvestable yield was also high, in both testing and training datasets.

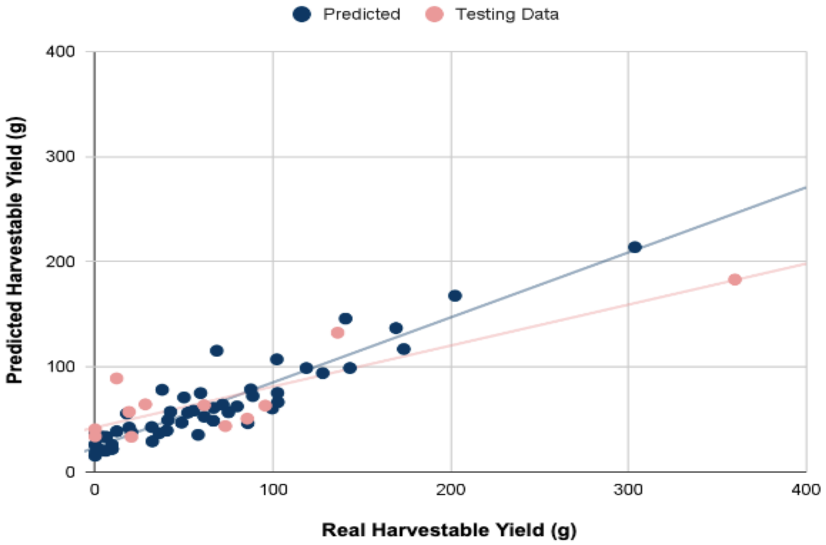

Figure 9. Predicted Harvestable Yield (PHY) plotted against Measured Harvestable Yield (MHY), in relation to both training and testing data

Additionally, the seven key variables highlighted by the stepwise methodology had correlations that were representative of MHY (See Appendix B). The highest amount of correlation was seen in mean temperature of the wettest quarter and lowest was seen in Soil pH (Table 8). In each correlation scenario the model overestimated the strength of relationship between the variables and fruit abundance, possibly suggesting overfitting. This is with the exception of mean temperature of the driest quarter, which was the only relationship where the strength of the correlation was underestimated. These results highlight that there are unexplained variables that need to be explored in greater depth. While these correlations are low, trends of fit direction remain relatively similar (Appendix B).

Table 8. Correlations of environmental variables and measured harvestable yield (MHY) and random forest predicted harvestable yields (PHY)

	MHY Correlation	PHY Correlation
Mean Temperature of the Wettest Quarter (BIO 8)	-0.311	-0.488
Total nitrogen (cg/kg)	-0.131	-0.232
Distance to Trees (m)	0.351	0.530
Mean Temperature of the Driest Quarter (BIO 9)	0.033	0.009
Cation Exchange Capacity of the soil (mmol(c)/kg)	-0.052	-0.097
Distance to Water (m)	0.117	0.234
Soil pH (pH)	-0.009	-0.044

The predicted mean of the model was 87 g while the mean value in the dataset was 62 g. The median value of the raster was 70 g predicted as opposed to a median of 55 g observed in the field. Thorough the raster (approximately 16,000,000 pixels), 9.5 % of pixels were between 0 g and 50 g, 63.3 % were between 51 g and 100 g, 19.6 % were between 101 g and 150 g, 7.2 % were between 151 g and 200 g, and 0.3 % was above 200 g. At the upper extreme of the dataset, the model's maximum prediction was 224 g, which is lower than the dataset’s observed maximum of 360 g however, this maximum was a strong outlier, as the next highest observed values were 304 g and 202 g. At the lowest extreme of the data set, the model did not predict any 0 g values, even though there were five observed values of 0 g. This lack of zero values is not surprising, given random forest outputs are averages of the individual tree outputs. Overall, the model seems to smooth extremes, slightly overestimating the lowest values, and underestimating the highest values.

Relative to ecosystem classification, the pixel value distribution varied across the two main ecosystem types represented in the study area: tundra and taiga. Among tundra sites, the abundance was typically predicted to be higher as opposed to taiga sites which saw a lower prediction of fruit abundance (Figure 11, Table 9). The taiga ecoregion had pixel values that ranged between 12.94 g and 165.44 g with a mean value of 68.26 g, tundra ecosystems had a range between 12.11 g and 223.71 g with a mean value of 111.00 g.

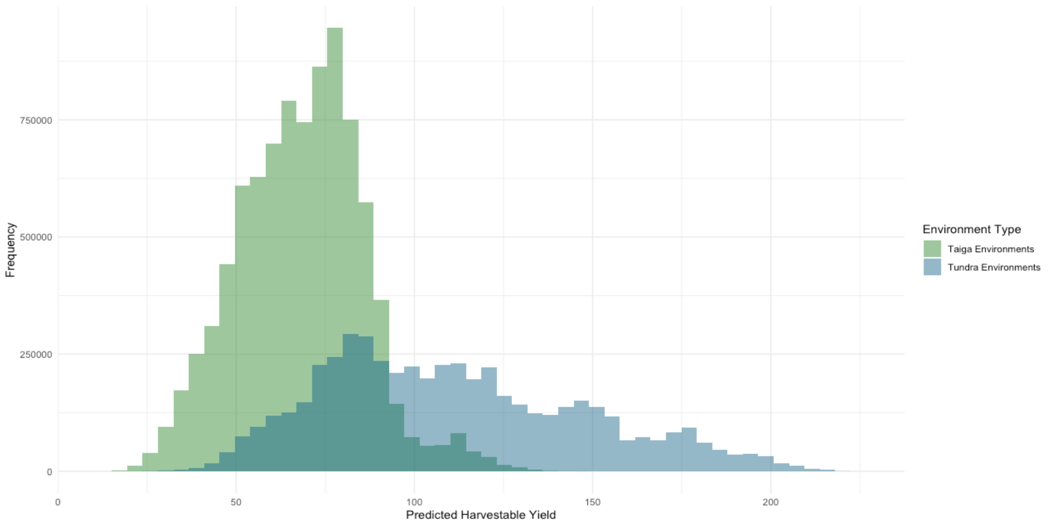

Figure 10. Comparison of predicted harvestable yield distribution between tundra and taiga ecosystems within the study area

Table 9. Details of Predicted Harvestable Yield (PHY) pixels Generated in Random Forest Model

	Total	Min	Max	Mean	Median
Taiga	8801789.00	12.94	165.44	68.26	68.80
Tundra	5149312.00	12.11	223.71	111.00	106.21
Total	15689765.00	12.11	223.71	87.44	79.07

3.4 Discussion

The results from the model were consistent with observations reported submitted in the interviews, where Gwich'in knowledge holders noted that cranberries had high yields in the northern and western extents of the study area. One knowledge holder shared, "You could go here and it won't be that much. Then you go to the border, there's more. But you got to go further, towards the mountain" (Mary-Ann Robert, Fort McPherson, 2023), highlighting the tundra cordillera ecosystem west of Fort McPherson. Similarly, a knowledge holder in Aklavik mentioned, "...right through the woods like a portage, there's a trail that goes… in the flats of Red Mountain, these places are real good for cranberries, there’s lots of good cranberries" (Bob Buckle, Aklavik, 2023), again highlighting the mountainous western portion of the GSA.

The northern extent of the study area, between Inuvik and Tuktoyaktuk, also considered a tundra environment, was highlighted by knowledge holders as ideal for cranberry abundance. This space is commonly accessed via the Tuktoyaktuk Highway, a new development that extends the Dempster Highway northward. Since its development, this area has become popular for harvesting cranberries, "There’s so much cranberries. And, I notice that the cranberries are bigger now. In this day and age, they're really more, twice the size of what I used to pick up on the Peel River. Tuk Highway, yeah" (Sarah Jerome, Inuvik, 2023).

As mountain cranberry are a ubiquitous fruit throughout the GSA, some comments from knowledge holders indicated that mountain cranberry also grows abundantly in tree dominated ecosystems, "Cranberries is mostly low ground where it's nice and dry...what you call it? I usually find them, you find lots on the TCH highway and sometimes you find lots around birch areas” (Jenny Andre, Tsiigehtchic, 2023).

