Mississaugas of the Credit First Nation, Anishinaabeg Ethnobiology: Burial Sites and Biodiversity

by

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Submitted in partial fulfilment of the requirements
for the degree of Master of Science

at

Dalhousie University
Halifax, Nova Scotia
November 2022

Dalhousie University is located in Mi'kma'ki, the ancestral and unceded territory of the Mi'kmaq. We are all Treaty people.

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Abstract

The present study provides a language-centered approach to a meta-analysis of Anishinaabe ethnobiology, and a burial mound detecting image recognition algorithm under the guidance of Anishinaabe place names. Ferrier lab collaborated with Mississaugas of the Credit First Nation, who is seeking to revitalize their culture, to make an attempt in understanding the Anishinaabe traditional way of living a good life through the lens of ethnobiology. Through quantitative study and possibility study, and intentional ambiguity to keep intellectual property within MCFN, traditionally used species are ranked. An image recognition algorithm was trained with maps retrieved from the Ontario Digital Terrain Model in TensorFlow, and successfully found ground elevation sites that are shaped like burial mounds. The study supports MCFN defending their land and water against proposed Highway 413 through data analysis, and will be used in protecting other culturally sensitive places.

Keywords: Indigenous, ethnobiology, meta-analysis, image recognition, burial mound

List of Abbreviations Used

ANN	Artificial Neural Network
CI	Cultural Importance Indices
CNN	Convolutional Neural Network
DCI	Disease Consensus Index
DSM	Digital Surface Model
DTM	Digital Terrain Model
ebDB	International Ethnobotany Database
MCFN	Mississaugas of the Credit First Nation
NishDB	Anishinaabe Ethnobiology Database
ON-DTM	Ontario Digital Terrain Model
R-CNN	Region Based Convolutional Neural Networks
ReLU	Rectified Linear Units
RFC	Relative Frequency of Citation
SSD	Single Shot MultiBox Detector
UV	Use Value
YOLO	You Only Look Once

Glossary

Anishinaabe[1]	(adjective, singular noun animate) a person; an Indigenous person; an Ojibwe person. Ojibwe.
Anishinaabeg	(plural noun animate) Anishinaabe people.
Anishinaabemowin	(noun inanimate) Anishinaabe language.
Anishinaabewaki	(noun inanimate) Anishinaabe land, Anishinaabe territory.
Manidoo	(noun animate) a manitou, a spirit, god.
Mashkiki	(noun inanimate) medicine, physical medicine.
Mishiibizhiw	(noun animate) an underwater panther, a great panther.
Peshinaaguining	(proper noun) Grand River, ON. Literally, "the one that washes the timber down and carries away the grass and the weeds" (Jones, 1796)

[1] All references of Anishinaabemowin on this page is from O, 2021.

Statement

Aaniin boozhoo. Zonghua nindizhinikaaz.. Baangi etaago Anishinaabemowin. Ninga-kagwejitoon ji anishinaabemoyaan. Nindoonjibaa aniibiishaaboo-aki (China). Kjipuktuk (Halifax) nindaa. Miigwech. Nii'kinaaganaa.

Hello, welcome. Glad to have you here. My name is Zonghua and I am from the tea country (China). I came to Kjipuktuk, Mi'kma'ki in 2019 as an international student to study food science. My whole family is from China and I am the only person who is currently abroad. My grandparents come from four different provinces and my parents are from different cities. I was born in a hyper-industrial city called Shijiazhuang. My grandpa told me my city was a turnip field 20 years before I was born. Because of this, I often feel like I grew up in a place that does not have much history; even my mother tongue is Mandarin Chinese, an artificially standardized language, which is usually not the case considering how rich our regional dialect diversity is in my homeland. I developed a retaliatory interest in traditional Chinese medicine and plant taxonomy as a response to the lack of nature and traditional culture around me. When I finally grew up and inserted myself into a pharmaceutical university, I was sad to find out our people are stripping the traditional knowledge out of our own medicine and only "validate" the plants through western science. Because we still carry the trauma of being pillaged, our own people still believe that since the colonizers were strong, we must ditch our culture to adapt to them. As a traveller to the Turtle Island (North America), I have observed a similar yet opposite side of the story: people are still battling and suffering from active colonization. I see Mississaugas of the Credit First Nation put "survived near extinction and a complete loss of culture" in the introduction of their community (MCFN, 2019 April 29). I see grieving of culture loss, but never admitting defeat; on the contrary, I see knowledge keepers and language teachers take on the responsibility even when they are still young and scared. I see my future in their way of teaching, learning, and surviving. This is the reason I do the work I present to you today. There are unavoidable human bias; I acknowledge the bias and see it as part of my relation to this study.

In this study I seek *Mino-bimaadiziwin. Mino-bimaadiziwin* can be translated as "the good life." *Mino*- is a preverb meaning good, nice, well. *Bimaadiziwin* means life, containing *bimaadizi*- and -*win* (noun forming final). *Bimaadizi* means (singular animate) she/he is alive, and consists of *bim*-, -*aad*-, -*izi*. *Bim*- is an initial meaning along in space or time and by, for example *bimose* "s/he walks along," *bimaaboode* "it drifts along on the current." -*aad*- means way of being or life; or one's character or nature. For example, *nookaadad* "it is soft, mild," *gizhewaadizi* "s/he is kind, is generous." -*izi* is a final meaning s/he is in such a state or condition, for example *biinizi* "s/he/it (animate) is clean."

D'Arcy Ishpemingenzaabid Rheault (1999) explains *Mino-bimaadiziwin* in following words:

> Mino-bimaadiziwin: The Way of a Good Life. In order to have a good He one must have a goal. This goal is to be free from illness, to live to the fullest. Bimaadiziwin is based on a concept of health and good living. One must work on prevention and not only healing. It is a Holy Me. One must eat well, act well, and Live physically, mentally, emotionally and spiritually well. Emotional well-being is a key to Bimaadiziwin.

A good life of an Anishinaabe contains well-being in a range of directions which can be roughly divided into physical well-being, mental well-being, emotional well-being and spiritual well-being. While mental, emotional and spiritual health are equally important, in this paper we are focusing in physical.

Physical well-being of Anishinaabe people contains traditional food, material and physical medicine culture. The clothing, food, dwelling, transportation, physical medicine, industrial work life, art and entertainment material and methods of Anishinaabe people from 1853 to 1998 are recorded in ethnographic reports and standardized with the Economic Botany Data Collection Standard (Cook, 1995).

Acknowledgements

My most sincere gratitude goes to Dr. Suzanne Budge, Paula Colicchio, Dr. Jen Frail-Gauthier, Dr. Sophia Stone, Michele Graveline, and Sulia'n Johnson, for helping me through the hardest time. And all my lab friends: Jessie Olson, Dianne Watkins, Susanna Zhang, Rahmah Ullah, Kate McElroy and Meera Baskaran. You helped me survived a place where a female Chinese international student is not necessarily always appreciated, and gave me courage to fight my own way out. I cannot imagine my life or the project without each and every one of you.

I would like to give a huge thank you to my supervisor, Dr. Jonathan Ferrier, for the support during my MSc program. Dr. Ferrier guided me through the constant changes coming from the pandemic. I would like to express my gratitude to Councillor Veronica King-Jamieson and members of the Mississaugas of the Credit First Nation, for supporting this project and welcoming me as a guest. I would also like to thank my supervisory committee, Dr. Gianfranco Mazzanti and Dr. Patrice Côté, who provided advice and guidance to the research project, and always be there for me.

I acknowledge the Social Sciences and Humanities Research Council for the financial support of this project.

Finally, thank you to all my family and friends, and all who supported this project.

Chapter 1 Introduction

1.1 Thesis Overview

In this study I discuss Anishinaabe ethnobiological culture linguistic heritage and its relationship with biodiversity in MCFN and Anishinaabewaki.

The thesis is divided into four (4) chapters including the current chapter. Chapter 1 provides a general introduction of Mississaugas of the Credit First Nation, the people I am studying with. It elucidates the relationship Mississaugas of the Credit have with biodiversity and draws on consensus knowledge MCFN has with other Anishinaabe communities. Chapter 2 discusses the relationship between Anishinaabeg and other species, and pictures who their relatives are through quantitative studies. This chapter establishes an Anishinaabe ethnobiology database and performs quantitative studies on traditionally used plants and fungi species. Multiple research methods are applied on the established database, such as amount of use reports, use value, relative frequency of citation, and Bayesian analysis. Chapter 3 discusses where the culturally significant burial site is, and how that relates to chapter 2. The traditional territory, defined as the places their relatives live on, are indicated by where their ancestors are buried. I analyse ground elevation through LiDAR-derived digital terrain model and train an image-classification model for burial mound identification, and finally apply the model on a map. Chapter 4 summarizes the study and offers insights into future research, followed by references and appendices.

1.2 Objectives

The objectives of this research work are:

A) To analyse Mississaugas of the Credit First Nation ethnobiology database with quantitative research methods and establish a standardized protocol;

B) To identify potential burial mound(s) along Peshinaaguining, traditional territory of Mississaugas of the Credit, with LiDAR-derived digital terrain model and deep learning methods.

1.3 Background and Literature Review

1.3.1 Mississaugas of the Credit: The Name

Mississaugas of the Credit First Nation (MCFN) is a Mississauga Ojibwe Anishinaabe First Nation. MCFN as a community has survived through near extinction and a complete loss of culture, faced trials and tribulations that have come with facing the Canadian government and those now occupying their traditional territory (Mississaugas of the Credit First Nation, 2019 April 29). The Ojibwe (Ojibway, Ojibwa, Chippewa) are an Anishinaabe people who live in what is now referred to as southern Canada, the northern Midwestern United States, and Northern Plains. “Ojibwe” is frequently taken as meaning “to pucker” (Densmore, 1929). Keewaydinoquay, an Anishinaabe medicine woman, states the name is “originally derived from *Ojibbeweg*, Writing-on-Birch-Bark” (1998). The Anishinaabeg, meaning plural Anishinaabe people, are a group of culturally related Indigenous peoples present in the Great Lakes region. There are different understandings of what the word “Anishinaabe” means. Some of the explanations include: “The-People-Who-Came-From-the-Place-Beyond-Where-the-Sun-Rises” (Keewaydinoquay, 1998). “The man who was lowered (from the sky)” or “man who is from a lower place", from an(i)- "away" + niisin "lower her/him" + naabe "a male of a species" (O, 2021). "Original people", from anishinaa "first, original" + naabe "a male of a species" (O, 2021). Anishinaabe ontologies are "non-human centered" and "devoid of hierarchy", as Dolleen Tisawii'ashii Manning (2017) states.

1.3.2 Anishinaabemowin: The Language

Mississaugas of the Credit speak an Eastern dialect of *Anishinaabemowin* (Anishinaabe language). The traditional writing system of Anishinaabemowin is *anishinaabewibii'igan*, meaning "something written in Anishinaabe" (O, 2021). Anishinaabewibii'igan can refer to the body of Anishinaabe writings found as petroglyphs, pictographs, on story-hides, and on *Mide-wiigwaas*, the *Midewiwin* (Grand Medicine Society) *wiigwaasabakoon* (birch bark scrolls) (O, 2021). Since these contents are usually considered sacred, the language is severely damaged by colonization (Angel, 2002). Peter Albinger has curated an incomplete and ongoing list of Anishinaabe pictographs in Ontario (2013-2022). Within the pictographs Albinger surveyed, some common contents include Thunder beings, Mishiibizhiw, Manidoo, caribous, snakes, turtles, sturgeons, beavers, moose, bears, people, canoes, water, etc. These pictographs out-live vandalism (Albinger, 2022) and keep records of Anishinaabeg relationships with their fellow dwellers on the land pre-contact, and describe biodiversity of Anishinaabewaki in different times.

The most commonly used Romanized spelling system for Eastern dialect of Anishinaabemowin is the double vowel orthography, attributed to Charles Fiero (Indoojibwem!, 2011; Burnaby, 1985). Another common Eastern dialect orthography is Nishnaabemwin with vowel syncope phenomenon (N, 2018), meaning some of the vowels are not pronounced or written. Anishinaabemowin is a polysynthetic language, meaning languages in which words are composed of many morphemes. A morpheme is the smallest meaningful lexical item in a language (Masbejosite, 2017). Being highly synthetic makes Anishinaabemowin word order and sentence structure relatively free (G, 2001).

Anishinaabemowin is a verb-based language. Being verb-based means there is a lot of verbal morphology in this language (prefixes, suffixes, conjugated tenses, and a wealth of other information encoded into verbs,) but very little for nouns; base words or roots are typically verbs, and noun forms often have to be expressed by adapting a verb or using a phrase (Native Languages of the Americas website, 2015). An important part of the verb conjugation in Anishinaabemowin is animacy (G, 2001). Animacy is a grammatical and semantic feature which expresses how sentient or alive the referent of a noun is. Some animate nouns are animals, people, spirits and manitou beings, trees, and celestial bodies (O, 2021). Animacy of a noun frequently reflect the relationship between Anishinaabeg and other life forms, and gives direction of highly valued biodiversity.

1.3.3 Aki: The land

MCFN is located 25 kilometres north from the shore of Lake Erie. Their traditional territory is shown in Fig. 2.1., reference to MCFN's Treaty Lands & Territory map (Mississauga of the Credit First Nation, 2019c).

