Modeling Climate Resilient Planting Locations of Culturally Significant Plants for Musqueam on UBC's Vancouver Campus

Final Research Project

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Land Acknowledgment

I acknowledge that my research is conducted on the traditional, ancestral, and unceded territory of the Musqueam people. I recognize their deep connections to this land, which have been maintained since time immemorial, and I express gratitude for the opportunity to learn and work here. My project aims to respectfully engage with the knowledge and stewardship practices of the Musqueam community, recognizing their ongoing relationship with this land and the importance of Indigenous perspectives in environmental and climate research.

Disclaimer

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Executive Summary

Urban greenspaces provide essential ecosystem services, enhance biodiversity, and hold cultural significance, particularly for Indigenous communities. However, these areas are increasingly threatened by climate change, urbanization, and invasive species. While greenspace planning and species distribution modeling are established tools for supporting ecological resilience, few studies integrate future climate suitability into site-specific planting guidelines. This represents a key gap in designing adaptive urban landscapes. Remote sensing offers a distinct advantage in this context by enabling fine-scale, spatially continuous assessment of environmental conditions, such as precipitation and shade, that are difficult to capture through ground-based methods alone.

This study addressed this gap by assessing habitat suitability and future climate impacts at a local scale. Specifically, it identified future habitat suitability and optimal planting locations for culturally significant plants of the Musqueam people on the University of British Columbia Vancouver campus. To achieve this, the study combined iNaturalist occurrence data, future climate projections from ClimateBC, and local environmental variables derived from LiDAR within a MaxEnt modeling framework. The analysis focused on two species: Salmonberry (*Rubus spectabilis*) and Sword Fern (*Polystichum munitum*), evaluating their suitability under different climate scenarios. The resulting suitability maps highlighted optimal planting locations based on projected climate conditions and environmental factors such as slope, aspect, and shade. Shade emerged as the most influential variable across all models, contributing between 74% and 92%. Other environmental variables had a limited effect on model outcomes, likely due to the study's small geographic scope. Overall, the model outputs aligned closely with the known ecological preferences of the studied species. These findings can inform climate-resilient planting strategies for culturally significant species in urban greenspaces.

Key Words: Greenspace, Species Distribution Modelling, Salmonberry, Sword Fern, Culturally Significant Plants, Climate Change Adaptation

1. Introduction

Urban greenspace such as urban forests, parks, planted boulevards and other organic zones, provide a host of ecosystem services, like air purification, essential to any city (Gill et al., 2007). These spaces also offer numerous public health services such as reduction in pollution, noise and dissipation of heat island phenomena through the urban greenspace cooling effect (Aram et al., 2019; Europe, 2016). This effect helps counteract the urban heat island phenomenon, a form of increased warming in city environments caused by heat-retaining surfaces like concrete and asphalt (Aram et al., 2019). By breaking up these heat-trapping materials, greenspaces help lower ambient temperatures in urban areas (Aram et al., 2019). Urban greenspace also impacts human health on the individual level. Access to nature has demonstrated a host of benefits ranging from improved mental health to a reduction of cardiovascular mortality (Europe, 2016). Culturally, greenspaces hold significance for many, particularly in regions with a history of colonialism, where Indigenous communities maintain deep, longstanding connections to the land (Dickinson & Hobbs, 2017). There has also been an increase in recognition of the importance of urban greenspace for biodiversity conservation and promotion, with parks in particular being of high interest due to their high levels of habitat diversity and microhabitat heterogeneity (Nielsen et al., 2014; Savard et al., 2000). As climate change and urbanization challenge the resilience of these spaces, remote sensing and suitability modelling offer promising approaches for guiding future management decisions that are both ecologically and culturally informed.

Despite these wide-ranging benefits and growing recognition of their value, urban greenspaces are increasingly vulnerable to a range of pressures, including densification and climate change (Aronson et al., 2017; Omann et al., 2009). The increase in extreme weather events like floods, droughts and heatwaves can cause stress to ecosystems, through events like plant deaths and changes to soil environment (Bogati & Walczak, 2022; Ummenhofer & Meehl, 2017; Zhang et al., 2022). On a more local level, densification is a threat to urban greenspaces that will need to be mitigated through careful and thoughtful planning (Haaland & van den Bosch, 2015). In addition to those mid to long term temporal challenges, areas such as parks are under constant stressors due to common management techniques like herbicide and insecticide use, pruning and introduction of non-native plants (Aronson et al., 2017). Non-native plants are especially a problem in urban settings where 73 species have been introduced as an ornamental or landscaping plant in Canada (*Canadian Food Inspection Agency - Invasive Alien Plants in Canada - Summary Report*, n.d.). This introduction of exotic species, while technically increasing plant species richness, has downsides such as decreasing animal species richness (Faeth et al., 2011).

Challenges faced by urban greenspaces highlight the importance of good landscape planning to not only preserve human and ecological health in relation to these areas, but as a tool to help reconciliation efforts with Indigenous populations. As discussed earlier, ample research exists outlining the ecosystem services from urban greenspace. Planting guidelines based on those services have been developed discussing topics including where to plant trees in order to improve cooling within a city (J. Wang et al., 2022). Additionally, studies are discussing how urban greenspace can be used as a tool for climate change adaptation (Gill et al., 2007). An example would be how greenspaces can be used to mitigate events such as urban flooding, which are a growing threat due to climate change (Qin, 2020; Rainey et al., 2021). Currently, a knowledge gap resides at the intersection of planting guidelines and future climate suitability. Researching this space is essential to ensure the long-term ecological prosperity of urban greenspaces.

While the importance of urban areas as opportunities to conserve and promote biodiversity is growing (Nielsen et al., 2014), few explore the ways to improve the long-term outlook of key native species while managing these spaces. Current papers concentrate on modelling current species distribution and suitability. In Hale et al. (2022), a maximum entropy machine learning algorithm called MaxEnt is used in order to model habitat suitability for *Stewartia ovata*. MaxEnt reappears frequently in papers attempting to determine plant community movements or possible future distribution (Hale et al., 2022; Hay et al., 2023; Morales et al., 2017; Zhao et al., 2021). One such study successfully modeled spatial distribution of Amah Mutsun culturally important plants in southern California (Taylor et al., 2023). Others concentrate on the potential future impact of climate change on suitable species habitat, including Hamann & Wang (2006), who through the use of climate scenarios and statistical modeling estimated province-wide habitat gain and loss for tree species in British Columbia. Local to British Columbia, research on future climate impacts, such as Ball's study on canola production, rely on ClimateBC projections to inform future environmental conditions (Ball, 2023). Building on the work done in these previous studies, this planting suitability paper aims to merge methods evaluating habitat suitability and future climate impacts while also shrinking the studied area to a local scale. In doing so, it endeavors to determine future habitat and thus planting locations for plants of heightened cultural significance for Musqueam on the University of British Columbia (UBC) Vancouver campus. While UBC's Vancouver campus will be used as a case study, special attention will be paid to developing a reproducible roadmap that can help create climate resilient planting guidance for urban planning professionals in a variety of contexts.