Taiga ecosystems in the GSA are suitable habitats for mountain cranberry. As such many participants mentioned that they harvest in this ecoregion. However, when knowledge holders commented on cranberries in terms of abundance, most comments were directed towards the Northern and Western spaces mentioned (Figure 12). Additionally, despite ecoregion classification layers were not used to create the model, the resulting model matched with delineated ecoregion borders, whereby higher yield areas typically occurred within tundra ecosystems and lower relative yield ecosystems were in taiga ecosystems (Figure 1 & Figure 9).

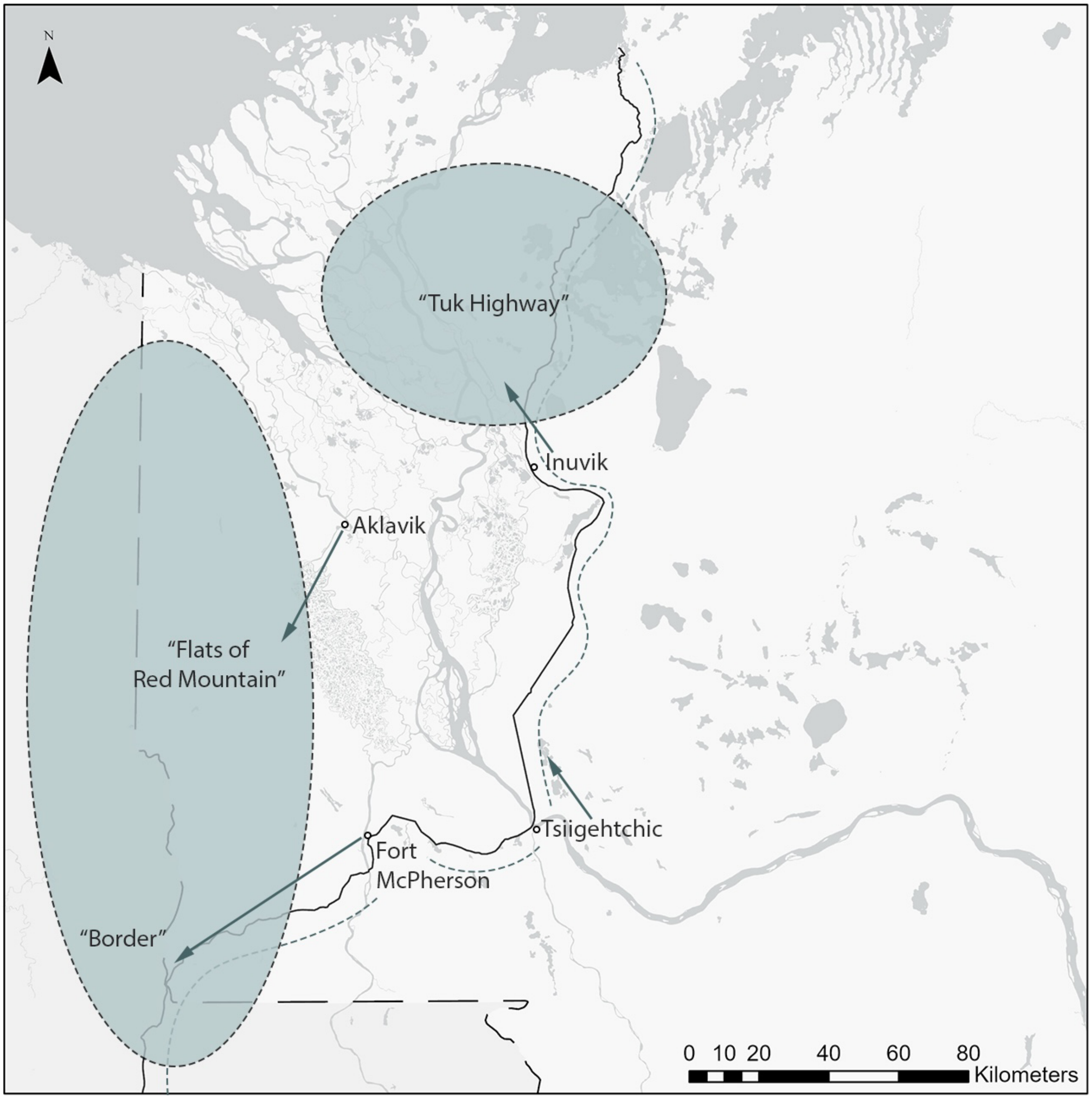

Figure 11. Regions with high reported mountain cranberry abundance based on interview data

Climate

In this study, nine independent climate variables were analyzed, mean temperature, maximum temperature of the warmest month, minimum temperature of the coldest month, mean temperature of the wettest quarter, mean temperature of the driest quarter, annual precipitation, precipitation of the wettest quarter, precipitation of the driest quarter, precipitation of the warmest quarter, and precipitation of the coldest quarter. Two of these variables were particularly significant for mountain cranberry abundance; mean temperature of the wettest quarter, corresponding to temperatures in July, August, and September, and mean temperature of the driest quarter corresponding to temperatures in February, March, and April.

When comparing MHY values to spring temperature values, this study found that there was a weak correlation, where higher abundance values were seen at sites with higher spring temperatures. This relation was similarly replicated in PHY values. Previous studies have emphasized the significance of timing and extent of warming on berry abundance (Mucioki, 2024; Boulanger-Lapointe et al., 2019; Li et al., 2016; Parkinson et al; 2024; Aparaschive et al., 2024). The trend found aligns with research in Labrador which indicated warmer spring temperatures enhance mountain cranberry fruit-set, likely due to increased pollinator activity associated with higher temperatures (Li et al., 2016). This trend, however, may not hold as high of a correlation in this study area because springtime temperatures have a dual effect on abundance. In northern environments, snow accumulation and melt dynamics has been tied with environmental conditions that greatly impact plant growth including, ground temperature, light conditions, growing season timing, and plant access to moisture and nutrients (Rixen et al., 2022). According to Mucioki (2024), large snow drifts provide protection for understory berry plants during the winter, delaying spring blooming and minimizing the risk of frost damage. Unlike deciduous species, mountain cranberry has the unique capability to capture light that comes through snow cover to start photosynthesis early (Lundell et al., 2008). This suggests that prolonged snow cover would be less of a disadvantage to mountain cranberry, as compared to deciduous plants, which do not have leaves at this time (Parkinson et al., 2024). Large snow patches also serve as an essential moisture source for many berry plants during the spring and summer, especially in hot and dry seasons, and protect berry plants from heavy spring winds and rain (Mucioki, 2024). This explains the weak correlation between fruit abundance and high springtime temperatures found in this study. In Li et al., 2016 no late spring frosts were reported, enhancing the correlation in their findings. However, in the study area, fruit abundance likely depends on a more complex relationship with spring temperatures, where lower temperatures offer refuge from frost and increase soil moisture, while warmer temperatures lead to greater pollinator activity and earlier plant phenology.

Mean temperature of the wettest quarter was the second most influential climate-related variable affecting the abundance of mountain cranberry. In the study, locations which experienced lower relative temperatures were more likely to have a higher abundance of berries. I hypothesize that this may be due to several cumulative factors including increased extreme temperature days, water availability, increased competing taller vegetation and altered resource allocation. First, higher summer temperatures are often accompanied by prolonged periods of extreme heat. Temperatures above 25 °C, during flowering, can decrease mountain cranberry fruit-set (Hjalmarsson, 1997; Parkinson et al., 2024). Extreme temperatures can also cause berries to dry up; this was something many knowledge holders noted during the interviews. Summer temperatures can also influence the likelihood of drought and dry soils which has been documented to reduce the growth of mountain cranberry (Myers-Smith et al., 2011; Lou et al., 2022). Severe drought during the flowering season may cause substantial losses of buds, resulting in lower fruit-set (Holloway, 1981; Parkinson et al., 2024). Lastly, a warmer growing season can promote the growth of other plants that outcompete mountain cranberry. Annual radial growth of willows in the Yukon has been explicitly tied with interannual variation in summer temperatures (Myers-Smith & Hik, 2018). Increases in shrubs have been noted to impact mountain cranberries largely due to their limited phenotypic plasticity in height growth (Siegwart Collier, 2020). Increases in shade caused by shrubs can lower the number of flowers produced and delay the peak flowering date (May et al., 2022). Further, increases in shading and decreased temperature caused by shrubs can reduce pollinator activity (Parkinson et al., 2024; Siegwart Collier, 2020). These cumulative impacts of higher summer temperature are all likely to play a part in the correlation seen in the data.