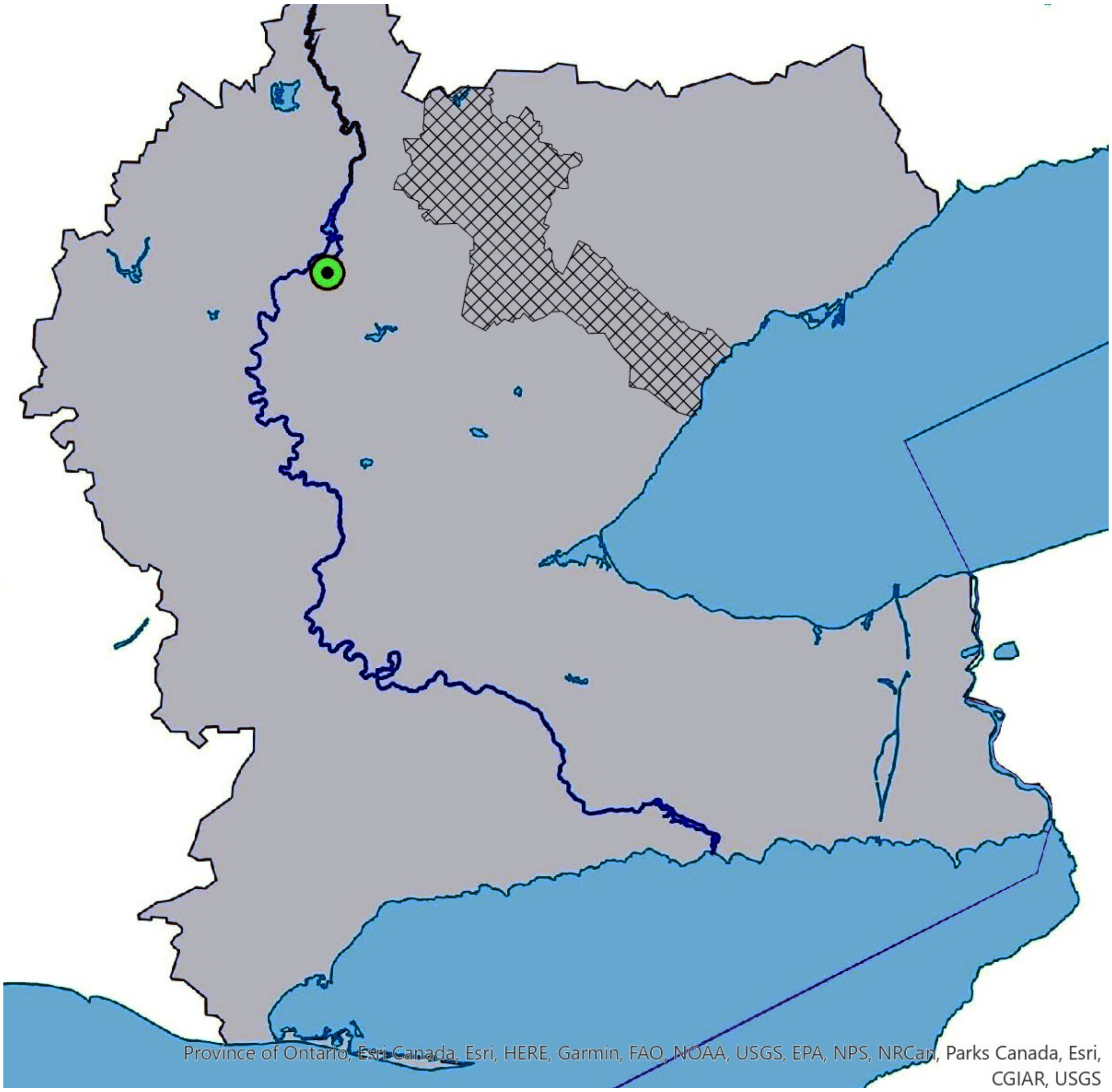

Fig. 1.1. Mississauga of the Credit traditional territory (shaded), Credit River watershed (Crosshatch), Peshinaaguining and Eramosa Burial Site highlighted (reference to Ontario Hydro Network (OHN) - Small Scale Cartographic Products)

Written records of Ojibwe migrations and settlements trace back to pictographs. These pictographs are recorded on rocks (Ferrier, 2022), regalia (Catlin, 1845), and books (Copway, 1850). The first known written record to identify and locate the Mississaugas by settlers is in 1640s (Mississaugas of the New Credit First Nation, 2021). As an aftermath of the 1600s Beaver Wars, after the Haudenosaunee retreated to their homeland south of Lake Ontario, the Mississaugas negotiated a peace treaty with the Haudenosaunee Nation circa 1695. Upon returning from these negotiations, the Mississaugas decided to settle permanently in southern Ontario. One large group established themselves in the valley of the Otonabee or Trent River, along Lake Ontario and the St. Lawrence up to Brockville; a second group established themselves to the west, in an area between Toronto and Lake Erie. This latter group are the direct ancestors of the present Mississaugas of the New Credit First Nation (Mississaugas of the New Credit First Nation, 2021). This group of Mississaugas were regularly involved in the regional fur trade, thus the river along which the trading post is established is known as Credit River, and this group of Mississaugas are referred to as Mississaugas of the Credit by Europeans (Mississaugas of the New Credit First Nation, 2021). The Credit River is recorded and translated by Augustus Jones (1796) as Missinnihe, "the trusting creek". Later Basil Johnston transliterated the name as Mazinigae-zeebi, "to write or give and make credit" (Smith, 2013). The American Revolution War led the British royal attempted to purchase the required land from the Mississaugas of the Credit. In 1781, Col. Guy Johnson, British Superintendent of Indian Affairs, met with Mississaugas of the Credit Chiefs and purchased a strip of land four miles wide along the west bank of the Niagara River from Lake Ontario to Lake Erie in exchange for 300 suits of clothing (GeorgiaL, 2019a). On May 22, 1784, Col. John Butler was sent to negotiate the sale of approximately 3,000,000 acres of land located between Lakes Huron, Ontario, and Erie for £1,180 from the Mississaugas of the Credit. This is referred to as the Between the Lakes Treaty (GeorgiaL, 2019c). By 1800, the territory of Mississauga of the Credit was referred to as the "Mississauga Tract" from Etobicoke Creek to Burlington Bay (Heritage Mississauga, 2018). The validity of these early "land surrenders" by the Mississaugas of the Credit is also questionable on other grounds. The Mississaugas understood these agreements very differently from the colonial government (Mississaugas of the New Credit First Nation, 2021). The British saw land as a commodity and thought they were purchasing land or rights to land once and for all; while the Mississaugas conceived of their relationship to the land in spiritual terms. They did not believe that land could be "sold," or that their rights to use land and access resources for food and living could be absolutely and permanently signed away (Jones, 2009). In 1805, the Mississauga and the British Crown signed Treaty 13, known as the Toronto purchase (Mississaugas of the New Credit First Nation, 2017). The treaty granted exclusive rights to fisheries for the Mississaugas in the Twelve Mile Creek, the Sixteen Mile Creek, the Etobicoke River, and the Credit River (Mississaugas of the Credit First Nation, 2019a). However, by the early 1840s the Mississaugas of the Credit realized that their ability to make a living at their settlement on the Credit River was in danger, and it was clear the community needed to relocate to an area less directly disturbed by Euro-Canadian settlement. In 1848 the Mississaugas accepted an offer from the Six Nations to establish a new settlement on a tract of land situated in the southwest portion of the Six Nations Reserve, the Confederacy offered to the Mississaugas, as a gift, 4,800 acres in Tuscarora Township (Jones, 2009). Later, in 1865, the Mississaugas asked for and received an additional 1,200 acres in Oneida Township. Both lands are in the area where the Between the Lakes Treaty was referred to. The relocated community became known as the Mississaugas of the New Credit First Nation (Mississaugas of the Credit First Nation, 2019b). The Mississaugas eventually purchased the land gifted as well as an additional 1,200 acres for a sum of $10,000 on June 15, 1903, for the all-time right of undisturbed use and occupancy of the land (Mississaugas of the Credit First Nation, 2019b). On January 8, 2019, the

Mississaugas of the New Credit announced that they would rename as The Mississaugas of the Credit. A detailed timeline has been curated by Margret Sault (Sault, 2019).

Table 1.1 Brief timeline of MCFN (Sault, 2019).

In the beginning	Creation stories, pictographs
1600-1700	Mississauga migration
1690s	Three Fires Confederacy formed
1695	Mississaugas recognised as the owners of southern Ontario lands
1781	Niagara Treaty
1784	Between the Lakes Treaty
1787	Toronto Purchase; no land description
1796	Augustus Jones' land survey published
1805	Treaty 13 (Toronto Purchase) taken again; granted exclusive rights to Mississaugas' fisheries
1840s	Unrest at the Credit; decide to relocate
1848	Received 4,800 acres in Tuscarora Township as gift from Six Nations. New home called Mississaugas of the New Credit
1865	Requested additional land, received 1200 acres in Oneida Township
1903	$10000 paid to Six Nations for all-time right of undisturbed use and occupancy of the land
2019	Rename as Mississaugas of the Credit

Chapter 2 Anishinaabe ethnobiology meta-analysis

2.1 Introduction

Ethnobiology is an area of consensus research that provides context and inspiration to culturally relevant frameworks of lifelong learning amongst communities. Community-engaged learning is a way to nurture the local use and understanding of native medicine, food systems, and cultural materials. Community-engaged learning in an equal and respected partnership with local Indigenous communities, is crucial in re-conceptualizing ways of knowing in Western educational institutions (Judge, Fukuzawa, & Ferrier, 2021).

2.1.1 Quantitative analysis methods in ethnobiology

There are existing statistical analysis methods on ethnobotany, usually focused on pharmacognosy studies. However, few quantitative studies have been performed on Anishinaabe ethnobiology. The existing statistical analysis can be crudely categorized into three categories: use report analysis, citation analysis, and probability analysis. The parameters are defined as Cultural Importance Indices (CI), and are thoroughly discussed by Tardio & Pardo-de-Santayana (2008). Following are some examples:

a. Use report analysis: Use value (UV) ranks plants according to how many times a taxonomic group, usually a species, is mentioned of certain usage. This index is modified by Phillips and Gentry (1993) and recently used by Hussain et al. (2018).

b. Citation analysis: Relative frequency of citation (RFC) ranks taxonomic groups according to the number of informants who mention it in interview or written forms. This index is created by Pardo-de-Santayana in 2003 (Tardio & Pardo-de-Santayana, 2008) and recently used by Iyamah et al. (2015).

c. Probability analysis: Bayesian analysis is a method to evaluate how possible a plant under a certain family will be used medicinally based on posterior possibility. This is first introduced to ethnobiological studies by Weckerle et al. (2011).

2.1.2 Current research situation of Anishinaabe ethnobiology

There are several databases existing on Anishinaabe and other North American Indigenous people's medicine; one of the most referred digital databases is Native American Ethnobotany Database by Dan Moerman (University of Michigan, 2003). These kinds of databases let people search according to species, tribe, usage, or citation. However, because they usually do not differentiate records of the same usage from different communities, and instead choose or combine one record from multiple citations, it is difficult to perform statistical analysis from these databases.

Compared with existing databases, the Anishinaabe Ethnobiology Database (NishDB) our lab build is in a unique category of focusing on both linguistics and usage. Steven Skoczen and Rainer Bussmann, the authors of the International Ethnobotany Database (ebDB), compared some existing databases in 2006 when ebDB was first published. According to Skoczen and Bussmann (2006), Dr. Duke's Phytochemical and Ethnobotanical database is large and focuses on phytochemistry but lacks public input; UC Riverside's Ethnobotany Database is broad but private; NAPRALERT is closed, and is a pay-per-use system. In 2022, most of the databases mentioned above, including ebDB, have either been taken down, archived, or privatized. Moerman's database has shifted its domain to the Botanical Research Institute of Texas, with a total of 4260 plants, and 44691 plant uses from 291 tribes. As of August 2022, Moerman's database has limited the search results to show 1000 reports maximum per search, making it difficult to navigate the database as a member of the general public; although this makes the data less accessible, it prevents leakage of Indigenous intellectual property. This also prevents quantitative study done with Moerman's database by general public. Dr. Duke's Phytochemical and Ethnobotanical database (1992-2016) is focused on compounds found in plants and less standardized in uses; the database contains global information and therefore is less focused on one ethnic group. UC Riverside's Ethnobotany Database and NAPRALERT do not exist as of August 30, 2022. ebDB aimed at building a multilingual database with "over 650 languages including English, German, Chinese, Russian, and less well-known languages like Oromo and Dzongkha" (Skoczen & Rainer, 2006). Unfortunately, it seems the project was not completely successful or ever publicized, as the Internet Archive Wayback Machine was only able to capture one snapshot of an empty login page under the URL prefix on September 5, 2008. Another noteworthy ethnobotany database, the Hawaiian Ethnobotany Online Database (2011-2021), contains not only the usage but also *ʻŌlelo Hawaiʻi* (Hawaiian language) terms and concepts. Some examples from the Hawaiian Ethnobotany Online Database (2011-2021) are *Mele* (chants and songs containing said plant), *ʻŌlelo Noʻeau* (proverbs or sayings containing said plant), and *Kino lau* (said plant is the body, or one of the bodies of this *akua* "deity, spirit"). The Hawaiian Ethnobotany Online Database is the nearest database to this project of all above, however it is less standardized and not suit for quantitative studies.