2. Study Site and Data Summary

2.1 Study Site Area – University of British Columbia Vancouver Campus

The University of British Columbia (UBC) main campus is situated on 400ha of land in the greater Vancouver area, Canada on traditional Musqueam territory (*Vancouver - UBC Campuses | The University of British Columbia*, n.d.). It sits on a peninsula surrounded by a forested green belt and the Salish Sea. UBC is part of the Southern Coastal Western Hemlock Zone in the Very Dry Maritime subzone (*CWH Subzone Maps*, n.d.). It has a mild climate with a mean average temperature of 9.3 degrees Celsius and an average precipitation of 1427 millimeters per year (*Subzone/Variant Climate Data*, n.d.). The built environment is a mix of housing, commercial and academic buildings. The campus is also home to a variety of parks and gardens that make up its collection of greenspace. This study concentrates on finding suitable planting locations on campus. Figure 1 highlights the area of interest for this study.

Figure 1: UBC's Vancouver campus and endowment lands. The study area is a collection of urban and suburban development surrounded by beaches and forested parks. Outline overlaid on top of ESRI's light theme base map.

2.2 iNaturalist Occurrence Data

iNaturalist is an occurrence recording tool powered by crowdsourced observations. It has over 213,870,000 observations for more than 490,000 species uploaded by millions of users (*Observations*, n.d.). It is an invaluable source of data especially in situations, such as this study, where gathering manual presence data is untenable. Despite its plethora of information, it is important to acknowledge that it is spatially biased towards points of access like roads and footpaths (El-Gabbas & Dormann, 2018; Geurts, 2023; Mair & Ruete, 2016; Rocchini et al., 2011). However, researchers still utilise iNaturalist occurrence data, as biases can be corrected to a comparable level as professionally collected data (Mesaglio & Callaghan, 2021). In a comparable paper modeling habitat suitability of *Stewartia ovata*, Hale et al. (2022) used iNaturalist research grade observations due to its peer reviewed nature offering a strong safeguard against mislabeled plant occurrences. Similar studies looking at future species distribution have also successfully incorporated iNaturalist in their modeling pipeline (Salgado et al., 2024; Taylor et al., 2023).

Occurrence data for the plants of interest was queried from the iNaturalist export tool on 08/10/2024 (*Export Observations · iNaturalist*, n.d.). Salmonberry (*Rubus spectabilis*) and Sword Fern (*Polystichum munitum*) research grade observations were extracted over a rectangular extent ranging from a southwest point of (49.240443, -123.269016) to a northeast point of (49.28067, -123.19523) over UBC's campus. In sum, more than 800 observations were retrieved, with occurrences erroneously intersecting with water removed from the dataset (Figure 2). This occurrence data will set a baseline used for calculating future probability distribution of the species of interest.

Figure 2: Salmonberry and Sword fern Occurrence overlaid on ESRI's satellite base map. The occurrences are mainly on the outer edges of campus and within pacific spirit park.

2.3 LiDAR Derived Models (DSM, DEM, CHM)

A Digital Elevation Model (DEM) represents the bare earth surface, excluding surface objects such as buildings or vegetation (Guth, 2006; Mukherjee et al., 2013). DEMs are commonly derived from Light Detection and Ranging (LiDAR) data, a remote sensing technology that accurately captures the elevation of terrain features (Liu, 2008). DEMs are commonly used in environmental studies because elevation influences climate factors such as temperature and precipitation. In modeling tools used in this study, such as ClimateBC, a DEM is essential not only for providing elevation data used in predictions, but also for defining the spatial extent and resolution of the output.

To visually interpret the topography of the study area, a hillshade render was produced. A hillshade render is a qualitative technique for visualizing terrain based on a simulated light source and the terrain slope. While it does not give elevation values, it is helpful in showing that UBC's elevation is relatively flat with low elevation and minimal variance mostly due to the escarpment from the main campus down to the beach (Figure 3).

Figure 3: Hillshade render of UBC's Vancouver Campus overlaid on ESRI's light theme base map showing the relative uniformity of its relief.

In contrast to DEMs, Digital Surface Models (DSMs) and Canopy Height Models (CHMs) include above-ground features (Mielcarek et al., 2018; Priestnall et al., 2000). A DSM models the surface including buildings and vegetation, making it useful for representing urban environments (Priestnall et al., 2000). A CHM is derived by subtracting a DEM from a DSM, resulting in a layer that shows vegetation height alone (Mielcarek et al., 2018). For this study, both a DSM and CHM were essential for estimating average shade across the study area, as the inclusion of above-ground features allows for modeling how sunlight interacts with buildings and vegetation.

The UBC published DEM, DSM and CHM used in this study were derived from a LiDAR survey conducted in September 2021 and includes the main campus as well as parts of Pacific Spirit Park. No control was available to verify the validity of the elevation data, but the data has a horizontal accuracy of ± 0.30m and vertical accuracy of ± 0.15m (Planning, 2022). The models are suitable for this study, offering a spatial resolution of 50cm, substantially finer than the 30m resolution commonly used in habitat suitability studies (Hale et al., 2022; Taylor et al., 2023).

2.4 Generating Future Climate Data (ClimateBC)

ClimateBC is a standalone Windows software, developed by the Centre of Forest Genetic Conservation at UBC, used to generate future climate data. To do so, it takes a pre-calculated climate scenario and downscales it in order to derive climate variables using latitude, longitude and elevation (Spittlehouse, 2008). This has the advantage of generating scale free climate data as the model can determine values for any point (T. Wang et al., 2016). Data generated by the program has been used for climate data estimation in studies that concentrate on climate impacts and mitigation of plants in British Columbia (Ball, 2023; Majidian, 2011; Rose & Burton, 2009). Beyond its wide use, ClimateBC can output environmental rasters, a key advantage streamlining integration with modeling steps in this study.