Soil

Of all the soil variables tested, results indicated that cation exchange capacity (at pH 7), nitrogen availability, and soil pH were the strongest indicators of mountain cranberry abundance. Mountain cranberry can often be found in soils that have low fertility and little calcium, but may be high in decaying organics (Holloway, 1981; Trajkovski, 1978; Tirmenstein, 1991). Additionally, soil type can range from drained peat to shallow poorly developed mineral soil (Tirmenstein, 1991; Kardell, 1986; Ritchie, 1955). These facts stress why, in this study, sites with lower relative cation exchange capacity were correlated with greater abundance of fruit-set. Findings suggest that mountain cranberry thrives in soil that has lower nutrient value.

Mountain cranberry is known for its ability to thrive in harsh environments, like those in the study area. The roots of the study species host ericoid mycorrhizae fungi, which have a symbiotic relationship with mountain cranberry. This relationship aids the plant in pulling nitrogen and phosphorus from its soil (Sharifi et al; 2024; Parkinson et al., 2024). By focusing on slow growth, root development, and symbiotic relationships the Vaccinium genus has adapted well to nutrient-poor and acidic soils (Sharifi et al., 2024). Although mountain cranberry is well adapted to extracting nutrients from poor soils, this does not necessarily indicate a preference for such conditions. Instead, this may be more indicative of reduced vegetative competition in areas that are nutrient poor.

In this study, there was a weak negative correlation between mountain cranberry and concentration of soil nitrogen. Past nitrogen fertilization trials in mountain cranberry populations in Finland have shown up to three times increase in berry yield. However, when broad-leaved competing plants were present in the habitat, no increase was observed (Karlsons et al., 2021; Lehmusovi, 1977). Other studies have noted that artificially added nitrogen can cause 14 % to 24 % increases in fruit yield (Chester and McGraw, 1983; Sharifi et al., 2024). Although there has been noted evidence of how increased availability of nitrogen in soil can enhance the yield, shoot growth, and population of cranberry plants, it has been proven that excessive fertilization may favor vegetative growth over fruiting and be harmful to populations which are adapted to low nitrogen causing reduced growth, poor root development, and potential increase of invasive species (Sharifi et al., 2024; Trajkovski, 1987; Holloway 1981; Ingestad, 1973). Nitrogen has an impact on the cold adaptability of plants, which should increase their ability to withstand stresses from early frost increasing overall health of the plant (Martinussen, 2009; Nestby et al., 2010; Aparaschive et al., 2024). Although higher nitrogen values typically mean higher fruit abundance in lab studies, the results do not show the same trend in this study area’s outdoor tundra and taiga ecoregions. Nitrogen is a critical limiting factor for growth in most tundra ecosystems (Elser et al., 2007; Tamm, 1991; Xu et al., 2021). As a result, there is high competition between plants and microorganisms for the limited supply of bioavailable nitrogen (Kuzyakov and Xu, 2013; Xu et al., 2021). The high amount of competition seen in limited nitrogen areas, along with mountain cranberry’s specialized symbiotic relationship to thrive in nitrogen poor areas demonstrate factors that contribute to a complex relationship between nitrogen, plant growth and fruit abundance. Although past studies have indicated that nitrogen contributes to higher fruit abundance, the findings here indicate that slightly more fruit can be harvested in areas with less nitrogen. This insinuates that the relationship between nitrogen and mountain cranberry fruit is likely dependent on additional factors in the study area, such as competing vegetation.

The final soil property highlighted by the stepwise methodology was soil pH. In the study area acidity usually ranged between 5 and 6 pH with two outlier sites that were more acidic. There was a weak correlation where more acidic sites commonly had more fruit. Mountain cranberry has been recorded surviving in soils ranging from pH 2.7 to 8.2 but growing best at pH 4.0 to 4.9 (Hall & Shay, 1981; Holloway 1981; Jeglum 1971; Tirmenstein 1991). Similar results were found in Slovakia and Estonia, where favorable conditions ranged from a pH of 3.5 to 4.5 (Šimala, 2004; Paal, 2006; Vilkickytė & Raudone, 2021). Despite the consensus that mountain cranberry prefers acidic soils, the ideal growing pH is still up for debate. An in-greenhouse study showed that for the most volume growth and biomass growth a pH of 6.5 is optimal (Sharifi et al., 2024). However, since this study took place with controlled settings, presence of competing vegetation was not evaluated. Although ideal pH for berry growth is debated, researchers recognize that pH is an important factor that, when in the optimal range, enhances cranberry plant health by increasing the availability of nutrients and improving overall growth (Sharifi et al., 2024; Tirmenstein, 1991; Vilkickytė & Raudone 2021).

Land Cover & Topography

The resolution of the raw data for landcover and topography variables assessed in the study ranged from an original resolution of 250 m to 2 m and were either upscaled or downscaled to a resolution of 30 m. The inclusion of high-resolution variables likely increased the accuracy of the model by picking up on land heterogeneities that may have been otherwise missed. These land cover and topography layers were often not as specific as the climate and soil layers, however, they were helpful in increasing detail of in-situ conditions. This was apparent in the distance to trees variable which was the 3rd most contributing variable (16.3 %). This was a useful layer as it was able to provide a proxy for several environmental conditions that influence cranberry growth such as light availability, microclimate, habitat structure, and soil nutrient conditions. Specifically, this layer indicates the potential presence of competing vegetation. In succession sense, cranberry is known to outcompete and invade tundra bog and cottongrass/tussock communities. After colonizing these environments spruce stands begin to form (Tirmenstein, 1991). Once established, cranberries often remain unless shaded out by conifers (Hall & Shaay, 1981; Tirmenstein, 1991). Shade has a complicated and poorly understood relationship with cranberries (Tirmenstein, 1991). Knowing that shade from spruce can influence the abundance of berries, it brings justification to distance to trees being the third most contributing variable. This is not to say that berries did not grow in tree ecosystems but rather, they were more abundant in ecosystems with less trees. Treed ecosystems also may be more prone to infilling from shrubs, which also have an impact on soil moisture (Niittynen et al., 2023).

Distance to water was the other landcover variable that was included in the model, contributing 10.1 %. Despite the contribution, it is difficult to determine a single factor that causes distance to water to be a leading factor in cranberry abundance. This is due to the complexity of this environmental variable, which has repercussions in soil moisture, pollinator activity, herbivory patterns, and the formation of microclimates. In general, water availability is a key determinant of plant productivity, with studies showing that moisture stress reduces cranberry stem and root biomass (Lou et al., 2022). The influence of distance to water may, however, vary across ecosystems. The taiga region, which contains more lakes and wetlands, may benefit more from proximity to water than tundra regions, which rely on different hydrological dynamics such as permafrost maintaining higher water tables (Natali et al., 2015). This environmental layer likely captured microclimates which coarser climate variables overlooked. In boreal environments, bodies of water can moderate local temperature due to their thermal buffering properties. In some cases, this can extend growing seasons through by warming soil and delaying freezing (Aalto et al., 2022; Yang et al., 2012). Additionally, pollinator presence, which is shown to be greater in mesic than xeric soils (Culjak-Mathieu, 2021), can be more concentrated near water sources, potentially boosting fruit-set. Lastly, water-adjacent areas may also have an impact on the type of tree cover in the area, influencing shade properties. In this study, it was found that locations further away from bodies of water typically had higher MHY. A hypothesis from these results is that the relationship between distance to water and fruit abundance is not inherently linear in our study area. Instead, this relationship correlation is more related to ecosystem classification, where tundra ecosystems had more MHY and less large bodies of water. This, however, is a complicated relationship that requires further research.