Table 2.1 Similar databases comparison

Databases	Geographic Coverage	Year of last update	Vernacular name	Geographical location indication	Accessibility	Accessible (as of Nov 2022)
International Ethnobotany Database (ebDB)	Ecuador, Perú, Kenya and Hawai'i	2008	N/A	N/A	Private	No
Dr. Duke's Phytochemical and Ethnobotanical database	Global	2022	English	No	Public	Yes
NAPRALERT	Global	2006	N/A	No	Private, pay per search	No
Native American Ethnobotany DB (NAEB)	North America	2022	English	No	Public	Yes
Hawaiian Ethnobotany Online Database	Hawai'i	2022	Hawai'i, English	No	Public	Yes
Ethnoecology Database of the Greater Southwest	Southwest US	2006	Unspecified, English	No	Public	Web archived
NishDB	Great Lake area	2022	Anishinaabe, English	Yes	Private	Yes

2.1.3 Anishinaabe medicine

Anishinaabe medicine is a medical practice done by Anishinaabe people (Anishinaabeg). Medicine in traditional Anishinaabewaki includes a range of health and healing practices, beliefs, Anishinaabe philosophy, food, herbal and fungal remedies, medical specializations, and ceremonies. The definition of "medicine" consists of both physical healing remedies (*mashkiki*) and spiritual healings (*mide*). *Mashkiki* is practiced widely by regular households; *mide* is commonly practiced by traditional healers in the Midewiwin (Grand Medicine Society). In this study I discuss *mashkiki*. Medicine can come from various sources: plants, fungi, animals, and minerals. A great spectrum of health care can be covered by Anishinaabe medicine, from injury, pain, organ systems, to mental health, dreams, even psychoanalysis and psychiatry. An example of psychiatry use is "used for young men who had sustained shock from their first battle" (Keewaydinoquay, 1998). Different routes of drug administration are recorded throughout history: medicinal tea, decoction, ointments, vapour baths, and washes are commonly used. Some advanced medical applications include medicinal tattoo or subcutaneous injections, amputation, dental surgery, and enema (Densmore, 1928).

2.1.4 Rationale

Through quantitative studies, I can generate ranks of high value biodiversity. Ranking traditionally used species lets MCFN know who their highly valued relatives are. Further biosurvey can link high value biodiversity to Anishinaabe burial sites.

An entry without Latin name would need to be cross referenced in Anishinaabemowin and English, to be compared with other entries. Due to the nature of ethnobiology reports, it is extremely difficult to analyse categories other than medicine to a species level; therefore, I choose to use medicine as the category to showcase the study.

2.1.5 Objective

Nish DB was started in 2019 by Johnson and Ferrier and is still an ongoing project. The papers I found to be highly pertinent to this included: *Use of plants by the Chippewa Indians* (Densmore, 1928); *Recollections of a forest life, or, The life and travels of Kah-ge-ga-gah-bowh, or George Copway, chief of the Ojibway nation*

(Copway, 1851); and *History of the Ojebway Indians; with Especial Reference to Their Conversion* (Jones, 1861).

My goal was to follow the established NishDB, adjust the standard of NishDB to fit for quantitative studies, and perform quantitative studies with NishDB and generate the rank of traditionally used species.

2.2 Methods

2.2.1 Study area

The presented study was conducted in Anishinaabewaki, the historical, traditional, unceded territory of Anishinaabeg. 39 informants from 37 communities are recorded in the ethnobiology reports NishDB is built on, but more remained unnamed because of culture difference and information loss.

Fig. 2.1. Communities recorded in ethnobiology studies

2.2.2 Data collection

2.2.2.1 Literature screening

Published studies and books in English from any date were retrieved by Dr. Jonathan Ferrier's lab members (referred to as "Ferrier lab" from now on) from the Novanet database. The members who contributed to NishDB are: Dr. Jonathan Ferrier, William Johnson, Dalhousie Integrated Science Program 2021, and Principles of Indigenous Medicine 2021. Ferrier and Johnson set the standard of NishDB. Search terms for literature include: Anishinaabe, Nishnaabeg, Anishinabeg, Anishinaabeg, Nishnaabe, Nishnaabeg, Otchipwe, Chippewa, Chippwea, Chippeway, Ojibway, Ojibwa, Ojibwe, Nipissing, Abenaki, Odawa, Ottawa, Mississauga, Michi Saagiig, Potawatomi, Pottawatomi, Pottawatomie, Saulteaux, Plains Ojibwe, Oji-Cree. Unpublished literature was searched with the ProQuest Dissertations and Theses database. Ferrier lab screened titles, abstracts, or sections of works from searches. Records considered include any treatment of life names or life relationships.

2.2.2.2 Data classification

Data was entered into the Excel (2019) spreadsheet under a classification system based on the Economic botany data collection standard (Cook, 1995). The standard was modified to include Anishinaabemowin names, reference locations, reference documents and context.

2.2.2.3 Taxonomy standard

Nomenclature was standardized via Tropicos (Missouri Botanical Garden, 2022). Flora of North America (2021) and Michigan Flora (2011-2022) were used for systematics, distributions, and statistical studies. For plant family analysis, APG IV

(2016) was used to standardize taxonomic groups when there is conflict between literatures.

2.2.3 Data analyzation

2.2.3.1 Frequency analysis

To analyse the documented data, I applied quantitative ethnobiological indices such as Use value (UV) and Relative Frequency of Citation (RFC) and performed a Bayesian analysis.

Use value (UV) indicates the amount of use reports of each taxonomic group.

$$UV = UR/N$$

Where UV stands for Use value, UR stands for Use report which represents an individual report of a species being useful for a certain usage, N represents the total number of informants or communities participating in the study.

Relative frequency of citation (RFC) indicates the local significance of each taxonomic group, based on the number of informants or communities who reported a taxonomic group in relation to the total number of the informants or communities in the study (Fatima et al., 2018). The most commonly used species in the study area will have the highest RFC.

$$RFC = FC/N \times 100\%$$

Where RFC stands for Relative frequency of citation, FC represents the number of informants or communities that mentioned the use of each species, N represents the total number of informants or communities participating in the study.

2.2.3.2 Probability analysis: Bayesian method

The medicinal flora of Anishinaabewaki is retrieved from the Anishinaabe Ethnobiology Database by applying filter "Medicine." The total flora of Anishinaabewaki was established based on Michigan Flora (2011) with slight adjustment based on Flora of North America (2021) and APG IV (2016). Altogether, 2905 different plant species were recorded belonging to 162 families.

This method is heavily based on a Bayesian approach proposed by on Weckerle et al. (2011), therefore will not be repeated; the logistics will be summarized here.

In order to evaluate the relevance of the possibility a plant species is selected as medicine and its taxonomic position, we form a hypothesis that can be statistically tested. The null hypothesis (H0) is: A taxonomic group (j) has a proportion of medicinal species (P_j) equal to the overall proportion (P).

Prior to sampling we assume P_j as a random variable between [0,1] and that P_j is uniformly distributed between [0,1]. After sampling the total number of species n_j and the number of medicinally used species x_j for all J groups, we update this uniform prior assumption obtaining the posterior probability of P_j, $\pi(P_j| x_j, n_j)$.

Here we compare the posterior probability of P_j and P. When the 95% posterior probability of P and P_j do not overlap, we reject the null hypothesis H0.

When H0 is rejected, the taxonomic group (j) does not have a proportion of medicinal species (P_j) equal to the overall proportion (P), therefore is either underused (when $P_j < P$) or overused (when $P_j > P$). Underused means the taxonomic group j has a significantly lower probability than the total flora to be used medicinally; overused means the taxonomic group j has a significantly higher probability than the total flora to be used medicinally

The interval of the most probable values of P and P_j can be calculated using the Excel function Inverse beta (Microsoft Excel 2019). For a taxonomic group (j) consists of

x_j medicinal species and n_j species in total, suppose we put x_j in A1 and n_j in B1, the formula is as follows:

Inferior 95% probability credible interval: “=INV.BETA(0.025; A1+1; B1-A1+1)”

Superior 95% probability credible interval: “=INV.BETA(0.975; A1+1; B1-A1+1)”

MATLAB R2021b was used in graph drawing.

2.3 Results and Discussion

2.3.1 Database size

As of November 3, 2022, the Anishinaabe Ethnobiology Database contains 13251 entries, in which 10064 were entered by me. 687 species, 1480 Anishinaabemowin names, and 279 secondary (“Level 2”) use categories were recorded. Our data come from 18 published ethnobiology reports, among which I have curated from 4. The largest category is medicines. I chose medicine to display frequency and probability studies in species level and all categories in family level.

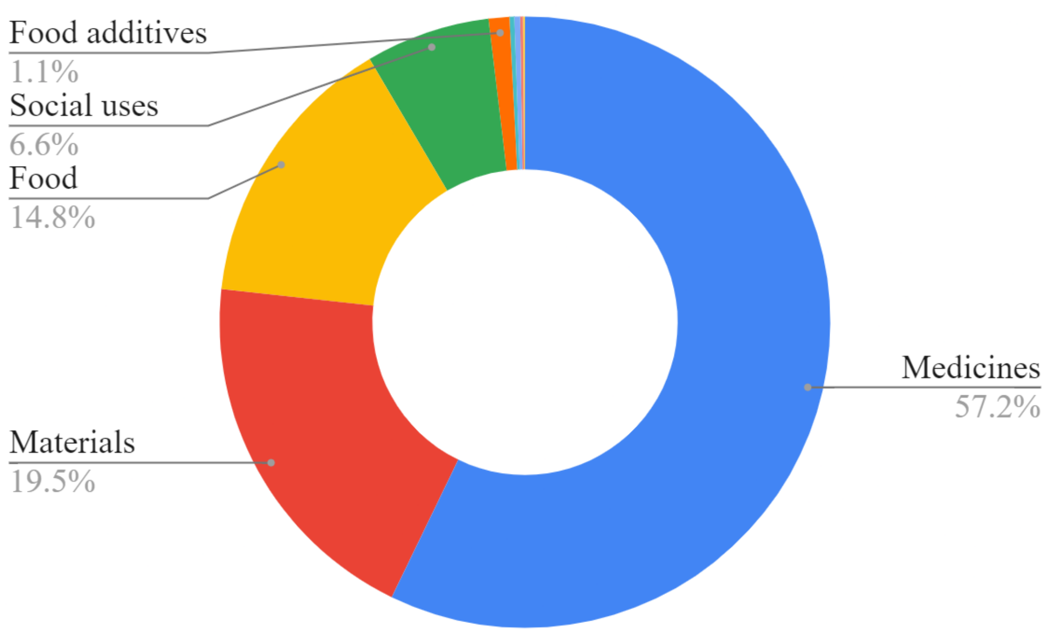

Fig. 2.2. Use report by primary (“Level 1”) categories

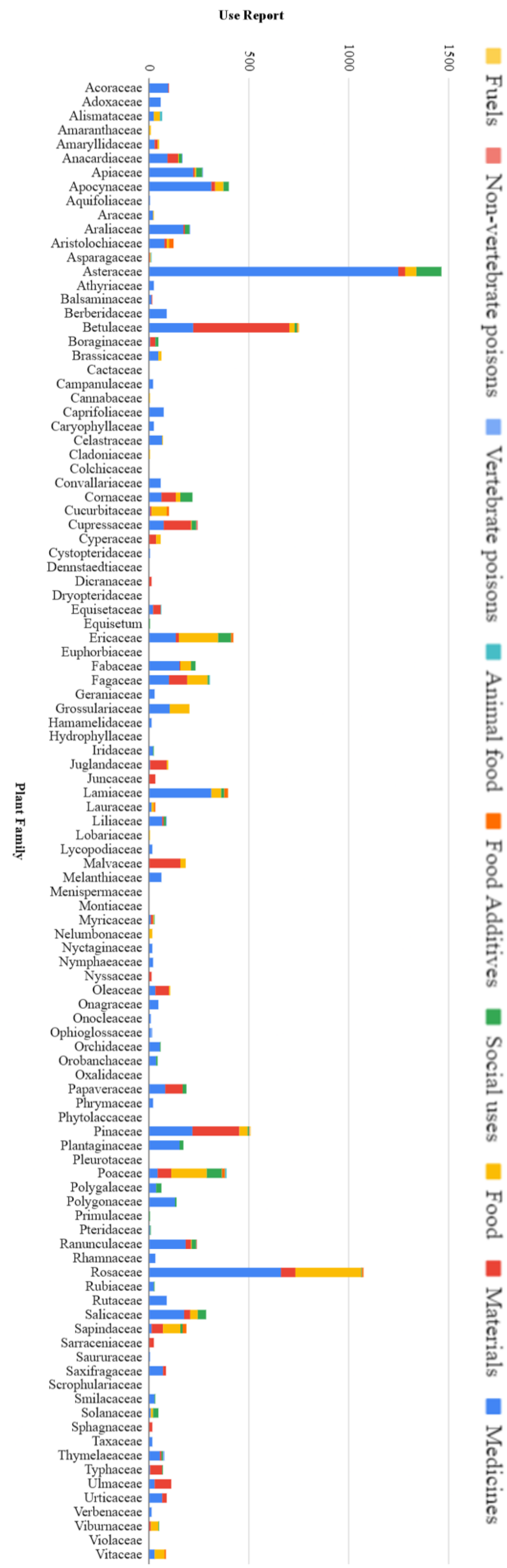

Fig. 2.3. Use report categories by plant families

2.3.2 Frequency study

2.3.2.1 High ranked plant diversity

In this study, a total of 348 plant and fungi species belonging to 93 taxonomic families were reported to be medicinal under 6493 use reports. In the total of 348 medicinal species, 294 species have at least 1 Anishinaabemowin name(s) recorded. The top 20 plant and families in all categories and their Relative frequency of citation (RFC) are presented in Table 2.1. In the medicinal species study, the UV ranged from 0.02 to 5.53, and the RFC ranged from 2.3% to 39.5%. The most commonly used families in medicine were Asteraceae, with 43 species, followed by Rosaceae with 33 species.

Table 2.2 Top 20 ranked plant families in all categories according to RFC, in alphabetical order.