In order to generate future climate data, it is necessary to choose appropriate settings for use with the ClimateBC model. First step was choosing a Shared Socioeconomic Pathways (SSPs). These socio-economic and emission scenarios attempt to give potential future scenarios on how emissions may evolve over time (van Vuuren et al., 2011). Two SSPs were chosen to model a moderate and pessimistic scenario of future climate. The first, SSP 2-4.5 is an intermediate scenario where radiative forcing stabilizes at 4.5 W/m^2 post 2100. The second is SSP 5-8.5, a high emission scenario where radiative forcing rises to 8.5 W/m^2 in 2100 (Environment and Climate Change Canada, 2023). Using two scenarios allows gauging how dependent on climate impacts planting locations are for each plant of interest. Finally, the model was run with the two scenarios to produce data for 2021 and 2100. Once the model tuned and run, resulting precipitation, temperature and relative humidity rasters of 2021 and 2100 were collected for use with the MaxEnt model.

3. Methods

This study aims to identify suitable planting locations of Musqueam plants of interest by leveraging future climate data with a distribution model. The following methods can be grouped into three main steps; Deriving categorical variables, Running the distribution model, Generating the suitability maps (Figure 4).

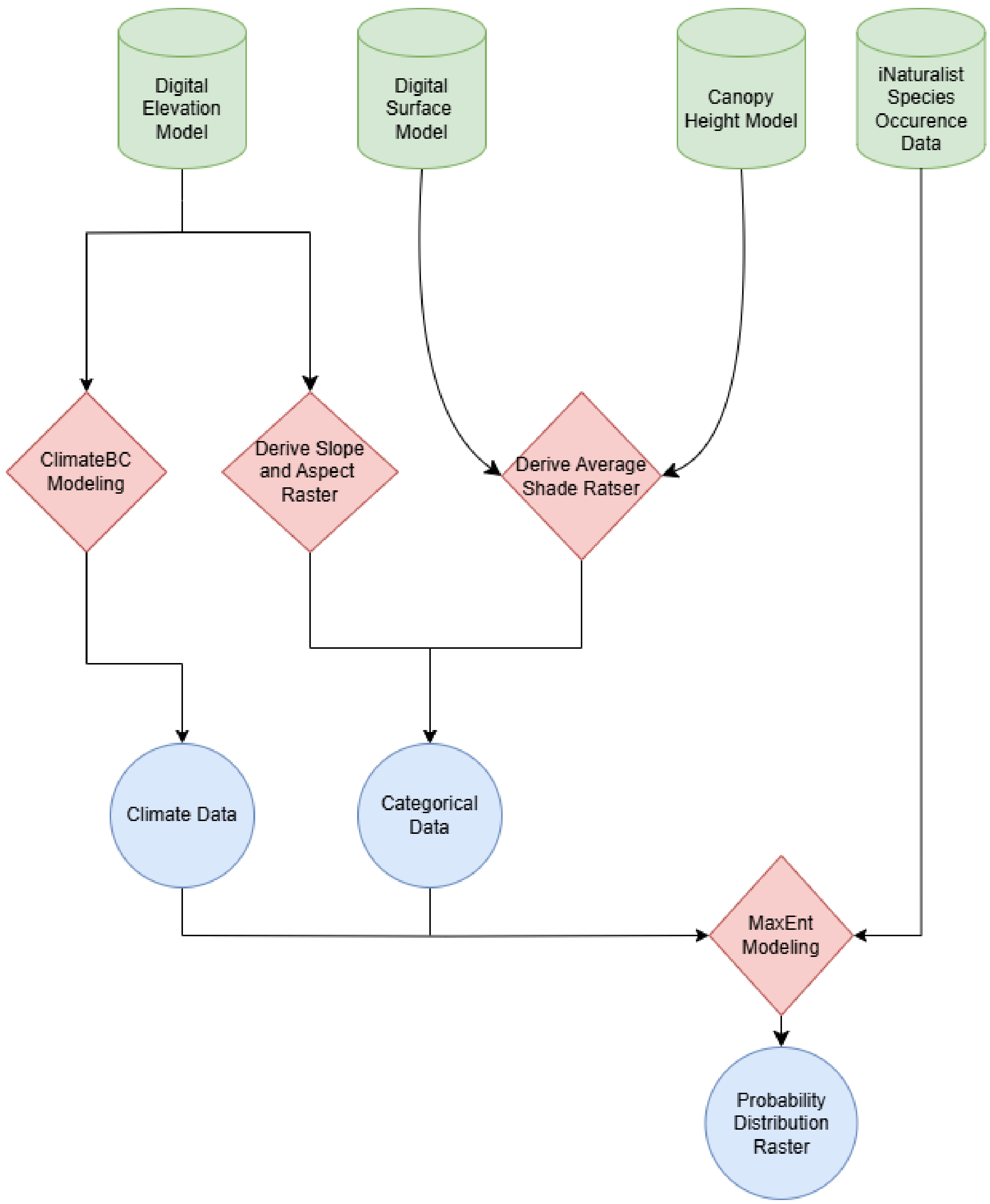


Figure 4: Workflow representing generating a planting suitability raster for a Musqueam plant of interest.

3.1 Preparing Data for MaxEnt

MaxEnt is a machine learning model that uses maximum entropy to predict species distribution and niches. It uses presence data along with climate rasters to calculate probability of presence over the studied area (Steven J. Phillips, Miroslav Dudík, Robert E. Schapire, n.d.). Studies have successfully used MaxEnt to derive future habitat and distributions of plant species in varied climates, including ones similar to the study site (Hay et al., 2023; Prevéy et al., 2020; Zhao et al., 2021). For this study, a high future presence likelihood was used as a proxy for a suitable planting location as both scenarios represent a case where a plant has the right conditions to thrive, regardless if it spawned there naturally or with human intervention. Furthermore, a key factor in choosing MaxEnt is its performance with limited data and ability to work with presence only information (Elith et al., 2011), as gathering field data was out of this study's scope.

To prepare the climate and categorical data for use with the MaxEnt model, raster data must have homogenous resolution, extent and projection. The Warp (Reproject) tool in GDAL was used in order to ensure each raster was projected to the EPSG:4236 (WGS 84) coordinate reference system and upscaled to a pixel size of 0.00004 degree (approximately 4.4 meters). The generated GeoTif's were then be converted to ASCII format using the Terra library in R as that is the only raster format supported by MaxEnt.

3.2 Running the MaxEnt Model

Similarly to ClimateBC, MaxEnt also needs to be set up for the specifics of this study. Two parameters must be set to run the model. The first, called the regularization multiplier, is responsible for reducing model overfitting (Sun et al., 2020). The next, feature types, are transformations of environmental predictor variables such as lineal (L), quadratic (Q), product (P), threshold (T), and hinge (H), that can be combined to best capture the relationship between the different environmental and categorical factors and species occurrence (Elith et al., 2011).