By focusing the modelling efforts on mountain cranberry fruit-set abundance as opposed to biological range or other growth variables such as shoot length or chemical composition, this chapter was able to take a plant community-driven approach to species distribution modelling. The results create relevant representations of cranberry fruit abundance that are specific to Gwich’in food sovereignty and traditional harvesting practices, adding to literature concerned with how environmental variables drive the abundance of mountain cranberries.

Through this research I advocate for new methodology to be explored in the field of species distribution modelling as it relates to fruit bearing country foods and the priorities of Indigenous communities. I found, specifically, that employing the use of random forest modelling connected to variables deemed important by knowledge holders, such as fruit abundance, can be more accurate and culturally significant, than simply modelling range. This is backed by other studies which have found that abundance modelling often leads to a more reliable and expandable product when compared to presence-absence models (Howard et al, 2014). The primary rationale for this being that presence-absence models treat all presence points at equal value, as opposed to abundance models which have a weighted value for each presence point (Howard et al, 2014; VanDerWal et al., 2009). Considering the context of the study, the results would have fared much differently if a presence absence model was employed rather than an abundance model. Out of the 60 study sites observed, 57 had the presence of mountain cranberry. However, this did not mean that these sites were equal since there was a large range of harvestability at each site (320 g to 1 g). If all 57 points had been treated as equal, the model would lack relativity and have different outcomes. This increased accuracy helped to simultaneously locate regions that have the highest abundance in fruit while assessing the environmental variables that make this so. As Gwich'in knowledge holders and northern academics are fearful of the impacts of climate change on this species, assessing the variables and regional context influencing the growth of mountain cranberry can inform strategies for mitigating the impacts of changing climates on landscapes. For instance, mitigation strategies could include the use of snow fences to increase snow cover (Mucioki et al., 2024) or improving access through initiatives such as food distribution programs or free harvesting tours.

The negative side of this methodology is that IK was not incorporated in presence data. By looking at a comparison between Chapter 2 and Chapter 3 results, it is clear that the evaluation is inverted. In Chapter 2, high RIO is typically closer to community centers, while in Chapter 3 high abundance is predicted further into tundra environments. In Chapter 2, high RIO is typically closer to community centers, while in Chapter 3 high abundance is predicted further into tundra environments. The original goal of the GTC was to create a distribution map of mountain cranberries across the region to facilitate land assessment. Chapter 3 offers the better answer to their question; however, if data from interviews were not screened, this could imply that berries only grow in areas further from communities. These more productive areas may actually be the less important spaces to community members as accessibility holds a lot of value in harvest location selection. So, in the scenario of land assessment, it would be key to have both SDM and context, which in this case would indicate that most of the land in the study area is suitable habitat for mountain cranberry and important for harvest purposes.

3.5 Conclusion

By focusing on fruit abundance as opposed to other variables such as species presence, biomass, shoot length, etc. this methodology was able to be tailored to what people in the GSA care about, mountain cranberry as a food source. Furthermore, abundance modelling as a whole is considered a more robust structure than presence/absence modelling, because the entry data is more specific (Howard et al, 2014; VanDerWal et al., 2009). For mapping a species that is ubiquitous across the land, it was beneficial to be able to differentiate high relative abundance vs low relative abundance. This is opposed to mapping presence as it was observed that it is rare for cranberries to be absent. This data performed well under conventional testing, but as we know from Chapter 2, this is not always the greatest indicator of how well a model performs. By including some context from interviews as well as information from literature, the analysis became grounded in the regional context as opposed to only being validated through statistics. In future studies, using an approach that incorporates interview data as validation would enhance the detail of validation efforts, making methodologies more comprehensive and regionally focused. In addition, to being tailorable, this methodology also gave an idea of the environmental impacts of certain environmental variables affecting the growth of mountain cranberry, which could lead to management solutions if taken into consideration.

4.0 Discussion & Conclusion

4.1 Key Findings

A clear example of including IK in decision-making is by applying Indigenous insight in species distribution models (SDMs), which is one of the most popular methods for qualitatively assessing species range (Lefebvre et al., 2018). This is a subject that has minimal research but has the potential to be impactful in the fields of land use planning, environmental assessment, and food sovereignty (Baumflek et al., 2015). While these methodologies show promise, certain aspects require refinement to become reliable and consistent approaches.

Through practice, this research has delved into the subject matter regarding methodologies that are currently in place which merge IK and SDM. Although Chapter 2 added to the literature regarding the status of mountain cranberry in the Gwich'in Settlement Area (GSA), most of the findings from this work pertain to the meaning of harvest data and methods for better inclusion in SDM process.

Chapter 2 highlighted the complexity and richness involved in working with traditional harvest points drawn on paper maps. At the beginning of this study, it was assumed that these annotations may represent the high abundance of a species. However, in this case, they indeed represented much more complexity than simply ecological presence. This difference has a lot to do with annotations of harvest locations, which at their core represent the nexus of human-plant relationships. The difference between harvesting locations and species occurrence creates discrepancies when a modeler and harvester have different aims. The modeler may be aiming to depict species range, while harvester is annotating values that include more substance than solely species occurrence. In such, it can be argued that more care needs to be implemented in the SDM space when utilizing socio-ecological information to ensure that results suit the needs of the communities whose information is being incorporated into analyses. More broadly, this illustrates the scientific fallacy of assuming lack of bias. Something that ecological modelers have the potential to bring in this type of research.

The compatibility of multiple different features (polygons, points and lines) within the same participatory mapping study is an area that requires more in-depth study (Brown & Pullar, 2011). In this case, the data supplied by the Gwich'in Tribal Council (GTC) was annotated for a previous study, which did not require that data be compatible with SDM methodology. In many ways, using different mapping features during participatory mapping can be positive as it has potential to allow participants to internalize different map scales for different place values (Brown et al., 2017). The tradeoff that was found here was non-uniformity of the dataset and the need for a Geographic Information Systems (GIS) technician to process the data, increasing the potential for dilution of IK. In addition, this work also highlighted the different meanings of feature types used during the participatory mapping process. As such it is important to understand the contextual meaning of feature types such as, polygons, points, and lines to not dilute the value of the information. Through validation sessions, it was acknowledged that lines were typically indicative of paths commonly traveled to harvest, and points represented specific locations where harvesting occurred. Polygons, however, represented more complex ideologies with a range of meanings. For instance, polygons could be annotated because 1) the area has high amounts of mountain cranberry abundance; 2) it is a large area that are traveled until harvest locations are found (similar to line annotations); 3) it is an area with specific locations, but trust played an issue, and the participant did not wish to describe specifically their harvest locations; 4) the base maps may not have been detailed enough to locate a more specific points; 5) the compatibility was not explained well enough, and people instinctually drew polygons; and 6) other compatibility issues that has not been considered. This begs the question of the best way to convert lines and polygons into point data.

Currently, most methods for polygon conversion generalize polygons through randomization, which we found in this study to be problematic.

Utilizing this as a case study, community mappers can better understand what a polygon has potential to represent and cater their methodologies to better suit the product desired by the community, avoiding the incompatibilities highlighted in this text. Increased recognition that polygons are less compatible with analysis methods such as SDM, may encourage participatory cartographers to explore strategies to ensure that data are more usable by the communities they are mapping for, saving time and resources for the community. If strategies recommended in this text were implemented, polygons could be retained for forward-facing data that preserves the detail polygons offer, while point data could be used for data analysis that is in high demand by communities.

The meaning of annotations did not strictly pertain to the physical characteristics, such as environment, but also has social dimensions, such as proximity to community. Exogeneous mechanisms can influence spatial dependence and further results and interpretation (Fletcher & Fortin, 2018). In Chapter 2, it proved difficult to utilize IK in the form of presence points to interpret habitat suitability. This is a result of the ubiquity of mountain cranberry in the GSA. Although many participants travel far on the land, more data points were annotated closer to community centers (Table 2). This difficulty is further exacerbated, because harvesting is not always done as a sole activity, it often takes place during other activities such as hunting or fishing (Singer et al., submitted; Parlee et al., 2005). Although modelling showed that taiga ecoregions areas are typically less suitable habitats for cranberry abundance, these areas are more accessible and still render significant yields. As a result, the tested study area was not suitable for presence-absence modeling using the data supplied by the GTC, as what was being mapped was not a relative index of occurrence but rather a relative index of occurrence of sites suitable for harvest. Some methodologies could be taken to try and attempt to quantify and overcome this spatial dependence, such as variograms, kriging, or manipulating the study area extent (Fletcher & Fortin, 2018), however the results of the area under the curve (AUC) test in Chapter 2 assed that a new approach should be taken. In Chapter 3, I chose to utilize classic methods in abundance modeling to gauge the variability between the two techniques.