Family	**RFC**	**UV**
Anacardiaceae	48.7%	4.69
Apiaceae	46.2%	7.50
Apocynaceae	43.6%	11.08
Araliaceae	43.6%	5.72
Aristolochiaceae	43.6%	3.44
Asteraceae	48.7%	40.67
Betulaceae	64.1%	20.83
Cornaceae	43.6%	6.03
Cupressaceae	59.0%	6.75
Ericaceae	48.7%	11.72
Fabaceae	43.6%	6.36
Fagaceae	61.5%	8.39
Juglandaceae	43.6%	2.61
Lamiaceae	46.2%	10.94

Family	RFC	UV
Malvaceae	59.0%	5.06
Oleaceae	46.2%	3.00
Pinaceae	61.5%	14.11
Poaceae	76.9%	10.75
Rosaceae	51.3%	29.78
Sapindaceae	61.5%	5.19
Solanaceae	56.4%	1.33
Typhaceae	43.6%	1.92

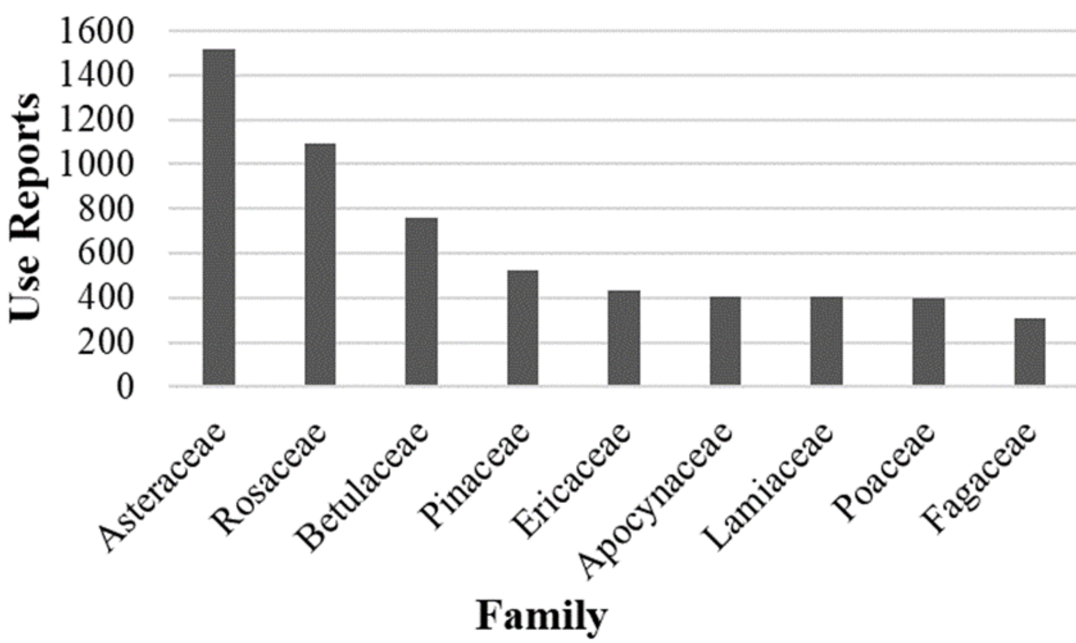

Fig. 2.4. Top 10 ranked plant families reported in all categories according to use report.

2.3.2.2 Plant parts used

In the medicine study, the most commonly recorded case is unspecified parts (2238 records, 34.5%). In cases with parts recorded (63.5%), the most frequently used plant part was root (2417 reports), followed by leaf (537 reports). The least commonly reported plant part used was entire plant (38 reports) followed by fruit (48 reports).

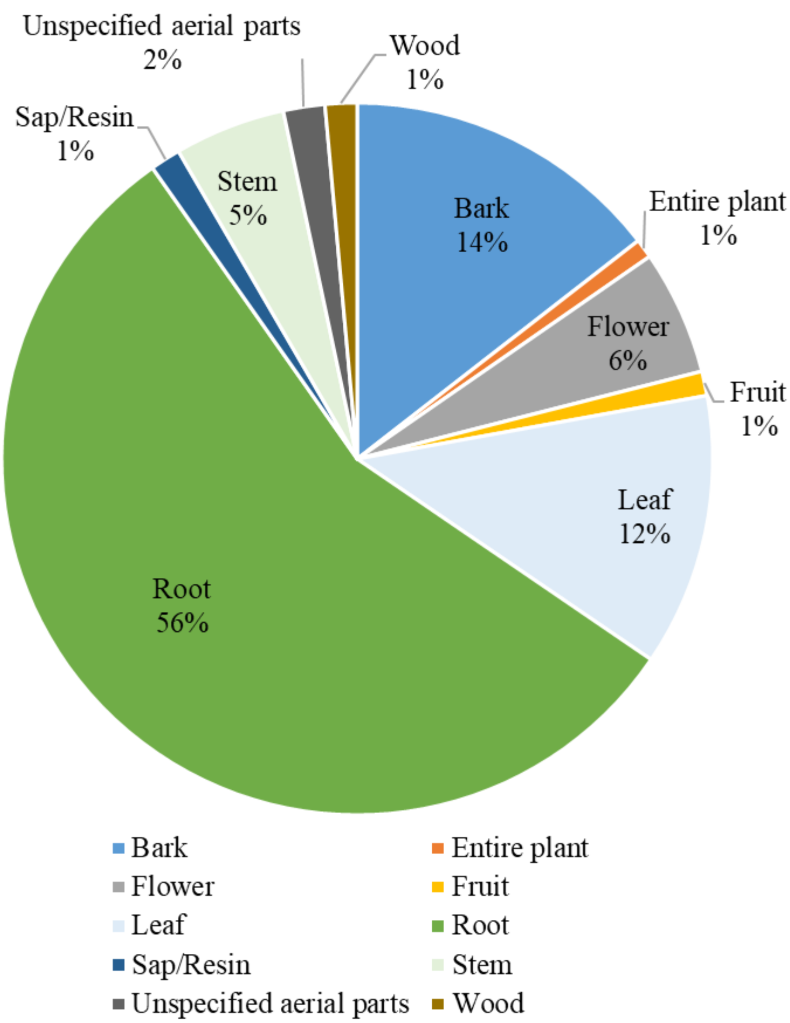

Fig. 2.5. Reported specified plant parts used in medicines.

2.3.2.3 Disorders treated

In this study, the most commonly recorded disorder category is digestive system disorder (1043 records), followed by genitourinary system disorders (740 records), pain (703 records), and skin/subcutaneous cellular tissue disorders (682 records).

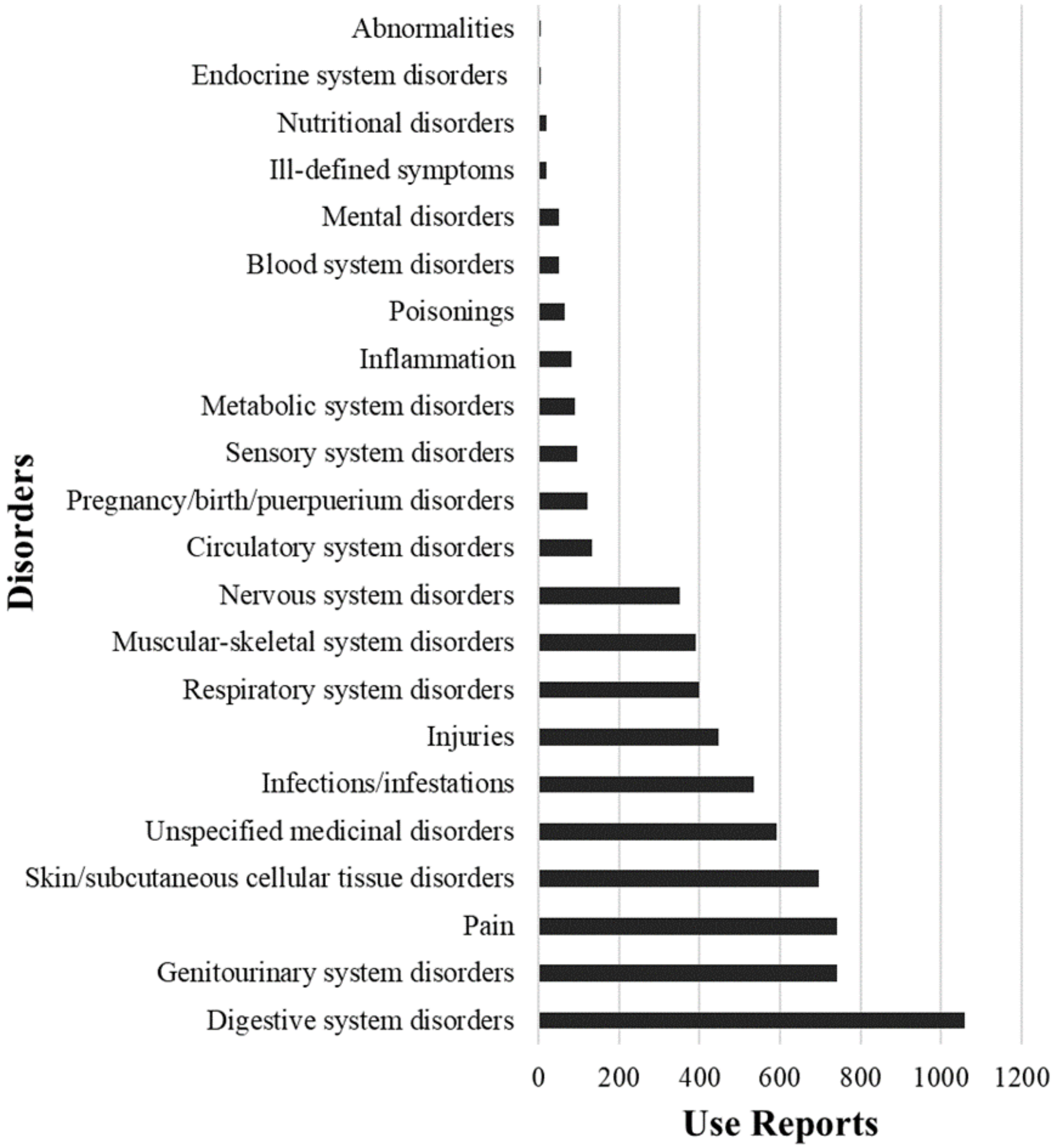

Fig. 2.6. Disorders treated by Use Reports.

2.3.3 Probability Analysis

2.3.3.1 Over- and under use of higher taxonomic groups

The 95% posterior probability interval for each taxonomic group and the common proportion is reported in Table 2.2. We see that four taxonomic groups differ from the common proportion, whose observed value is around 12% (t/n=0.124957) and with 95%

probability lies between 11% and 14%. According to the results, the groups 2, 3, 4 and 5 differ from H0, which means Monocots are underused and Gymnosperm, Early diverging angiosperm, Magnoliids are overused. We can see that some taxonomic groups have exceptionally large 95% posterior credible intervals compared to others; this is mainly because these families contain fewer species.

Figure 2.6 illustrates the posterior probability distribution of the overall proportion P and of the proportion P_j of each taxonomic group.

Table 2.3. Over- and underused higher taxonomic groups of the Anishinaabe flora. The 95% posterior credible interval of P_j and P (n=2905, t=363) are shown.

Taxonomic group (J)	**x_j**	**n_j**	**Inf.**	**Sup.**	**Mean P_j**
Pteridophytes	16	108	0.093	0.227	0.15
Gymnosperm	14	23	0.406	0.779	0.61
Early diverging Angiosperms	3	7	0.157	0.755	0.43
Magnoliids	11	19	0.361	0.769	0.58
Monocots	33	826	0.029	0.056	0.04
Early diverging Eudicots	17	91	0.120	0.279	0.19
Superasterids	143	1072	0.114	0.155	0.13
Superrosids	126	759	0.141	0.194	0.17
Total/Common	363	2905	0.113	0.137	0.12

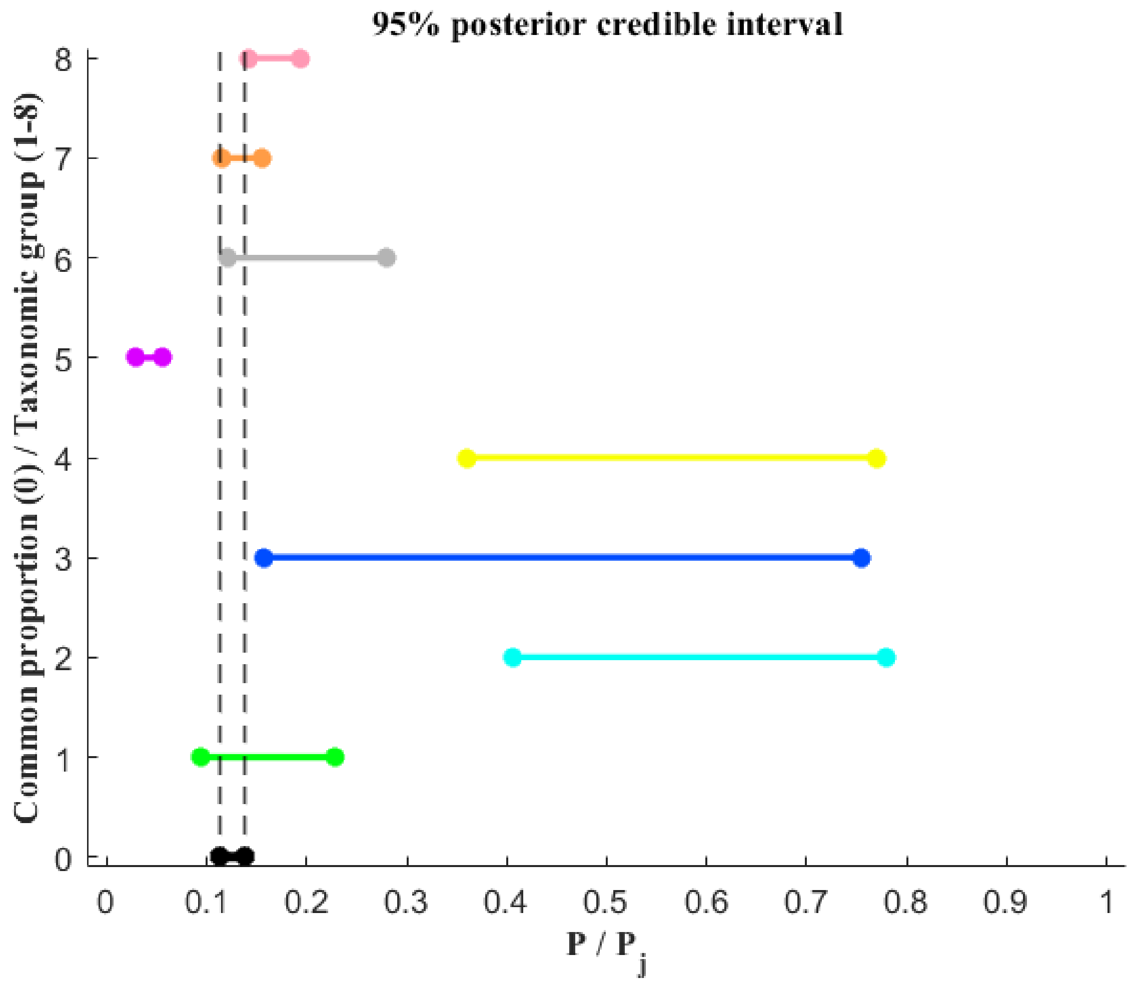

Fig. 2.7. The 95% posterior credible interval of P and of P_j of the 8 higher taxonomic groups.