To find the best combination of parameters, the ENMevaluate function from the ENMeval package was used. This function systematically tests models with different combinations of regularization multipliers and feature types reporting resulting evaluation metrics including Area Under Curve (AUC), Omission Rate (OR) and Corrected Akaike Information Criterion (AICc) (*ENMevaluate Function - RDocumentation*, n.d.). For this study, the model with the lowest AICc determined final parameters as AICc outperforms AUC and OR as a criterion for parameter selection (Warren & Seifert, 2011).

Once ideal model parameters were selected, environmental data was fed into MaxEnt as described in Figure 4. MaxEnt was run for each plant of interest twice, once for each climate scenario, and a mean probability raster was generated for the year 2100. The final probability rasters were used as the base for the final planting suitability maps.

3.3 Generating Suitability Maps

Building final planting suitability maps was accomplished using QGIS. The two probability rasters for each plant were masked with polygons of unplantable areas on UBC's campus such as buildings, roads, and abiotic landscape features. In turn, this returned a layer of physically possible planting locations along with a scale of the planting suitability of said plant. The scale of suitability was symbolized from least suitable to most suitable enabling ease of understanding for a non-technical audience.

3.4 Deriving Categorical Data

Average shade, aspect and slope were calculated using the UBC DEM, DSM and CHM, for use with the MaxEnt model as all three can have an impact on plant suitability (Holland & Steyn, 1975; Sack & Grubb, 2002). Once each layer generated, shade, slope and aspect rasters were reclassified to an Integer value to turn them into classified data.

3.4.1 Deriving Slope and Aspect from DEM

Slope and aspect rasters of UBC were derived using the UBC DEM described in the data section of this paper. Employing the native slope and aspect tools found within QGIS with the DEM as input yielded high resolution rasters.

3.4.2 Deriving Average Shade Values

To build an average shade raster, both a DSM and CHM of the study area were required. Firstly, the DSM was used to generate hourly binary hillshades of the study area on July 15th 2024. These hourly shade rasters were combined into an aggregate raster and normalized. To ensure forested areas of pacific spirit were correctly shaded, a binary shade mask was created from areas above 15m in height in the canopy height model and subsequently applied to the normalized shade raster. The result was a finalized shade raster of the entire study site.

4. Results

A range of factors impact the suitable planting locations of Musqueam plants of interest in this study. Both data and methodological decisions influence the MaxEnt model and final planting suitability. Results are expressed as suitability maps for each modeled climate scenario (Figure 7, 12), species distribution model performance metrics (Figure 8, 9, 13, 14) and results of evaluated model parameters (Figure 5, 6, 10, 11).

4.1 Salmonberry (*Rubus Spectabilis*) Results

4.1.1 Evaluated Parameters

Model performance varied between different regularization multipliers and feature class combinations for Salmonberry under the SSP 5-8.5 scenario. The best performing parameters, with lowest Delta AICc, were LQHP-1, which were selected for the final model (Figure 5).

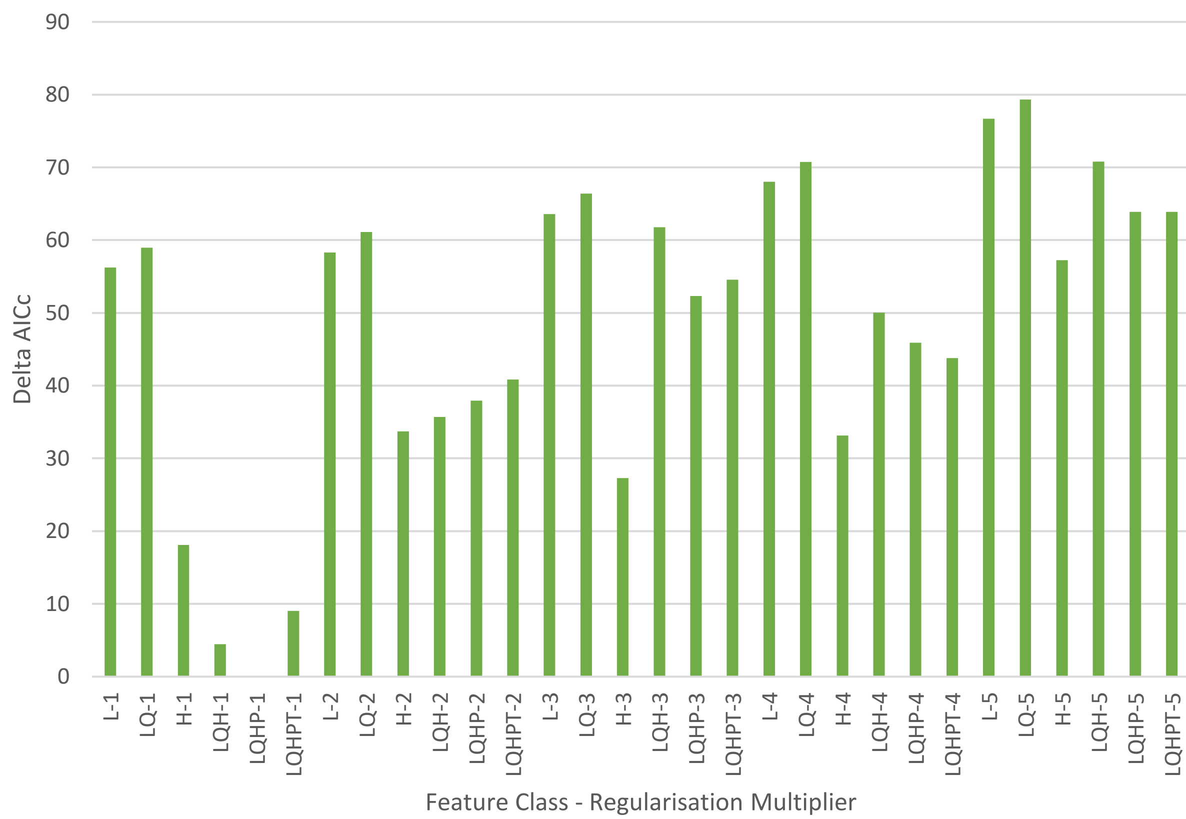


Figure 5: Comparison of MaxEnt model performance across different feature class and regularization multiplier combinations for Salmonberry under the SSP 5-8.5 climate scenario. The y-axis represents the change in AICc (Delta AICc), where lower values indicate better model performance. Each bar corresponds to a unique combination of feature class (L, LQ, H, etc.) and regularization multiplier (1–5), illustrating their impact on model complexity and predictive power.

Model performance also varied between different regularization multipliers and feature class combinations for Salmonberry under the SSP 2-4.5 scenario. The best performing parameters, with lowest Delta AICc, were LQH-1, which were selected for the final model (Figure 6).