Chapter 3 demonstrates how, in this case, abundance modeling offered a more robust solution to understanding habitat suitability of mountain cranberry in the GSA. However, in doing so, it also highlighted the blind spots that arise when western methodologies are used in isolation to assess meaningful biological range of a culturally significant species. Management decisions can become problematic when model outputs are treated as equivalent to quality land-use locations, without also considering the social and cultural values identified by knowledge holders. This could be exemplified by the difference between fruit abundance and good harvesting locations. Although models can incorporate certain social or cultural data, they cannot fully capture the human significance of particular locations. As such, models should be seen as supportive tools rather than definitive indicators for environmental decision-making. These blind spots seem to be concrete example of how western methodologies such as traditional modelling efforts, which have been critiqued by academics for their lack of inclusion of IK, have the potential to lead misguided management solutions (Gadamus et al., 2015).

Using information from interviews, literature, and testing data. I was able to validate the model in terms of how well it explains mountain cranberry fruit-set abundance within the GSA. Through this analysis, I was able to isolate variables that were important to fruit-set abundance in the region, information that could be used by planners who wish to try techniques to increase yield in times of food crisis. At the beginning of this work, one of the core objectives was to create an accurate habitat suitability model of mountain cranberry. However, upon working with interviews and analyzing the spatial data, it has come to attention that habitat suitability may not be the most important variable for safeguarding food security in the GSA, but rather accessibility. In doing so, this highlighted the need to increase community centered methods in both spatial analysis and decision-making.

Although this should be apparent to researchers and industry, some participants expressed that this data analysis does not express consultation. This concern was raised to address the issue that if a map highlights important areas, developers may take that as an opportunity to plan development in areas that are deemed "less important" by this methodology. As such, it is important to note that this analysis does not represent consultation but rather a tool to be used by the GTC as a means for enhancing food security in the region. When comparing the blind spots highlighted in Chapter 2 and Chapter 3, the importance of consultation efforts becomes apparent. The first model was limited in predicting suitable habitat, and the second model was limited in predicting where people harvest most often. The limitations of both results call to attention the need for contextual decision making that includes IK. During validations sessions, participants often asked if they could circle the entire map, implying that everything is important and every area is utilized. Therefore, a mapping technique trained to indicate low and high value is limited in this scenario.

4.2 Implications

This study demonstrates that the methodologies used in this type of analysis must be chosen carefully and, on a case-by-case basis, catering to the specific needs of the partners involved (Drawson et al., 2017). Maintaining context is key to avoiding misinterpretation of IK and illfitting policy (Gadamus et al., 2015; Ellis et al., 2005; Nadasdy et al., 1999). Certain practices, especially those relating to respectful engagement, should be at the core of studies exploring similar methodologies to those discussed in this paper. Part of this is recognition of the complexity of the data and the careful considerations required to ensure meaningful and accurate outcomes. It should be clear that much needs to be considered to render an accurate result. As such, more resources need to be allocated to this field of study to compensate for its intensive and time-consuming process. More resources would enable more Indigenous communities, who would benefit from this methodology, to engage with it.

Relevance offers a core guiding principle when fusing SDM with IK, as objectives must be centered around community values (Baumflek et al., 2015). In this case, the community value was berries which are known to hold incredible cultural value in the North. Knowing that the fruit is more widely used than the plant, I made methodological choices which centered fruit abundance as the subject for this study. For example, fruit abundance is a more meaningful variable as opposed to stem length, leaf count, or biomass. By focusing on fruit, I made a product that predicts harvestable yield, a variable that addresses issues of food access. Although this is just one example of a choice made, it demonstrates how small choices can have big implications for communities, and why it was essential that every decision is made intentionally.

In addition, some methodologies arose that should be approached with care. Part of improving this process is through robust participatory mapping practice that takes a best practice approach to inclusion. Mappers should remain mindful of how communities may wish to utilize this data in the future and take precautions to ensure the data remains versatile to meet community needs. This does not necessarily mean that data must be framed in a strictly scientific context, as it could also involve creating maps as communication tools, where artistic or culturally relevant cartography is just as important.

Acknowledging the limitations that come with modeling IK can help limit the production of incomplete or misleading results. Furthermore, the general capability of the field of environmental modeling needs to be communicated, as modeling is strictly an interpretation, not a direct representation of real data (Nordstrom, 2012). Additionally, priorities and capacities within Indigenous communities vary, which can influence desired end products. As a result, methodologies from one study should not be directly copied to another.

The two methodologies displayed in this text have promise as modelling efforts which include the use of IK in SDM. IK has been used as presence points, notably successful in both Baumflek et al. (2015) and Campbell et al. (2022). These proved useful methodologies because the species were either rare or understudied, limiting the use of other data collecting techniques. This study's experience with this methodology resulted in an analysis with considerable human bias. This was likely because of the ubiquity of the species and may not have been so problematic if the species was rarer.

Chapter 3 offers a better representation of fruit abundance but did not include IK in its development. Although this model can accurately predict productive sites, it could lead to misguided results if not grounded in interview data. Chapter 3's methodology may be a more viable technique when looking through a resource lens, being that harvest would be more productive in areas with higher abundance, but regarding country food access this methodology is less valuable. As such, abundance modelling of country foods, such as berries, may be a beneficial technique if the Indigenous governance group is seeking more precise understanding of the food resource, however, less so if they are seeking to protect locations people harvest. This methodology requires in-field surveying which may be difficult and expensive if the area is remote or expansive. In study areas where surveying is accessible, collecting data directly may be the most practical and time-sensitive solution, especially when paired with interview data, which can provide important contextual value. While methodologies should meet the different needs of different community partners, they must always be grounded in a community context (Drawson et al., 2017).

4.3 Limitations

During this research, I used environmental layers that are applied in other studies and are considered global standards for species distribution modeling (Hamilton et al., 2024; Hirabayashi et al., 2022; Karger et al., 2017; Bobrowski et al., 2021; Rammig et al., 2020). These layers are often used in large-scale and global datasets, and in many SDM scenarios must be downscaled to correctly depict species occurrence (Meineri & Hylander, 2017). Supplementing models with smaller-scale layers is one way to downscale the model and make it more relevant for localized areas. While these layers were suitable for mapping cranberries in Canada in other studies (Hamilton et al., 2024; Hirabayashi et al., 2022), they have limitations in accurately representing spatial areas in the North. Global climatic datasets are known to be less accurate in regions that have deficient or unevenly distributed network of weather stations. This can be highly problematic for SDMs in landscapes with major climatic extremes, where species distributions are mainly shaped by climate (Morales-Barbero & Vega-Álvarez, 2018). Because of the shortage of region-specific GIS data in northern Canada, geographers are forced to work with a limited selection of environmental resources, which, in turn, can decreases the accuracy of their models. Furthermore, many of the available datasets are multi-year composites and do not reflect a single point in time. For example, the temporal resolution of layers ranges from 16-day NDVI data to 30-year climate normals from CHELSA and Bioclim. This issue could be addressed by developing more specific and up-to-date environmental layers for northern regions, which ideally could be created in collaboration with Indigenous communities. This study also attempted to create two models at a resolution of 30 m. Given the varying scale of the original environmental layers used in this model, it may have been more appropriate to model at a less fine resolution (250 m). Despite this, it was positive to test the viability of a 30 m resolution with the best possible data sets, as 250 m would be much less valuable to the GTC.