2.3.3.2 Over- and underuse of plant and fungi families

A total of 2905 species belonging to J=162 families were considered in the study.

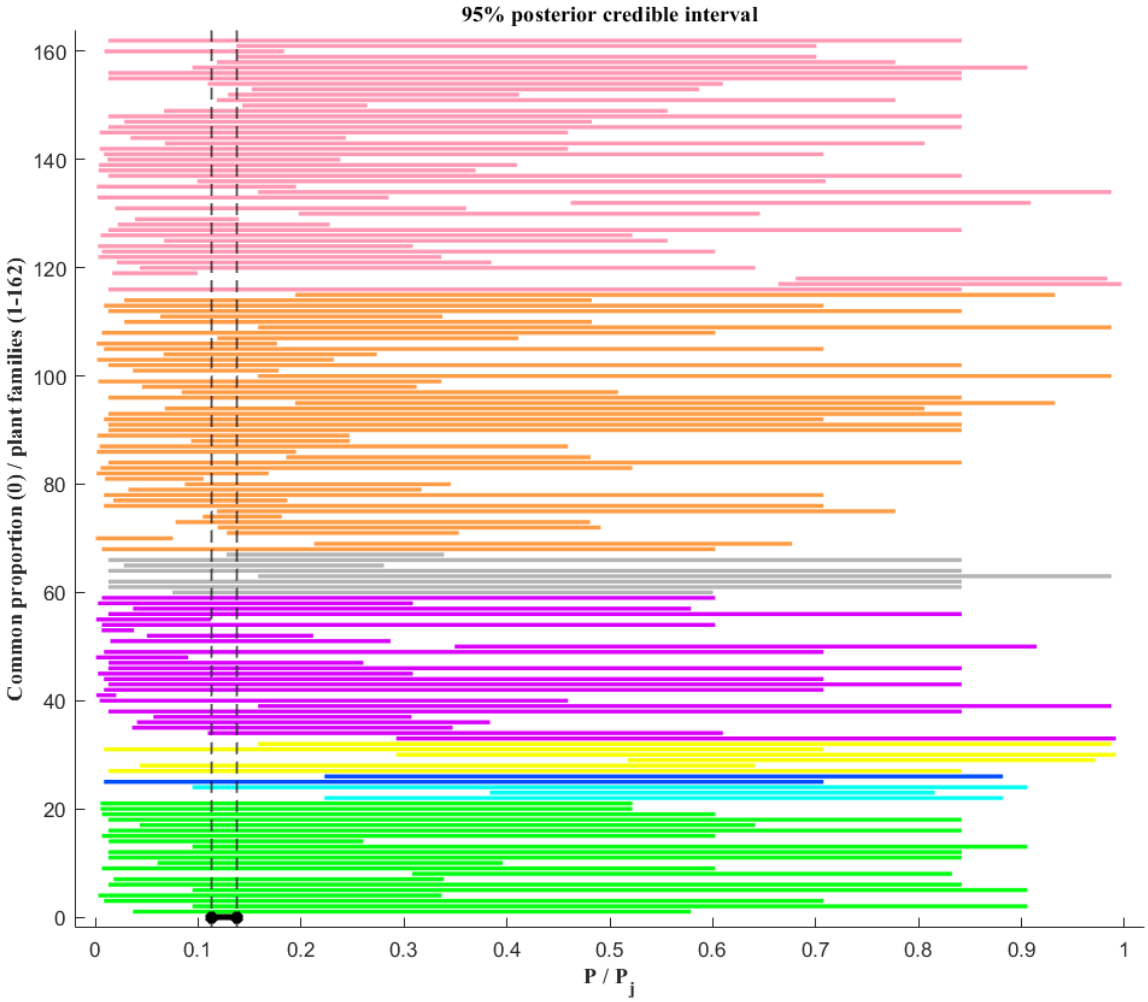

Fig. 2.8. The 95% posterior credible interval for J=162 families.

Table 2.4 Underused plant families. Families whose 95% posterior credible interval lies below the 95% posterior credible interval for the overall proportion P (0.113, 0.137)

Family	**x_j**	**n_j**	**Inf.**	**Sup.**	**Mean P_j**	**Margin**
Cyperaceae	1	272	0.001	0.020	0.00	0.093
Poaceae	4	269	0.006	0.037	0.01	0.076
Amaranthaceae	0	46	0.001	0.075	0.00	0.038
Juncaceae	0	38	0.001	0.090	0.00	0.023
Brassicaceae	4	99	0.016	0.099	0.04	0.014
Caryophyllaceae	2	65	0.009	0.105	0.03	0.008
Potamogetonaceae	0	30	0.001	0.112	0.00	0.001

Families are ranked according to the difference (margin) between the interval of P (0.113, 0.137), and the superior interval of P_j.

Table 2.5. Overused plant families. Families whose 95% posterior credible interval lies above the 95% posterior credible interval for the overall proportion P (0.113, 0.137)

Family	**x_j**	**n_j**	**Inf.**	**Sup.**	**Mean P_j**	**Margin**
Betulaceae	13	14	0.681	0.983	0.93	0.544
Anacardiaceae	8	8	0.664	0.997	1.00	0.527
Cornaceae	7	8	0.518	0.972	0.88	0.381
Grossulariaceae	9	12	0.462	0.909	0.75	0.325
Pinaceae	10	16	0.383	0.816	0.63	0.246

Family	x_j	n_j	Inf.	Sup.	Mean P_j	Margin
Liliaceae	5	7	0.349	0.915	0.71	0.212
Equisetaceae	6	10	0.308	0.833	0.60	0.171
Lauraceae	2	2	0.292	0.992	1.00	0.155
Acoraceae	2	2	0.292	0.992	1.00	0.155
Cupressaceae	3	5	0.223	0.882	0.60	0.086
Nymphaeaceae	3	5	0.223	0.882	0.60	0.086
Adoxaceae	6	14	0.213	0.677	0.43	0.076
Fagaceae	6	15	0.198	0.646	0.40	0.061
Nyctaginaceae	2	3	0.194	0.932	0.67	0.057
Aquifoliaceae	2	3	0.194	0.932	0.67	0.057
Ericaceae	11	35	0.186	0.481	0.31	0.049
Saururaceae	1	1	0.158	0.987	1.00	0.021
Colchicaceae	1	1	0.158	0.987	1.00	0.021
Menispermaceae	1	1	0.158	0.987	1.00	0.021
Phytolaccaceae	1	1	0.158	0.987	1.00	0.021
Sarraceniaceae	1	1	0.158	0.987	1.00	0.021
Hamamelidaceae	1	1	0.158	0.987	1.00	0.021
Sapindaceae	5	15	0.152	0.587	0.33	0.015

Family	x_j	n_j	Inf.	Sup.	Mean P_j	Margin
Rosaceae	32	163	0.143	0.264	0.20	0.006

Families are ranked according to the difference (margin) between the interval of P (0.113, 0.137), and the superior interval of P_j.

2.4 Ways forward

Anishinaabewaki is a land with a diversity of plant and fungi species used in all perspectives of life in time immemorial, with a rich history of traditional plant and fungi medicine. With the ongoing colonization causing constant knowledge loss, it is crucial that a standardized, accessible traditional Anishinaabe knowledge database be established right now. In the present study, 348 plant and fungi species were documented as medicinal. It was observed that root is a common part of a plant to be used in medicine, and digestive system disorder is the most common category of disease treated with herbal or fungal medicines. The results of quantitative analysis methods such as RFC and Bayesian analysis are useful for MCFN to reclaim their medicine, language, and culture, and guide the selection of the potentially safer and more effective species, leading the lab towards further pharmacological and clinical research, eventually creating financial opportunities for MCFN. The least possibly used plant families according to this study are *Cyperaceae, Poaceae, Amaranthaceae, Juncaceae,* and *Brassicaceae*. The most possibly used plant families according to this study are *Betulaceae, Anacardiaceae, Cornaceae, Grossulariaceae*, and *Pinaceae*. Conservation of these species, families, and the land and water they live in are recommended to ensure their availability for continuous use and further research.

Anishinaabewaki is a huge country covering several principal administrative divisions across different ecozones, so it is hard to find a provincial plant database to compare with, causing information loss. However, there are ecozones in Turtle Island that Anishinaabewaki does not fit in such as Pacific Maritime and the cordilleras. Therefore, Flora of North America (2021) will provide species that do not live in our studied region, causing bias. Furthermore, Flora of North America is less focused and records less species in the studied region. However, Michigan Flora (2011) is not a perfect fit either. While using Michigan Flora (2011) in Bayesian analysis, I have encountered problems when NishDB records more species in a family than Michigan Flora. This causes potential bias because the formula cannot function when $x_j > n_j$.

The time span of the literature NishDB uses is from 1861 to 2003. In such an extensive time span with human activities and climate change, the distribution of plants and fungi might have changed. New medicinal plants are being introduced with colonization and globalization. Furthermore, botanical records such as Michigan Flora do not differentiate native, introduced, and naturalised species. Therefore, there will be unavoidable errors in statistical analysis.

I did not find a fungi list that is comprehensive enough to perform a statistical analysis. Fungi are an important part of traditional Anishinaabe medicine, it is a huge pity that NishDB have yet to have enough fungi entries to form a coordinating fungi list for quantitative studies.

Chapter 3 ArcGIS LiDAR modelling Burial mounds

3.1 Introduction

3.1.1 Background

3.1.1.1 LiDAR-Derived Digital Terrain Model

A Digital Terrain Model (DTM) is a 3D computer graphics representation of elevation data to represent terrain. Compared to a Digital Surface Model (DSM) which includes elevation data of buildings, trees and other objects, a DTM represents bare ground.

LiDAR is a method for determining ranges (variable distance) by targeting an object or a surface with a laser and measuring the time for the reflected light to return to the receiver. The word "LiDAR" is an acronym of "light detection and ranging." LiDAR data are collected from aircraft using sensors that detect the reflections of a pulsed laser beam. The reflections are recorded as millions of individual points, collectively called a "point cloud," that represent the 3D positions of objects on the surface including buildings, vegetation, and the ground. A high-resolution DTM can be derived from lidar point-cloud data by stripping away the surface features and sampling the ground elevation in uniform increments to produce a bare earth model (U.S. Department of the Interior, 2022).

3.1.1.2 Pattern recognition

Most people are easily able to recognize a dog despite different breeds of dogs having very different appearances. Being able to identify and classify dogs is an example of pattern recognition in human's behaviour. Pattern recognition is the automated recognition of patterns and regularities in data. In machine learning, pattern recognition is the assignment of a label to a given input value. For example, your mailbox automatically determines whether an email is spam or not, or video websites decide which video you would like to watch. Both are examples of classification which attempts to assign each input value to one of a given set of classes.