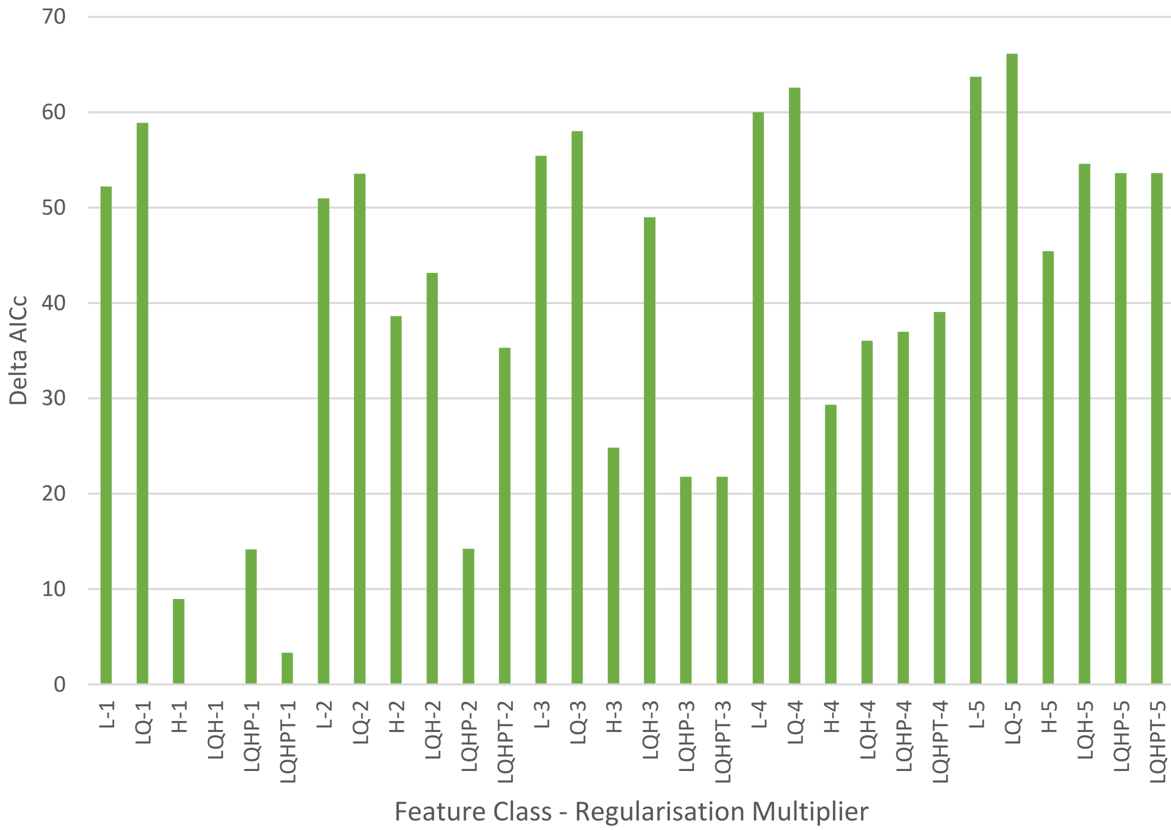


Figure 6: Comparison of MaxEnt model performance across different feature class and regularization multiplier combinations for Salmonberry under the SSP 2-4.5 climate scenario. The y-axis represents the change in AICc (Delta AICc), where lower values indicate better model performance. Each bar corresponds to a unique combination of feature class (L, LQ, H, etc.) and regularization multiplier (1–5), illustrating their impact on model complexity and predictive power.

4.1.2 Salmonberry Planting Suitability Maps

The generated normalized suitability raster of Salmonberry in the year 2100, using the SSP 5-8.5 scenario has planting suitability values ranging from 0.048 to 0.933. Values for the planting suitability raster using the SSP 2-4.5 range from 0.008 to 0.362. Planting suitability is higher for the SSP 5-8.5 scenario compared to the SSP 2-4.5 scenario. The top inset demonstrates how densely forested areas on campus have high suitability values whereas other areas, as seen in the bottom inset, are more dependent on individual features such as buildings and trees. The insets also demonstrate the uniform impact of different climate scenarios on suitability values across the entire study area (Figure 7).

Figure 7: Map highlighting mean planting suitability of Salmonberry on UBC's campus in the year 2100. Results generated with climate scenario SSP 5-8.5 and SSP 2-4.5 are on the left and right respectively.

4.1.3 Response Curves and Significant Variables

For the SSP 5-8.5 scenario, shade had the largest contribution to the final Salmonberry MaxEnt model (Table 1). The response curves for shade, temperature, and precipitation indicate that Salmonberry prefers shaded areas with higher precipitation and temperatures. Specifically, the shade response shows a smooth peak at shade classification 4, while temperature exhibits a sharp increase in probability before leveling off at 16.7°C. Precipitation follows an exponential increase before becoming noisy beyond 1350 millimeters (Figure 8).

Table 1: Contribution of Every Variable to the Final Salmonberry MaxEnt Model for the SSP5-8.5 Scenario.

Variable	Percent Contribution
Shade	74.8
Mean Average Precipitation	14.5
Mean Average Temperature	4.7
Aspect	3.9
Slope	1.9
Relative Humidity	0.2