In addition to the limitations present in both models, there were specific constraints that prevented a direct comparison between the MaxEnt modelling in Chapter 2 and the random forest modeling in Chapter 3. The MaxEnt model in Chapter 2 was created using R (R Core Team, 2024), while the random forest model in Chapter 3 was developed in ArcGIS (ESRI, 2025). The choice of software dictated the outputs that were available. Because I used R to model MaxEnt, certain outputs, such as those used in the stepwise analysis in Chapter 3, were not easily accessible. These outputs may have been available had the MaxEnt Java software been used instead of MaxEnt in R. Consequently, it resulted in not applying the same stepwise approach used in Chapter 3 to the MaxEnt results in Chapter 2.

Further, there were slight differences in the study area sizes. The study area in Chapter 2 was larger than that in Chapter 3. This adjustment was made following analysis of the initial results, which led this study to reevaluate the spatial extent to produce a more dependable outcome for the GTC. This change was made to improve local relevance, not with the intention of comparing models. Furthermore, some environmental layers were substituted, specifically, BioClim climate data was replaced with CHELSA datasets, based on their improved accuracy and suitability for northern regions (Karger et al., 2017; Bobrowski et al., 2021; Rammig et al., 2020). While these differences limit direct comparison between results of Chapter 2 and Chapter 3, a standardized study area and equal set of environmental layers could hypothetically make such comparisons feasible in future research.

Beyond the limitations encountered in the modeling and comparison processes, there were also constraints in the field survey itself. The survey was conducted over six days, during September 2024. While cranberries tend to remain on the plant into the winter (Parkinson et al., 2024), the timing of the survey could have influenced in-field observations. For example, tundra environments may have retained berries longer due to cooler conditions, making them appear more abundant in September compared to areas in the taiga. Additionally, the survey was limited to areas accessible by road. While this is not necessarily a major issue, as it aligns with an accessibility focused approach, it does not fully capture the range of harvest access. In the region, people also travel by boat and ATV, so road access alone does not provide a complete picture of accessibility. The surveying method itself, as mentioned, was prone to inconsistency, however the positive aspect of surveying more in less time made it the best method.

Lastly, and perhaps most importantly, as previously mentioned, the western methods used in some ways dilute IK. As a result, there is a fundamental limitation in that the story being told about mountain cranberry, harvesting practices, and the meaning of space within the GSA, which can never be entirely captured by this research. This work represents only a small aspect of what was shared and cannot fully portray the richness or depth of the full story.

4.4 Future research

As mentioned, past efforts to fuse IK and SDM have been criticized for utilizing IK as supplementary (Campbell et al., 2022). This is a consequence of IK being additional, as opposed to central. Historically, Indigenous people have been subject to research often without benefiting from that same research (Drawson et al., 2017). Research that does not robustly include Indigenous perspectives often lacks community involvement and results in data that is unusable by communities (Drawson et al., 2017). Future research in the field of exploring collaborations in IK and species distribution modelling should continue to explore new ways of including IK in their methodology. Specifically, this study has shown that there is room for improvement in this process, both in terms of community usability and community engagement.

Authentically meaningful Indigenous research methods should incorporate Indigenous perspectives in every step of the process, "from the conception of the research question through knowledge translation and exchange." (Drawson et al., 2017). By simply including IK as a single step in the SDM process, just the observations, a researcher is not necessarily fusing IK but rather utilizing it for a single quantitative purpose. Chapter 3's traditional abundance modelling technique had community context interwoven since its start (i.e., modelling fruit abundance); however, IK was not thoroughly used until validation. In this way, this study's efforts could also be seen as supplementary.

This thesis demonstrates that each choice during the SDM process should not necessarily be inherent when engaging in an Indigenous research framework. Community needs ought to be central in each of these decisions, and by "adapting methods in order to meet Indigenous community expectations," methods can better incorporate Indigenous values, beliefs, and ways of knowing (Wilson, 2001). This thesis showed that this is possible regarding IK fused with SDM, from the community mapping process to the modelling methods. As such, future research should aim not just to include Indigenous knowledge in their methods but rather to centralize it at each step.

I believe that SDMs will not be authentically created with IK until each part of the process is produced using IK. Attempts at this have been made (Gryba et al., 2025), which offer a promising step in the direction of adding Indigenous knowledge at each step, from model creation to validation.

Knowing this, I believe that there are two paths future research may be able to take in this field. First, researchers should continue to explore completely new spatial methodologies that authentically centralize IK, unbeholden to the bounds of traditional Western methods. Second, researchers should continue to fuse IK in SDM if community partners express a want for such a project and the situation is fitting. Although this text showed that the process has the potential to have blind spots, with thorough investigation that is context-specific, a robust analysis can be produced that benefits community.

In all, future research regarding the use of IK in ecological spatial decision-making may be promising as long as scientists continue to maintain the integrity of exploring the needs of Indigenous communities, build relationships, respect the intricacy of IK, and aim to decolonize the research sphere.

6.0 Appendences

Appendix A.

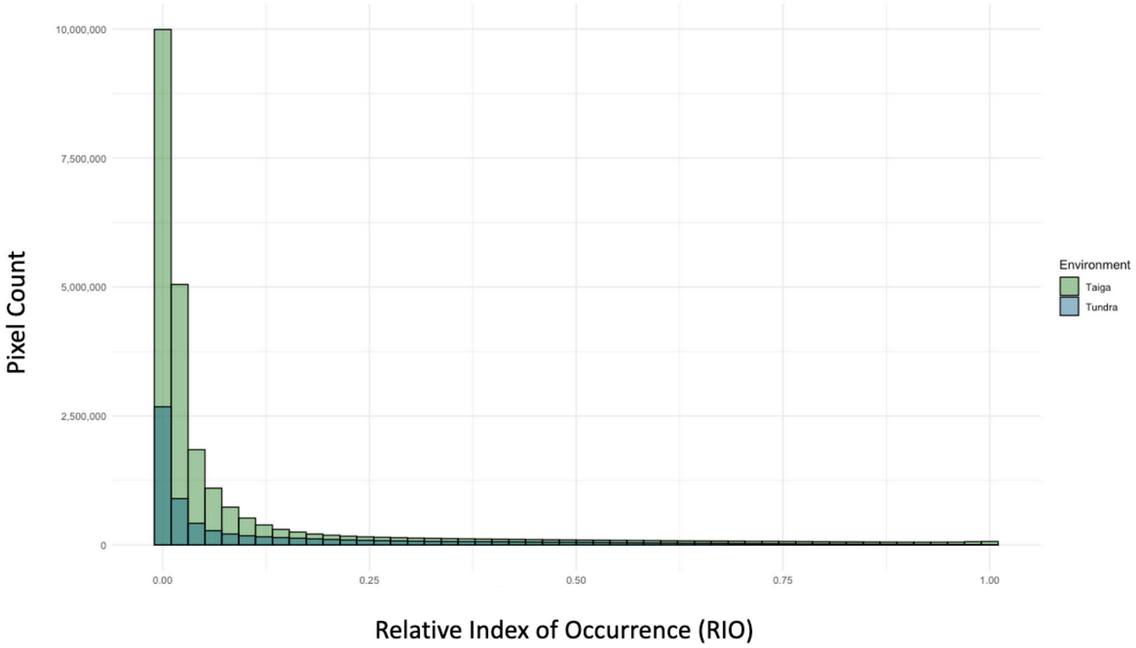

Figure A. 1. Difference in pixel distribution value for MaxEnt raster between taiga and tundra ecosystems