3.1.1.2.1 Artificial Neural Network (ANN) in pattern recognition

Artificial neural networks (ANNs) are computational models mimicking the biological neural networks in pattern recognition that constitute animal brains. The relationship between ANNs and the brain is "somewhat similar to that between aeroplanes and flying animals" (Boddy & Morris, 1999). ANN is based on a collection of connected units or "nodes," which are conceptually derived from neurons in a biological brain. ANNs are trained (or learn) by processing examples, of which each contains an input and a known result. The node is shown in Figure 4.1, in which X = input, Y = output, w = weight, b = bias. (Dawson & Wilby, 1998)

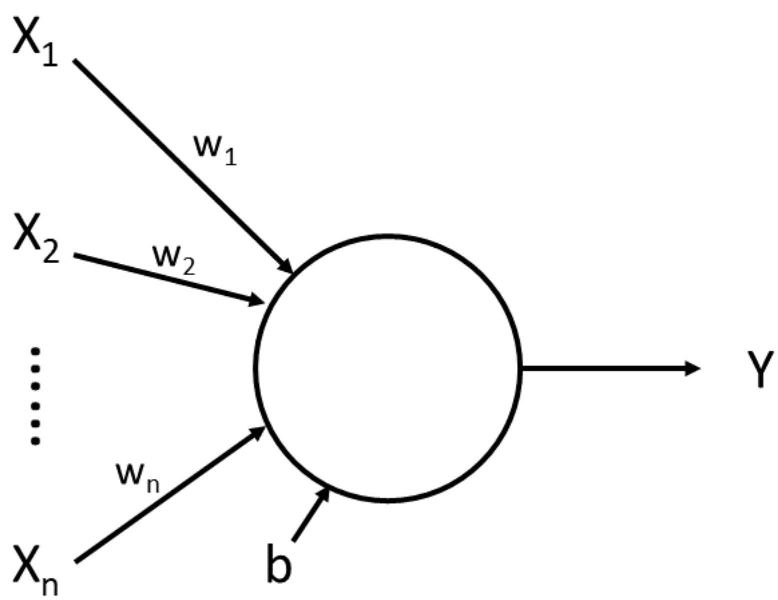

Fig. 3.1. A schematic diagram of node in ANN

Once the input is determined, each input is assigned a weight to determine the importance of given variables. Then the output is passed through an activation function, which determines the output. If that output exceeds a given threshold, the data is passed on to the next layer. This continues until a result is reached.

3.1.1.2.2 Convolutional Neural Network (CNN) and its structure

Convolutional neural network is a class of artificial neural network (ANN), most commonly applied to analyze visual imagery (Valueva et al., 2020). A CNN consists of an input layer, hidden layers, and an output layer, as shown in Figure 4.2 in the former section. In a CNN the hidden layers include layers that perform convolutions.

Some of the most important concepts in a CNN are convolution layer, Rectified Linear Units layer (ReLU layer), and max pooling layer. Following are brief explanations of their functions.

A convolutional layer is the main building block of a CNN (Mostafa & Wu, 2021). Convolutional layers convolve the input and pass its result to the next layer, similar to how neurons in the visual cortex respond to specific stimuli.

The Rectified Linear Unit (ReLU) is the most commonly used activation function in deep learning models (Dansbecker, 2018). An ReLU is a non-linear activation function that performs on multi-layer neural networks. (e.g., $f(x) = max(0,x)$ where x = input value) (Challa, 2022). As explained in the former section, ReLU is the activation function which determines the output and will only pass on the data to the next layer once the output exceeds a given threshold.

Max pooling is used for downsampling. In max pooling, the filter selects the maximum pixel value in the receptive field. A receptive field of a sensory neuron is the area in that location where the appropriate stimulus can elicit the neuron's response. With pooling, a specific feature is extracted into a smaller, more general map that indicates whether the feature exists in that particular area. The map shrinks with each pooling layer, retaining only vital information about the presence of features of interest. As the map gets smaller, it becomes increasingly independent of the location of features. As long as a feature is detected in the approximate vicinity of the original location, it should be similarly reflected in the map generated by the pooling layer (Seb, 2022).

3.1.1.2.3 Image classification and object detection algorithms

Some popular object detection algorithms are Region Based Convolutional Neural Networks (R-CNN), Single Shot MultiBox Detector (SSD), and You Only Look Once (YOLO). Rather than classifying the whole image by labels, object detection algorithms scan through an image and annotate the features that match the labels. The size of training database limits the accuracy of an ANN program. I attempted in using YOLO to automate the detection procedure, but poor accuracy was observed. Therefore in this paper I apply the most primitive and robust method, CNN, to classify images.

3.1.2 Study site

Our study site is the Peshinaaguining area and Eramosa burial site (Fig 4.2). Peshinaaguining, in English referred to as “Grand River”, is the mother river of traditional MCFN territory. In Augustus Jones’ Documentation of River and Creek Names (1796), Peshinaaguining (as “Ouse” by Jones) was translated as “Washes the timber down and drives away the grass weeds.” The double vowel transliteration comes from Dan Secord (J. Ferrier, personal communication, October 31, 2022) Eramosa is conjectured to originate from *Animosheg* (dogs).

Eramosa burial site is a burial ground recorded by Mildred Roadhouse in Wellington archive. In the record, John Cormie, who bought the farm Lot 14, Con. 4 on March 14, 1834, stated that his father referred to a woodlot at the Northwest corner as an “Indian burial ground” (Ferrier & Pye, 2019).

Fig. 3.2. Wellington map with highlighted Eramosa burial site (Wellington County, 1861)

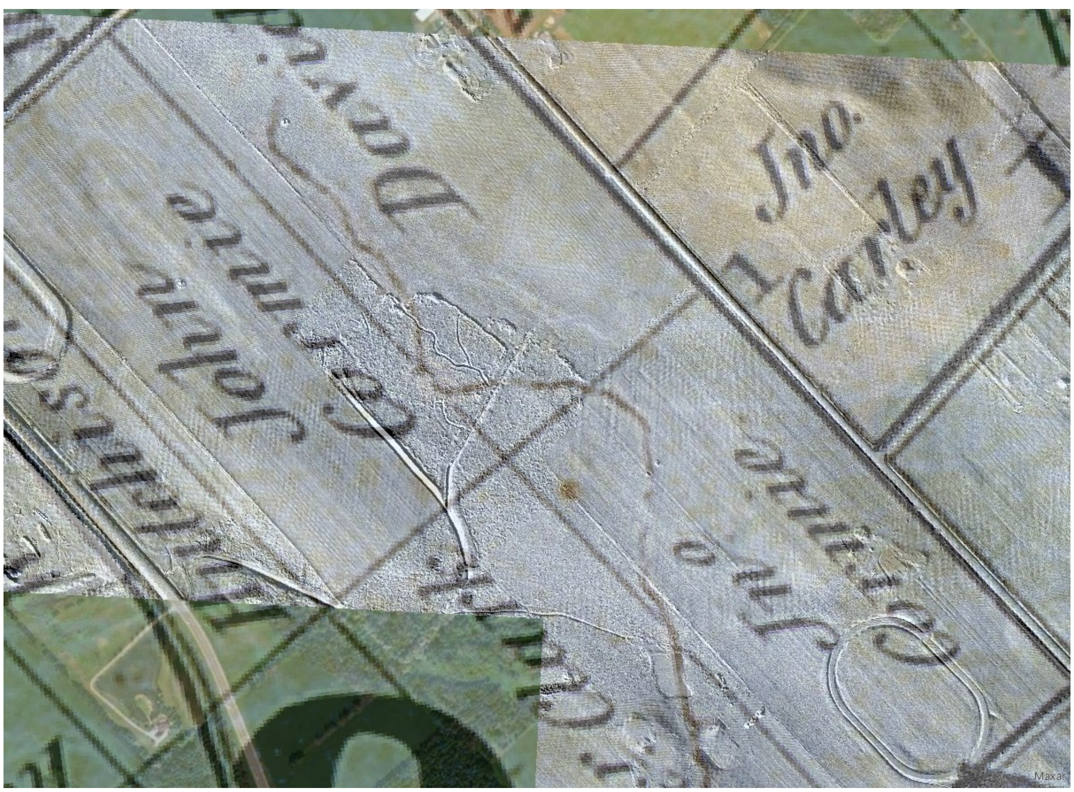

Fig. 3.3. NW Lot 14 Con.4 hillshaded (Wellington County, 1861)

3.1.3 Rationale

Indigenous health is based on a holistic relationship with life, especially foods and medicines from the land. MCFN is interested in these relations and continue to acknowledge their relations through projects such as Burial Mound Identifier. Ethnobotanical studies can help demonstrate why the Mississaugas walked and inhabited these areas. MCFN would like to gain more access and insights of their traditional burial sites and how do the burial site locations relate to the land and the water, therefore asked our lab to conduct this study.

3.1.4 Objective

My goal is to train an image classification algorithm model to classify map chips based on whether they contain burial mound(s), and then apply the model to a greater study area (along Peshinaaguining) to find new potential burial mound(s) and site(s).

3.2 Methods

This method of image detecting is inspired by Mahavarkar et al. (2020) and Wu & Zhou (2018) and is recorded in Appendix A.

3.2.1 Image enhancement with ArcGIS

This research takes a MCFN burial mound site, Eramosa Burial Site (Fig 2.2), in the Lake Erie area of Ontario as a training area, and areas along Peshinaaguining as a testing area. I used ArcGIS Pro to generate the hillshade of the map of the study area. Package W from Ontario Digital Terrain Model (Lidar-Derived) (2020) was used. In the package, Digital Terrain Model (DTM) was divided into 1km×1km tiles. The tile used was 1km17552048372018LLAKEERIE.img. Using Analysis - Tools - Hillshade, an enhanced image of the map was generated (Stanchev et al., 2009). Then I exported the map as image chips of the individual mound and recorded the longitude and latitude of the center on each burial mound as the location. Combining the map chip and the location, I generated geo-tagged images for future use. Exported maps were segmented with online cutting tools (www.imgonline.com.ua, 2018) into varied sizes. Segmented images were labeled as “mound” if they contain at least 1 burial mound(s) from the Eramosa Burial Site and “nonmound” if not, then put the segment into two folders accordingly.

3.2.2 Image recognition with Python in TensorFlow

3.2.2.1 Model Training

I retrieved the labeled picture fragments from the previously mentioned procedure. I then inputted the pictures into my program for training image recognition models (Appendix A), which was developed based on The TensorFlow Authors (2018). This research is based on the Convolutional Neural Network (CNN). During this process, the program learned features of burial mounds. After the initial learning process with validation in a small size, I put all marked images into TensorFlow to train a more robust burial mound detection model which can detect burial mounds in other situations. 10 image segments were categorized as “mound” and 358 segments as “non-mound” were feed in to the model.

3.2.2.2 Model Application

I inputted pictures and picture fragments from Package W (Ontario Digital Terrain Model (Lidar-Derived), 2020) into the trained model and recorded the possibility of each picture containing burial mounds. I then choose pictures with more possibility containing potential burial sites and burial mounds along Peshinaaguining.

3.3 Results and Discussion

3.3.1 Image enhancement with ArcGIS

Hillshade pictures of the examined area were generated and exported from the Ontario Digital Terrain Model (ON-DTM).

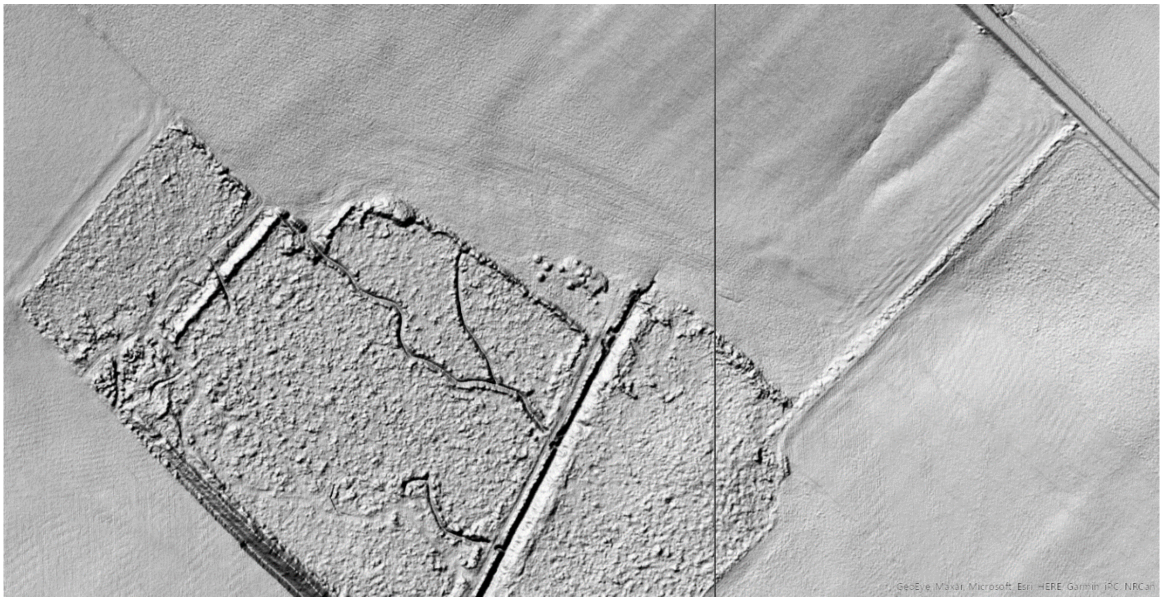

Fig. 3.4. Hillshade image of the training area

Fig. 3.5. Hillshade image of the burial site

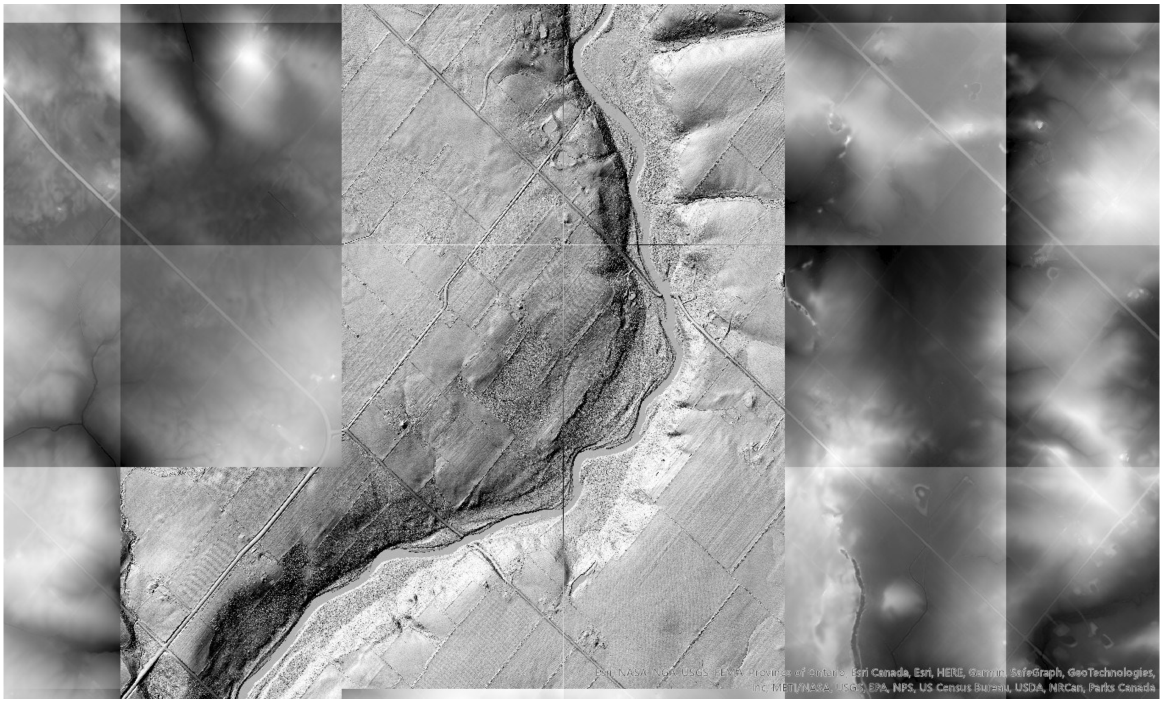

Fig. 3.6. Example of hillshade images of the testing area

Exported images from a tile were segmented with an online cutting tool (www.imgonline.com.ua, 2018) into 20×20 (50m×50m per segment). 10 image segments were categorized as “mound” and 358 segments as “non-mound.” Following are two examples of the cut images.