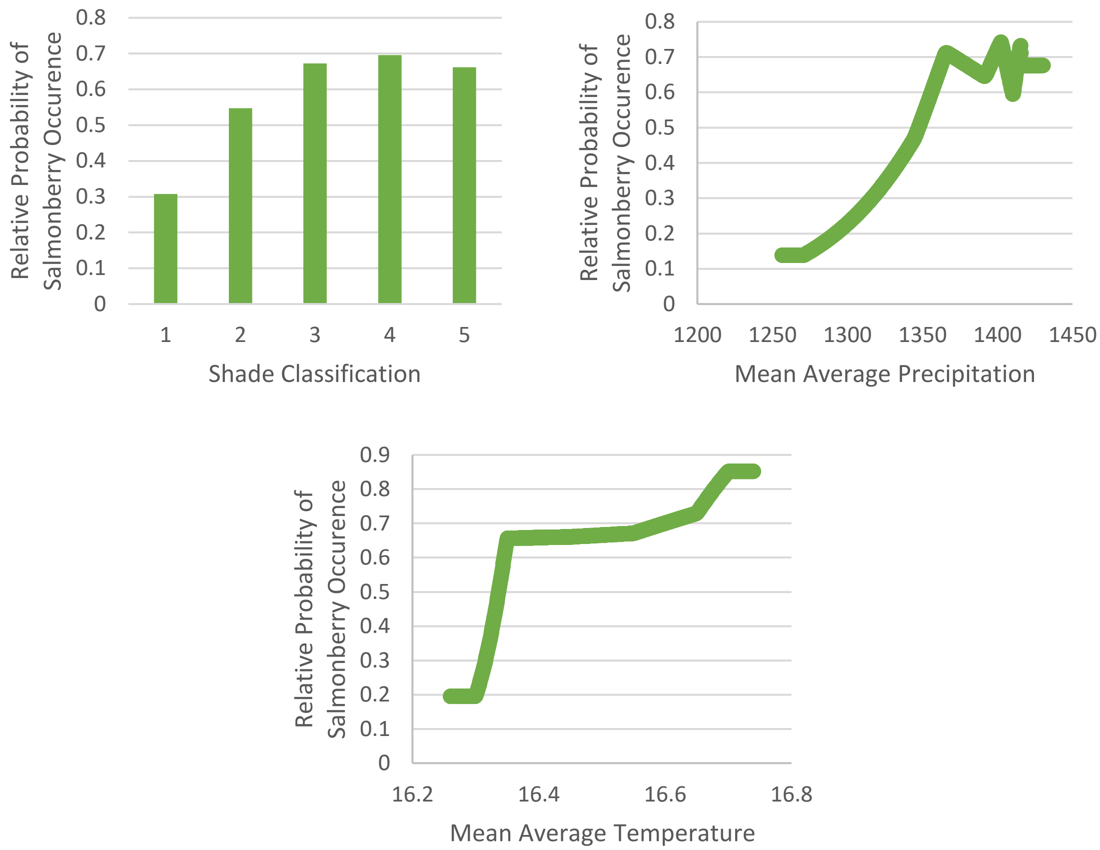


Figure 8: Response curves of the three most impactful variables (Shade, Mean Average Precipitation and Mean Average Temperature) on the MaxEnt model for Salmonberry using the SSP 5-8.5 scenario. Response curves show how each variable impacts the model's prediction. The curves show how the predicted probability of presence changes as each environmental variable is varied. The curves show the effect of changing a single variable.

For the SSP 2-4.5 scenario, shade had the largest contribution to the final Salmonberry MaxEnt model (Table 2). The response Curves for Shade, Temperature and Precipitation highlight that Salmonberry has a preference for shaded areas with higher precipitation and higher temperatures. Specifically, the shade response shows a smooth peak at shade classification 3, while temperature exhibits a sharp increase in probability followed by slight cratering before leveling off at 16.7°C. Precipitation follows an exponential increase before becoming noisy beyond 1350 millimeters (Figure 9).

Table 2: Contribution of Every Variable to the Final Salmonberry MaxEnt Model for the SSP2-4.5 Scenario.

Variable	Percent Contribution
Shade	81.7
Mean Average Precipitation	9.3
Mean Average Temperature	4.4
Aspect	2.6
Slope	1.9
Relative Humidity	0

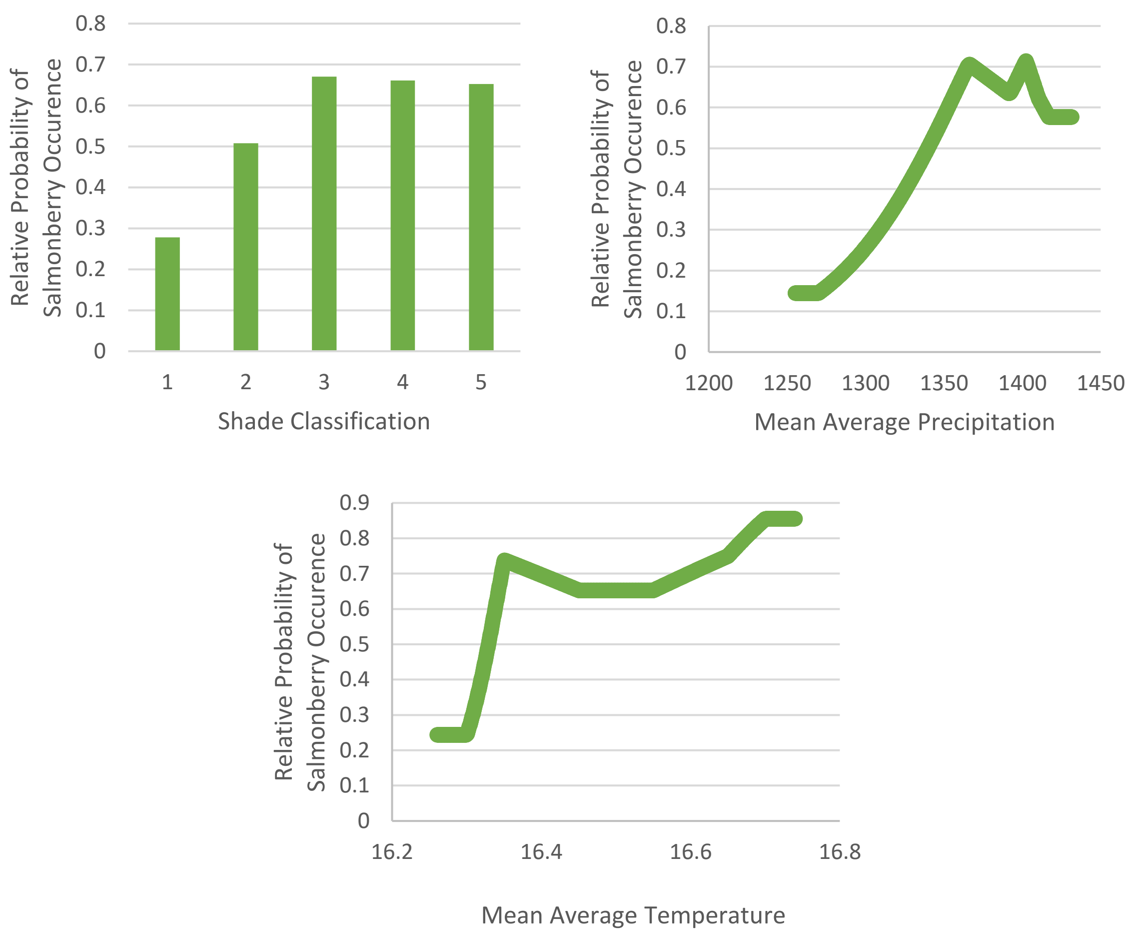


Figure 9: Response curves of the three most impactful variables (Shade, Mean Average Precipitation and Mean Average Temperature) on the MaxEnt model for Salmonberry using the SSP 2-4.5 scenario. Response curves show how each variable impacts the model's prediction. The curves show how the predicted probability of presence changes as each environmental variable is varied. The curves show the effect of changing a single variable.