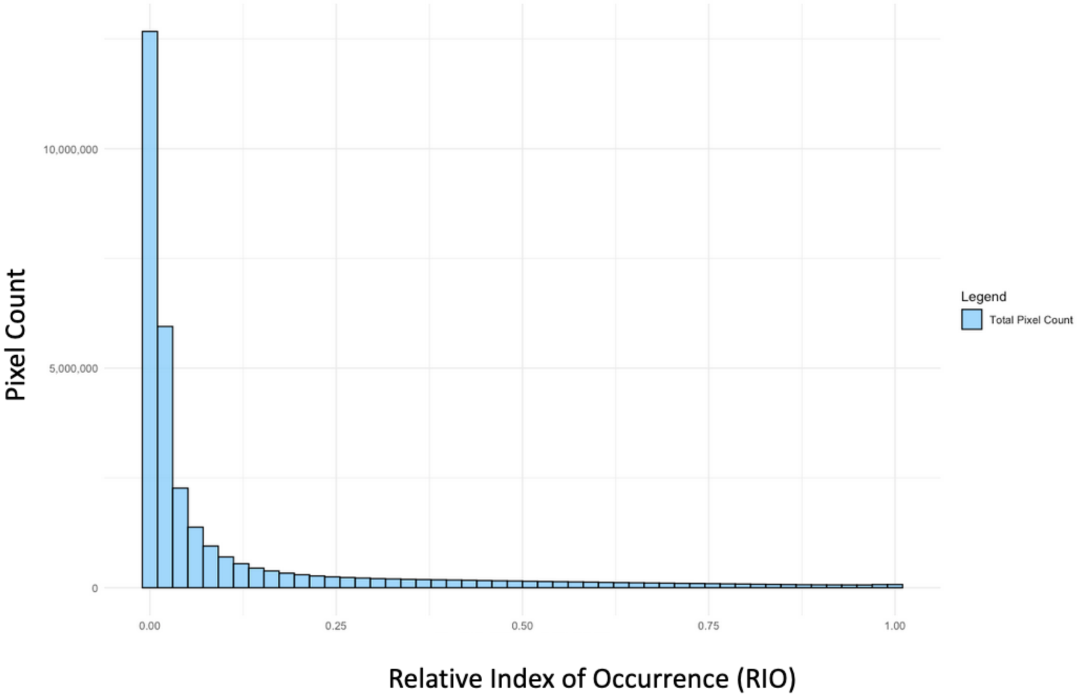

Figure A. 2. Total pixel distribution for MaxEnt raster including both taiga and tundra ecosystems

Appendix B.

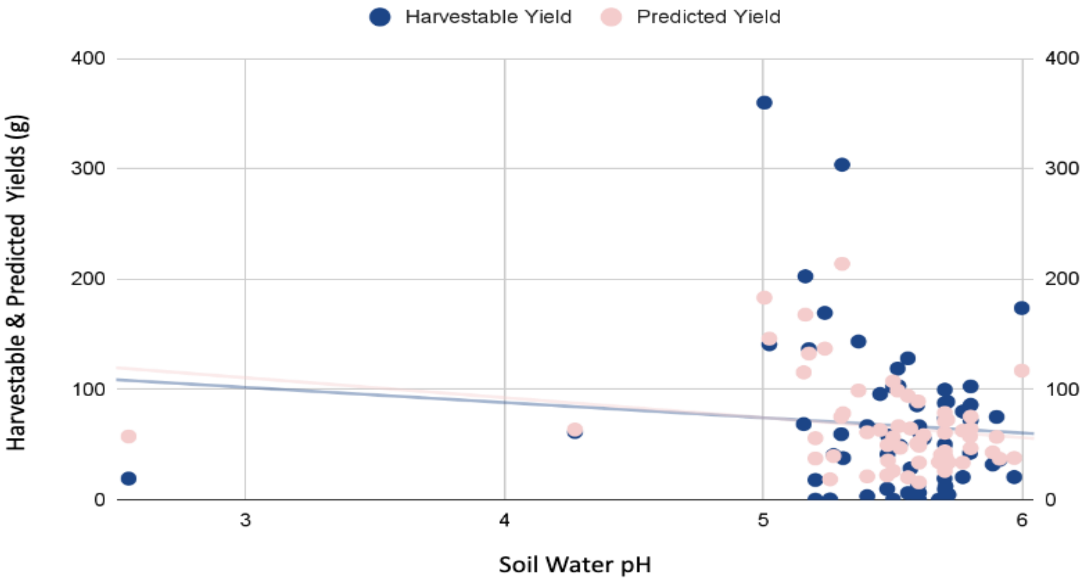

Figure B. 1. Comparison of predicted harvestable yields (PHY) from random forest model and measured harvestable yield (MHY) at the same location as they compare to soil pH

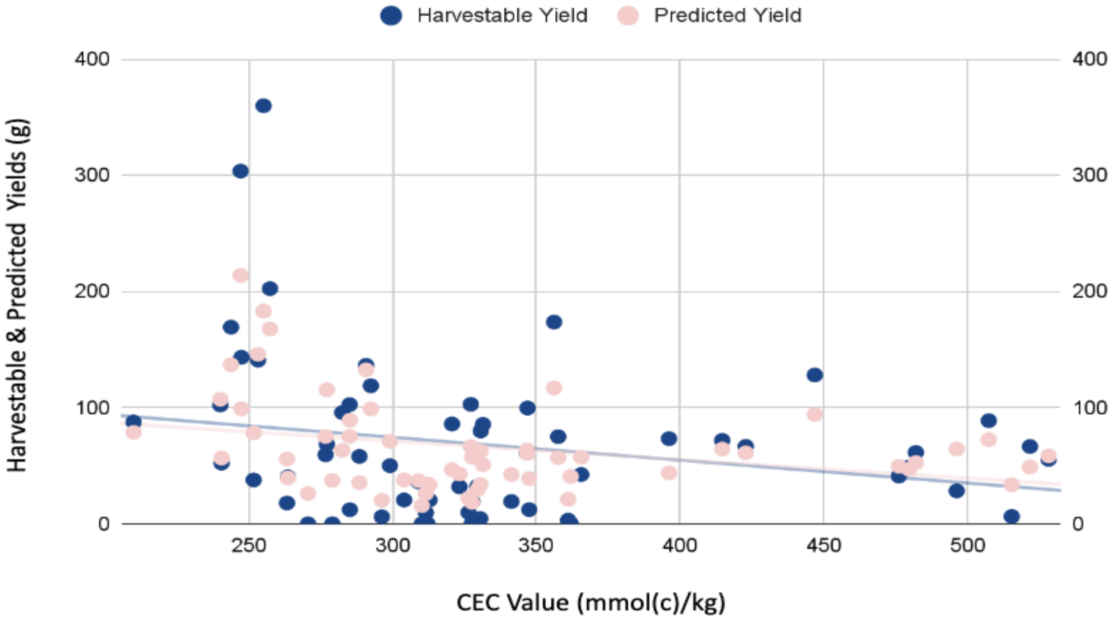

Figure B. 2. Comparison of predicted harvestable yields (PHY) from random forest model and measured harvestable yield (MHY) at the same location as they compare to cation exchange capacity of the soil

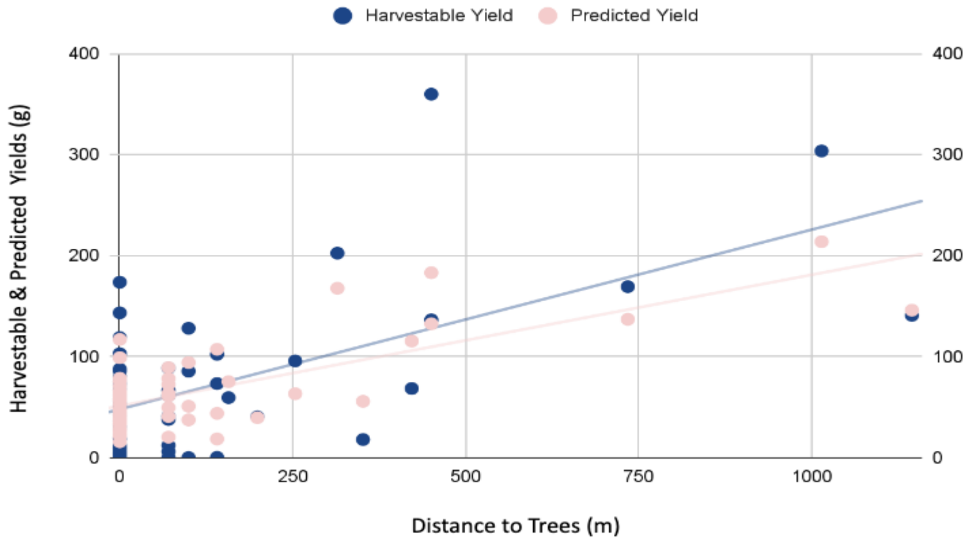

Figure B. 3. Comparison of predicted harvestable yields (PHY) from random forest model and measured harvestable yield (MHY) at the same location as they compare to predominantly treed landcover