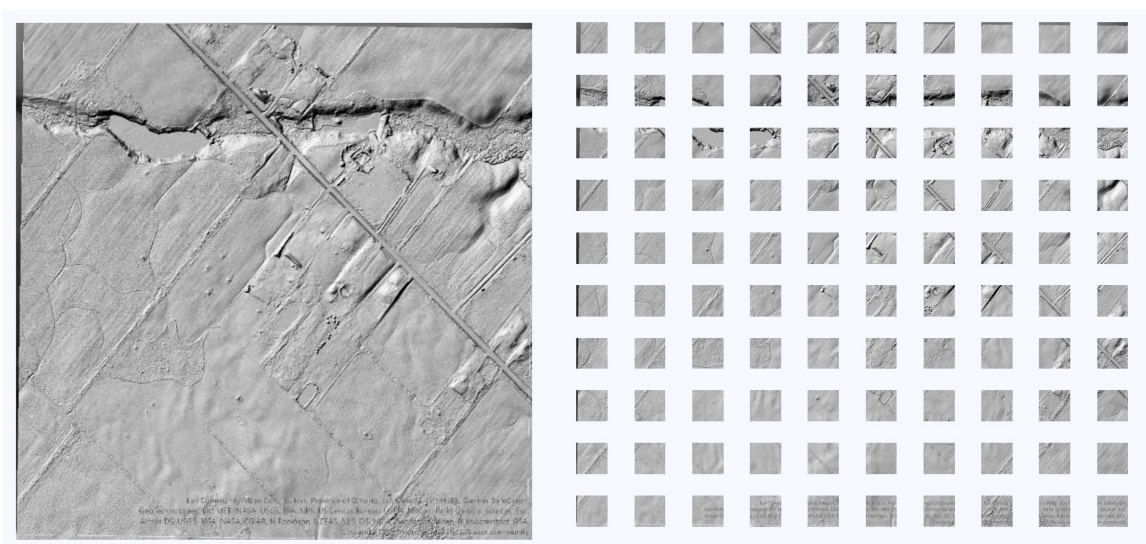

Fig. 3.7. Example of picture segmenting (10×10)

3.3.2 Image recognition with Python in TensorFlow

3.3.2.1 Model training

The categorized segments were zipped and sent in an image recognition and data augmentation program (Appendix A).

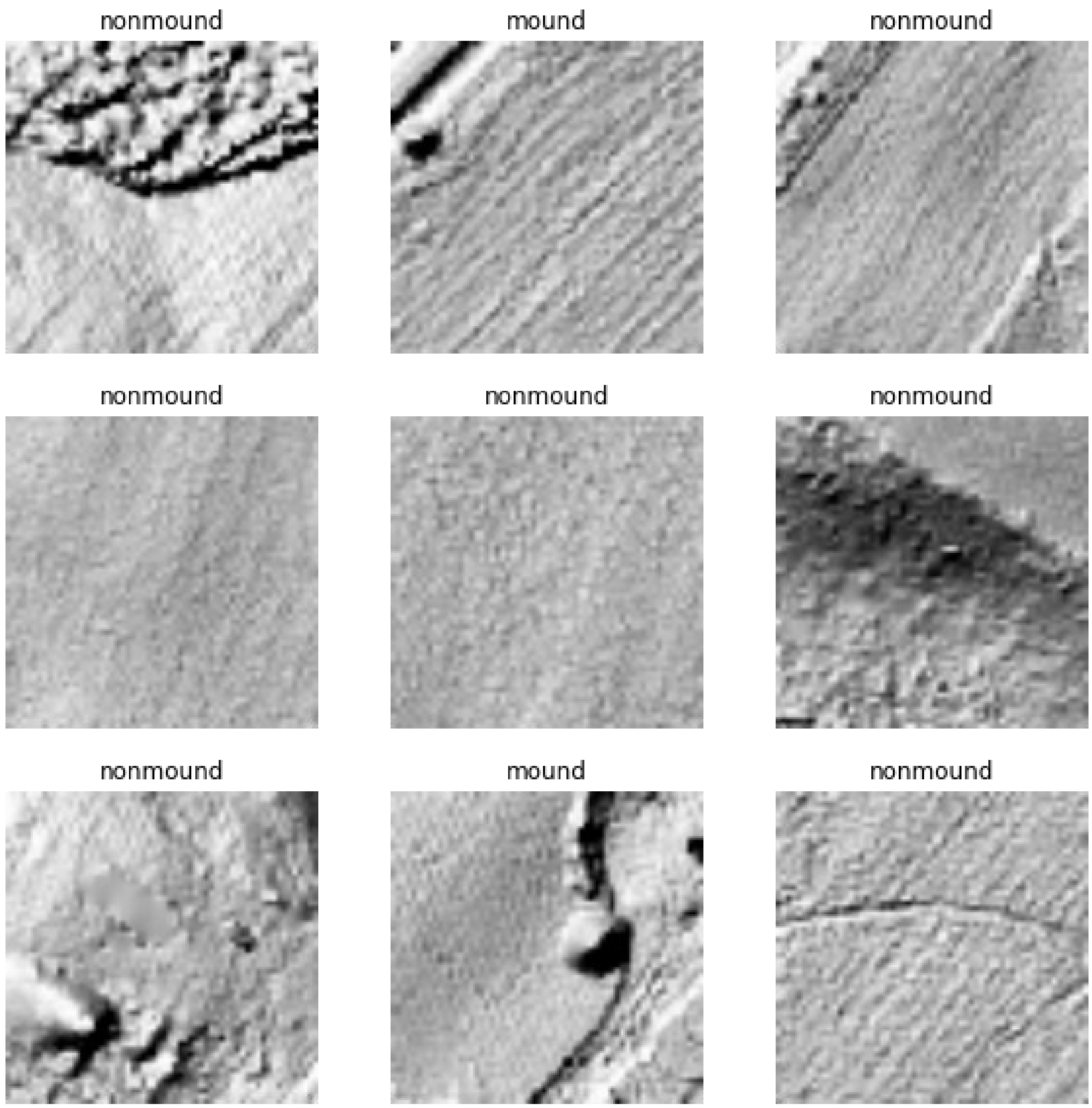

Fig. 3.8. Examples of categorized image segments (50m×50m).

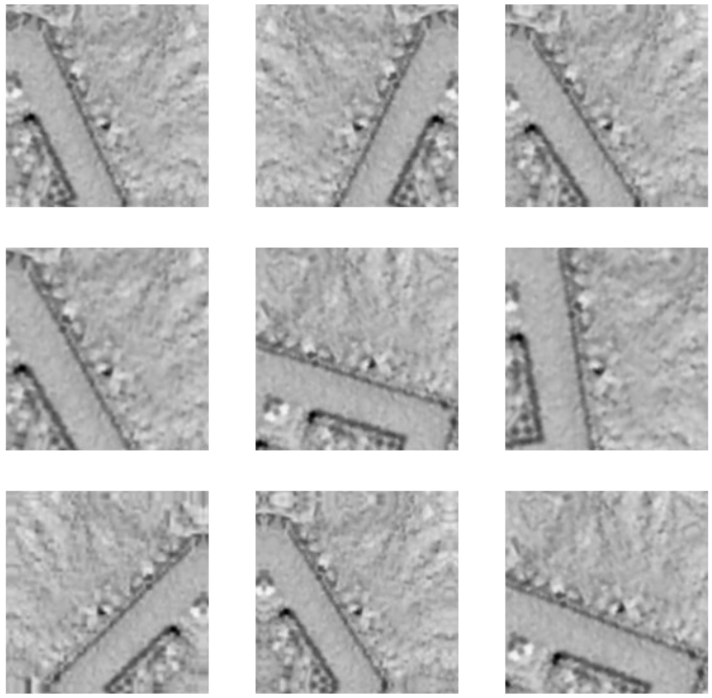

Fig. 3.9. Example of a method of data augmentation - random rotation.

3.3.2.2 Model Application

The trained model was applied to the studied sites and image segments that were identified more likely to be a burial mound were picked and located on the map. Presented are the sites that are less possible to be actual burial mounds; that is, ground elevation which are thought to result from other kinds of human interference, to prevent possible poaching and vandalization.

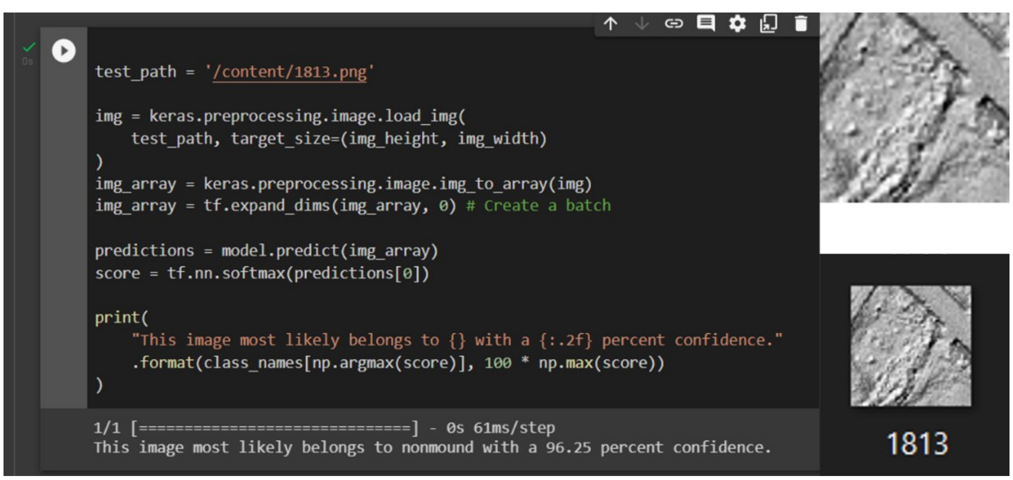

Fig 3.10. An output of the model with responding input

Fig. 3.11. Hillshade image of a potential burial site

Fig. 3.12. Satellite image of a potential burial site (Google, n.d.)

3.4 Ways forward

A method of generating standardized map segments with ArcGIS for image classification programs was established. I trained an image recognition model and applied the model on my study site and received images that may contain burial mound(s).

There is only 1 site with 9 mounds used as the positive control. The amount of positive controls given to this study is extremely limited, therefore it is difficult for the model to establish a general pattern of a burial mound or burial site. With more publicized data like digital terrain models and LiDAR-derived images of Anishinaabewaki, this model has a high possibility to improve drastically. On the other hand, the negative control, non-mound sites, are in abundance. This means the Burial Mound Identifier can screen non-mound elevation feature fast and accurately.

The trainer is inexperienced in correctly identifying burial mounds, more specifically differentiating a dirt pile and a burial mound. Image recognition is heavily based on training categories, so errors from human bias can affect the accuracy of trained models greatly.

For the next step, more time in burial mound finding will expand the training dataset, especially positive controls. Once enough positive controls can be secured, object detection algorithm such as You Only Look Once (YOLO) will be used to further automate the process of burial mound identification. Once mound-shaped ground elevation sites are detected, ground penetration radar can be used to determine whether the site is a burial ground or not.