4.2 Sword Fern (*Polystichum munitum*) Results

4.2.1 Evaluated Parameters

Model performance varied between different regularization multipliers and feature class combinations for Sword Fern under the SSP 5-8.5 scenario. The best performing parameters, with lowest Delta AICc, were LQHPT-2, which were selected for the final model (Figure 10).

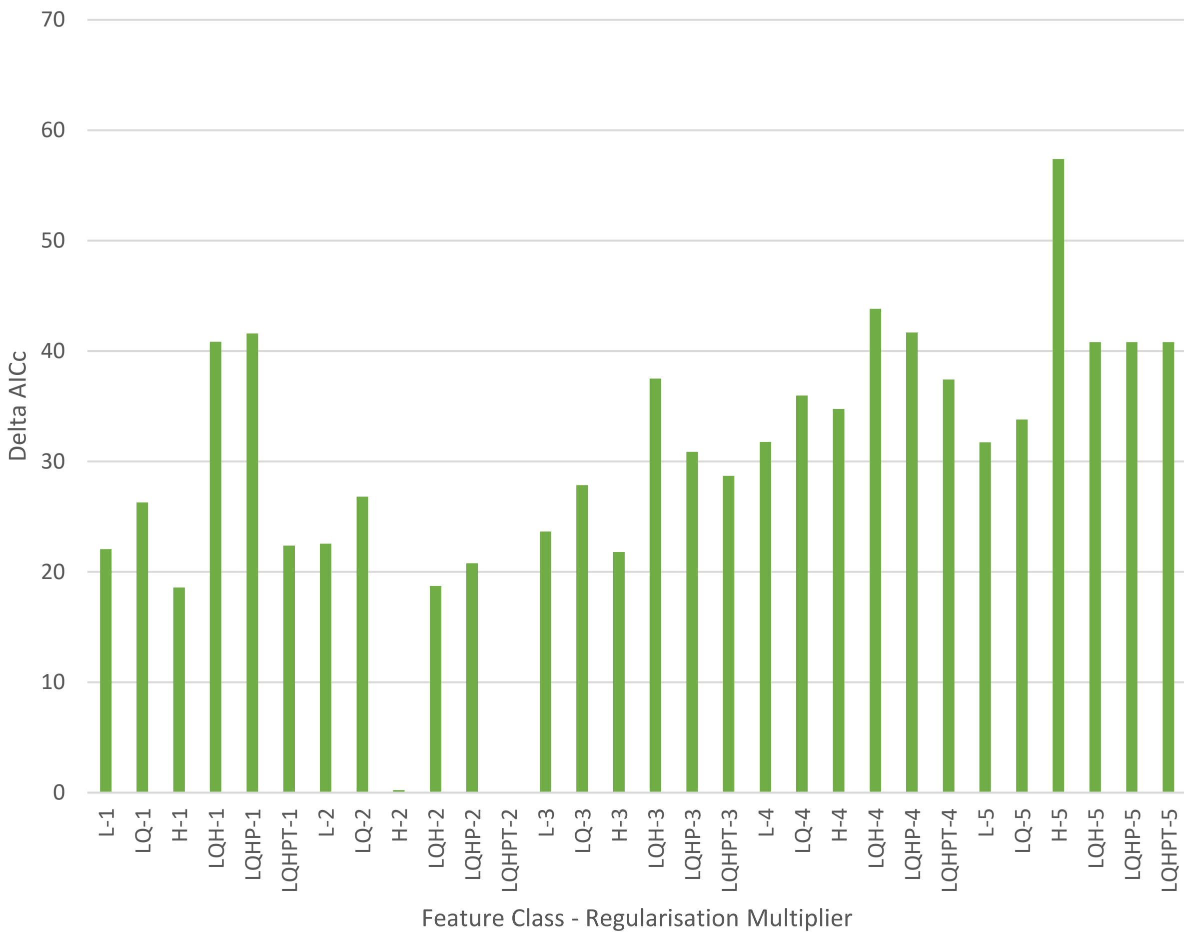


Figure 10: Comparison of MaxEnt model performance across different feature class and regularization multiplier combinations for Sword Fern under the SSP 5-8.5 climate scenario. The y-axis represents the change in AICc (Delta AICc), where lower values indicate better model performance. Each bar corresponds to a unique combination of feature class (L, LQ, H, etc.) and regularization multiplier (1–5), illustrating their impact on model complexity and predictive power.

Model performance varied between different regularization multipliers and feature class combinations for Sword Fern under the SSP 2-4.5 scenario. The best performing parameters, with lowest Delta AICc, were H-2, which were selected for the final model (Figure 11).