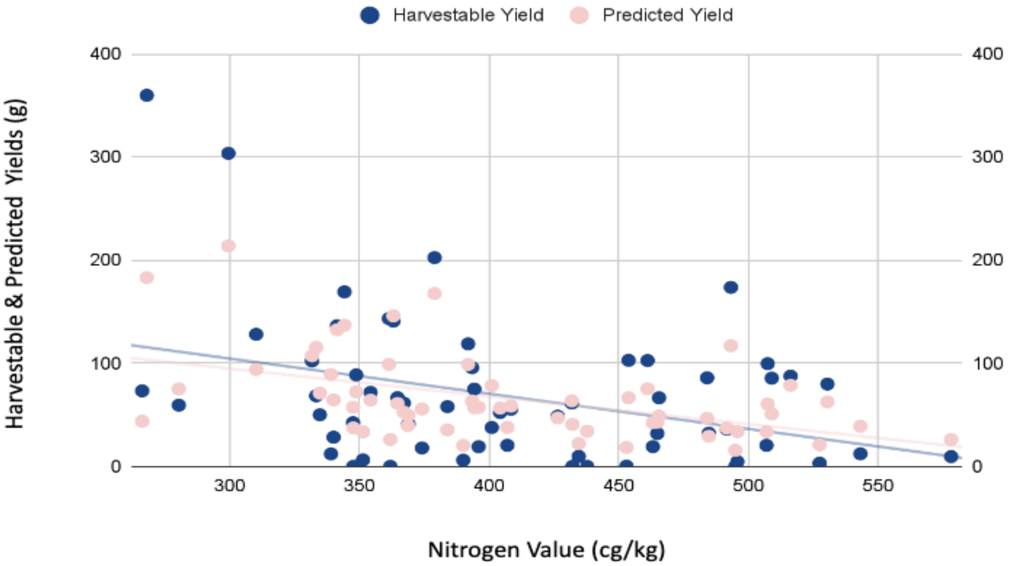

Figure B. 4. Comparison of predicted harvestable yields (PHY) from random forest model and measured harvestable yield (MHY) at the same location as they compare to soil nitrogen concentration

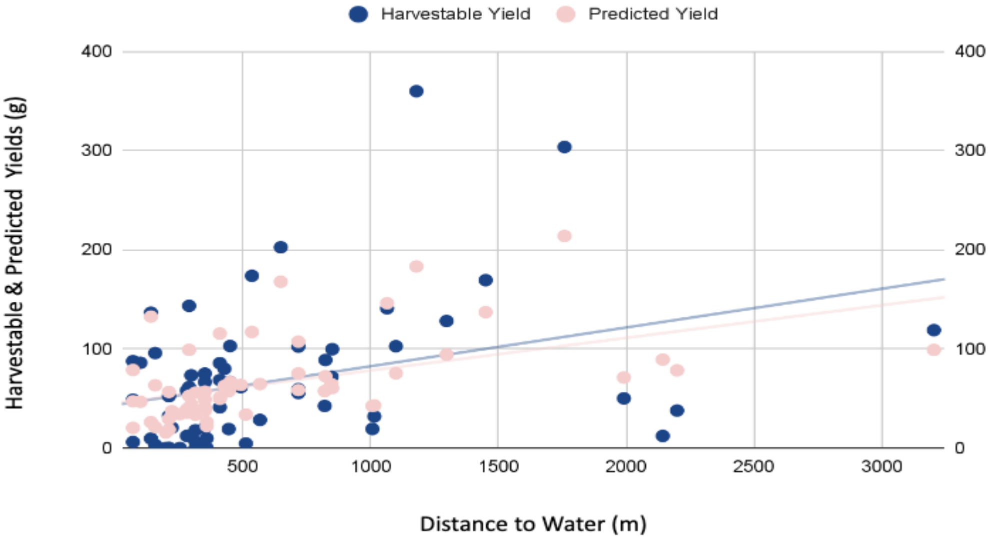

Figure B. 5. Comparison of predicted harvestable yields (PHY) from random forest model and measured harvestable yield (MHY) at the same location as they compare to water dominated land cover

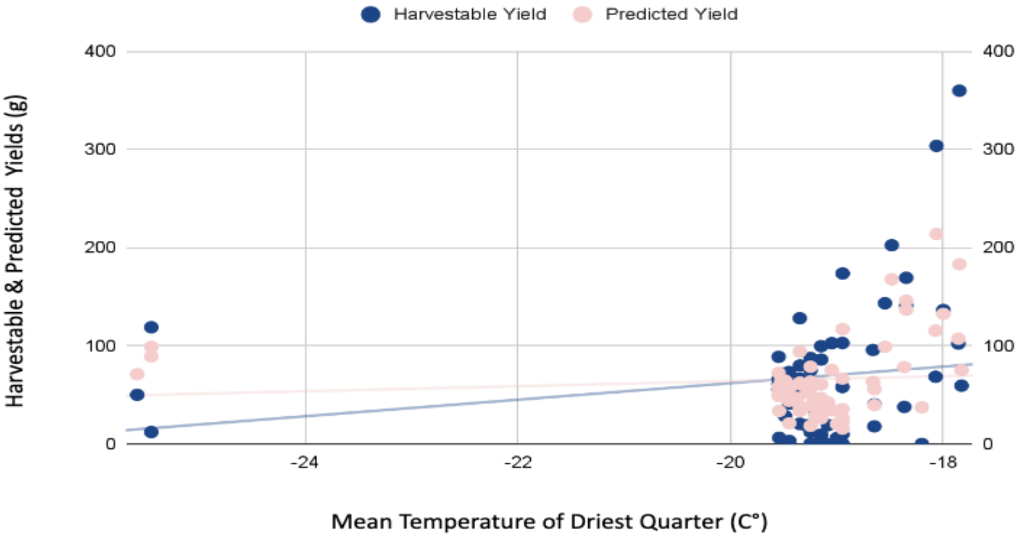

Figure B. 6. Comparison of predicted harvestable yields (PHY) from random forest model and measured harvestable yield (MHY) at the same location as they compare to mean temperature of the driest quarter

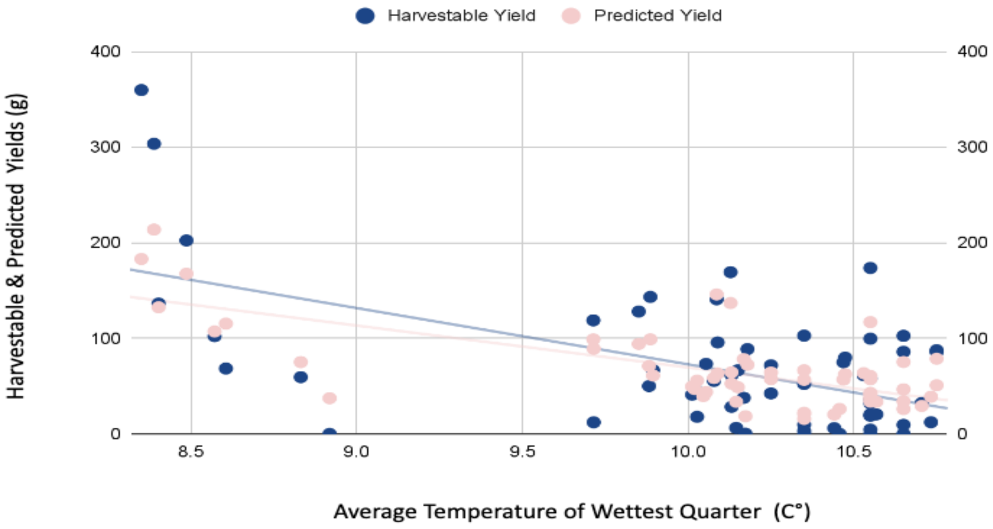

Figure B. 7. Comparison of predicted harvestable yields (PHY) from random forest model and measured harvestable yield (MHY) at the same location as they compare to mean temperature of the wettest quarter

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