Chapter 4 Discussions

In this study, a method to rank species value based on NishDB and a method to find burial mounds are established separately. With travel restrictions caused by the global pandemic, biosurvey on MCFN land was not feasible during my study. However, with citizen scientist-based social network such as iNaturalist, special concerned species can be mapped. Distribution pattern of the species can be compared with locations of burial sites with this method. Qualitative study can be done with this method to show the existence and diversity in an area. This framework has supported MCFN to defend the land and water against the proposed Highway 413 (J. Ferrier, personal communication, August 2, 2022)

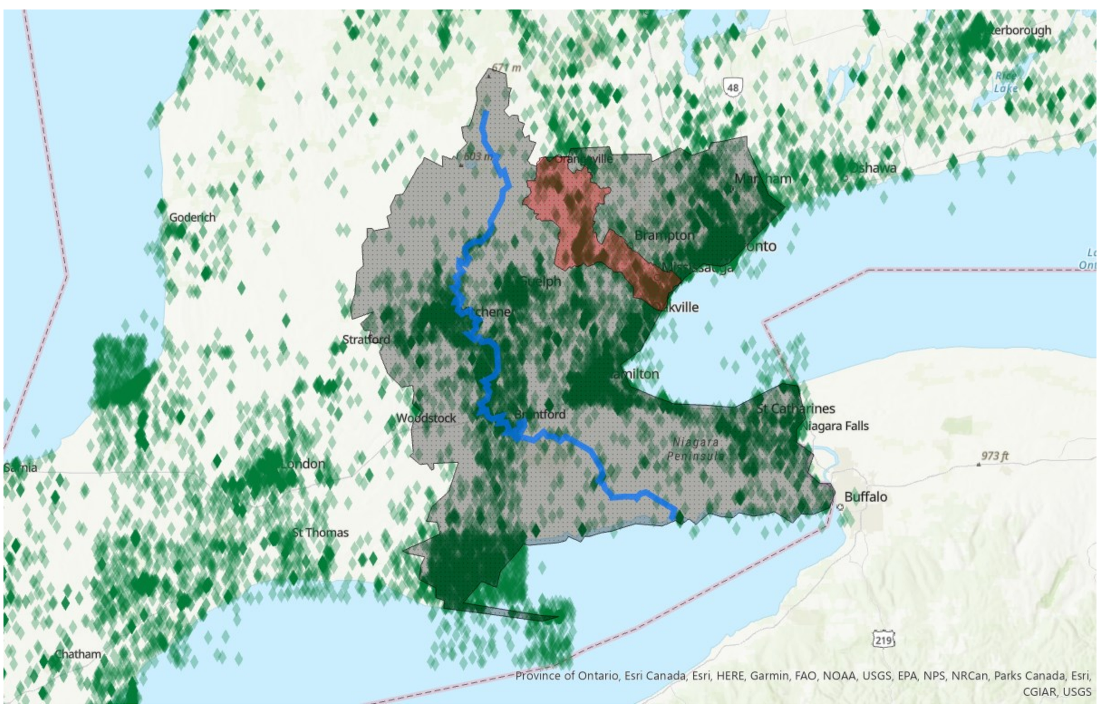

Fig. 4.1. Map of threatened plant species according to iNaturalist in MCFN traditional territory (iNaturalist contributors & iNaturalist, 2022)

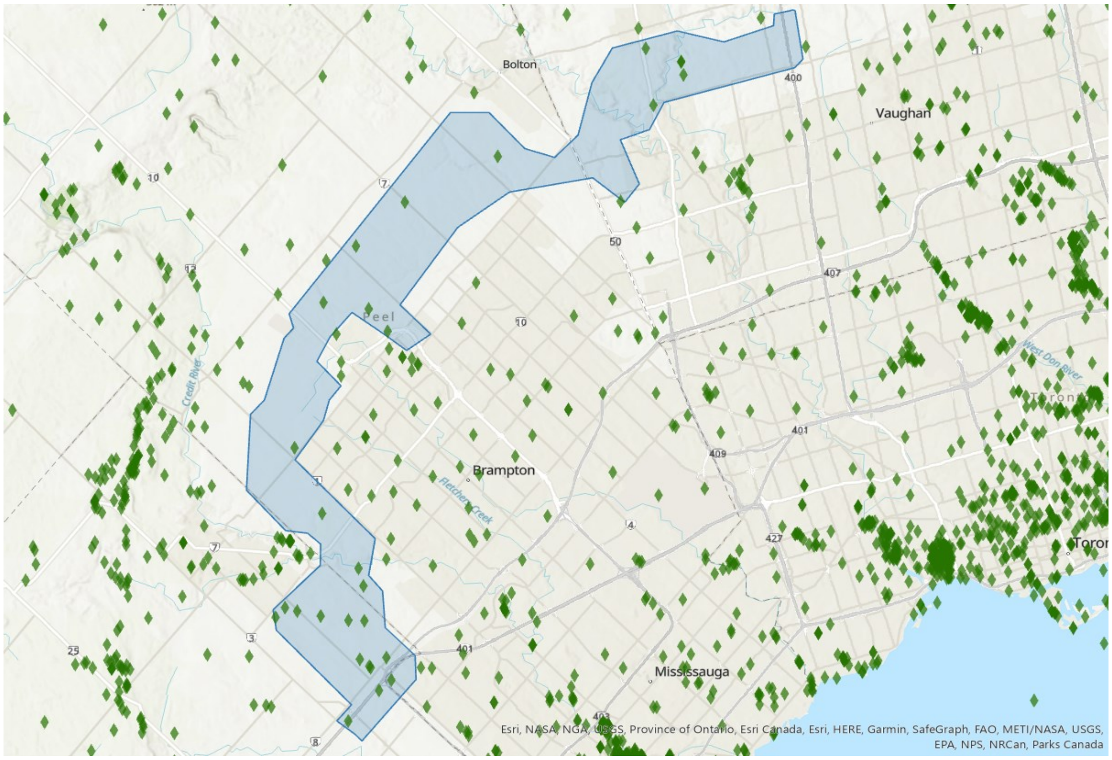

Fig. 4.2. Map of threatened plant species around the proposed Highway 413 area (iNaturalist contributors & iNaturalist, 2022; Highway 413, 2022)

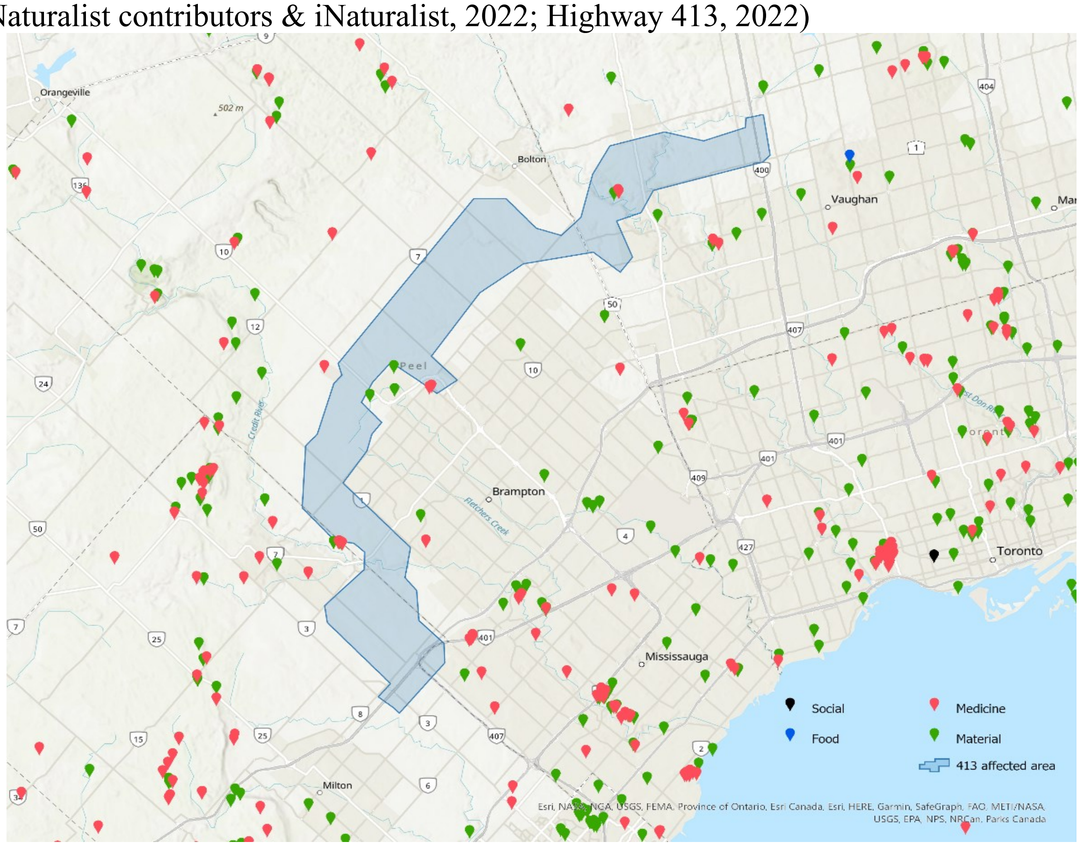

Fig. 4.3. Map of the top ranked species around the proposed Highway 413 area. (iNaturalist contributors & iNaturalist, 2022; Highway 413, 2022)

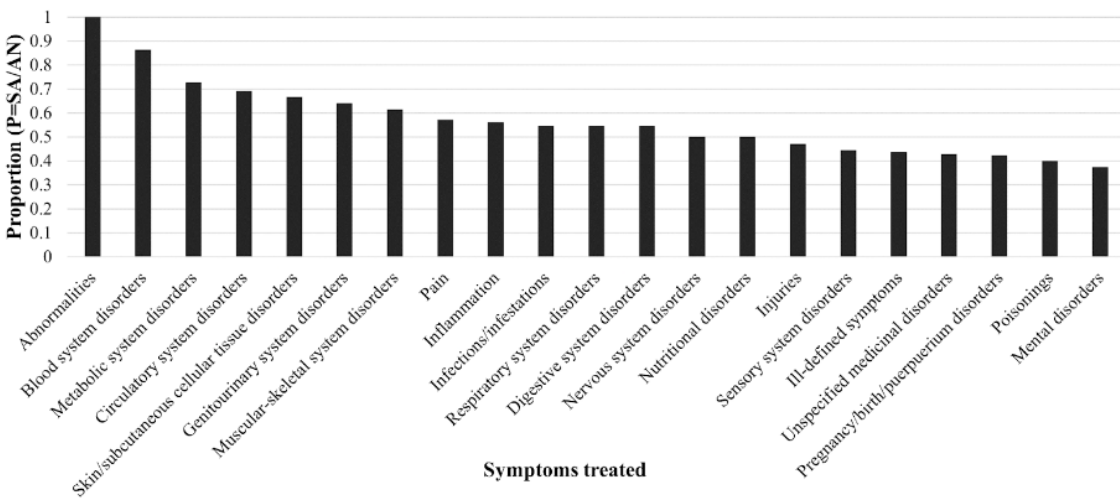

Fig. 4.4. Medicinal plant diversity proportion in proposed Highway 413 area. Proportion of medicinal plants growing in study area (P) = Species presented in study area (SA)/ Species used traditionally by Anishinabek (AN).

However, this comparation method comes with limitation. Accessible places, such as city and public parks, have more exposure to citizen scientists. This heavily affects the quantitative study. As shown in Fig. 4.1., the recorded species show up significantly more frequent by cities and conservation areas. No significant difference can be observed between burial sites and similar non-burial locations from the data retrieved from iNaturalist. As discussed in chapter 3, the “Indian burial ground” described by Cormie was privately owned since 1834, which would limit accessibility to the site to both citizen scientists and researchers. Therefore, a land survey will be favorable for further study. Further study might reach potential burial sites on public land, which will be helpful for land survey.

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Appendix A Code of ArcGIS LIDAR detecting burial mounds

```
"""ArcGIS LIDAR modelling Burial mounds

Automatically generated by Colaboratory.

Original file is located at
    https://colab.research.google.com/drive/1jKYO-Yr2VrxqfpoEUFOB-QEEqBwpIAqD

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"""

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#distributed under the License is distributed on an "AS IS" BASIS,
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#limitations under the License.

import matplotlib.pyplot as plt
import numpy as np
import os
import PIL
import tensorflow as tf

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential

image_path = '/content/training.zip'
!unzip training.zip
image_path = os.path.join(os.path.dirname(image_path), 'training')

batch_size = 32
img_height = 180
img_width = 180

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
  image_path,
```

```
  validation_split=0.2,
  subset="training",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
  image_path,
  validation_split=0.2,
  subset="validation",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)

class_names = train_ds.class_names
print(class_names)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
  for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(images[i].numpy().astype("uint8"))
    plt.title(class_names[labels[i]])
    plt.axis("off")

for image_batch, labels_batch in train_ds:
  print(image_batch.shape)
  print(labels_batch.shape)
  break

AUTOTUNE = tf.data.AUTOTUNE

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)

normalization_layer = layers.experimental.preprocessing.Rescaling(1./255)

normalized_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
image_batch, labels_batch = next(iter(normalized_ds))
first_image = image_batch[0]
print(np.min(first_image), np.max(first_image))

num_classes = 2

model = Sequential([
```

```
  layers.experimental.preprocessing.Rescaling(1./255, input_shape=(img_height,
img_width, 3)),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])

model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

model.summary()

epochs=10
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

```
data_augmentation = keras.Sequential(
  [
    layers.experimental.preprocessing.RandomFlip("horizontal",
                                                 input_shape=(img_height,
                                                              img_width,
                                                              3)),
    layers.experimental.preprocessing.RandomRotation(0.1),
    layers.experimental.preprocessing.RandomZoom(0.1),
  ]
)

plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")

model = Sequential([
  data_augmentation,
  layers.experimental.preprocessing.Rescaling(1./255),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Dropout(0.2),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])

model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

model.summary()

epochs = 15
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()

test_path = '/content/site1a.jpg'

img = keras.preprocessing.image.load_img(
    test_path, target_size=(img_height, img_width)
)
img_array = keras.preprocessing.image.img_to_array(img)
img_array = tf.expand_dims(img_array, 0) # Create a batch

predictions = model.predict(img_array)
score = tf.nn.softmax(predictions[0])

print(
    "This image most likely belongs to {} with a {:.2f} percent confidence."
    .format(class_names[np.argmax(score)], 100 * np.max(score))
)
```