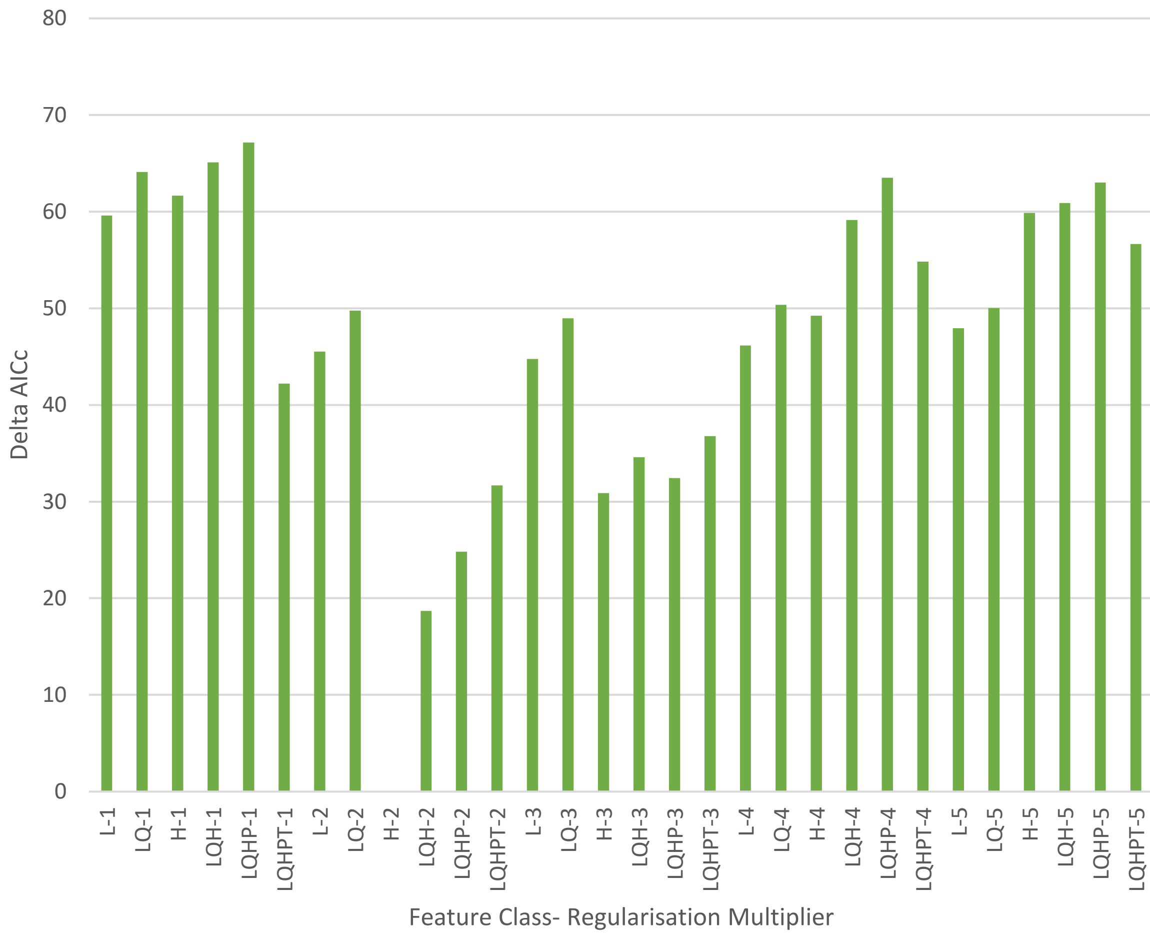


Figure 11: Comparison of MaxEnt model performance across different feature class and regularization multiplier combinations for Sword Fern under the SSP 2-4.5 climate scenario. The y-axis represents the change in AICc (Delta AICc), where lower values indicate better model performance. Each bar corresponds to a unique combination of feature class (L, LQ, H, etc.) and regularization multiplier (1–5), illustrating their impact on model complexity and predictive power.

4.2.2 Sword Fern Planting Suitability Maps

The generated normalized suitability raster of Sword fern in the year 2100, using the SSP 5-8.5 scenario has planting suitability values ranging from 0.145 to 0.896. Values for the planting suitability raster using the SSP 2-4.5 range from 0.089 to 0.715. Planting suitability is higher for the SSP 5-8.5 scenario compared to the SSP 2-4.5 scenario. The top inset demonstrates how densely forested areas, with full shade, have the highest suitability values with forest edges even seeing drops in suitability. Other areas, as illustrated in the bottom inset, contain individual features that provide limited shade and therefore do not produce the same depth of shading, resulting in lower values. The insets also demonstrate the uniform impact of different climate scenarios on suitability values across the entire study area (Figure 12).

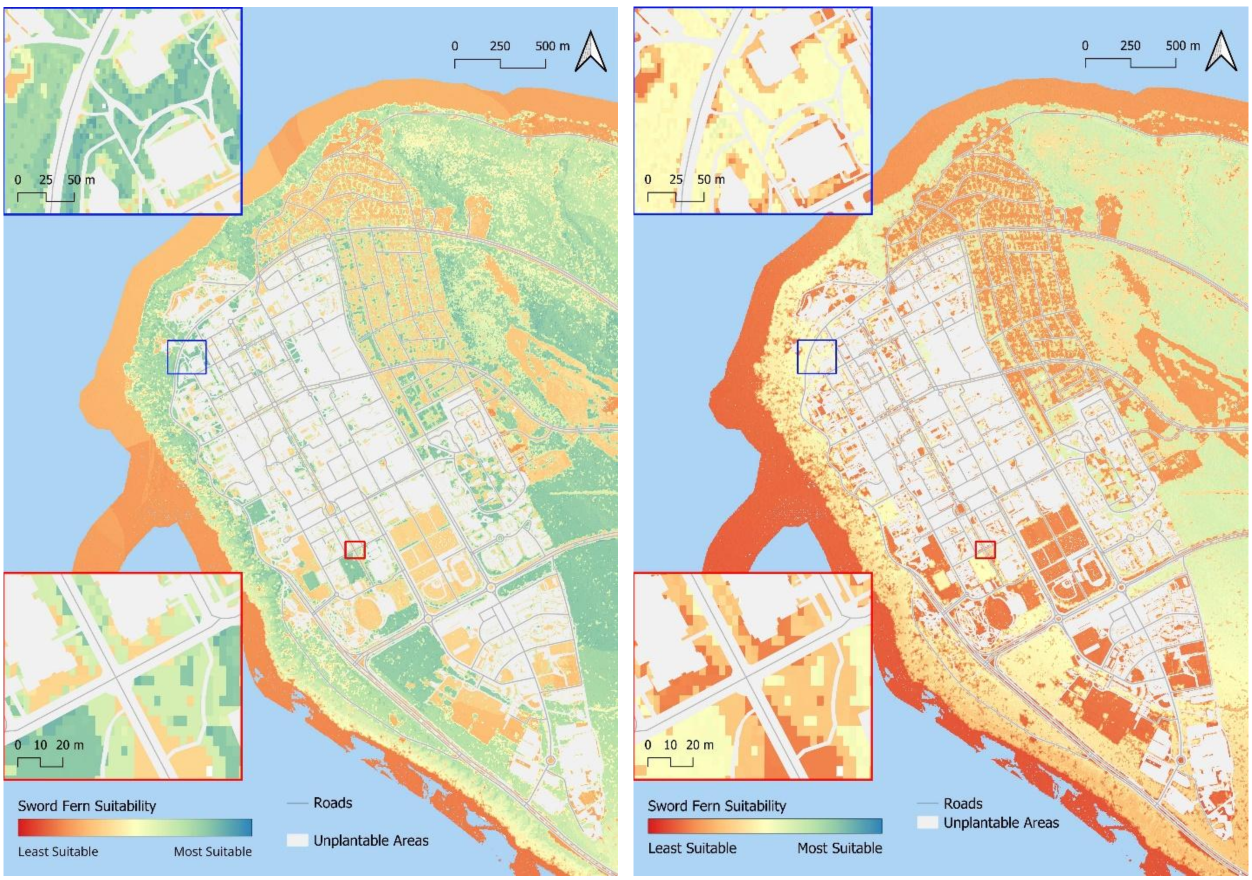


Figure 12: Map highlighting mean planting suitability of Sword Fern on UBC's campus in the year 2100. Results generated with climate scenario SSP 5-8.5 and SSP 2-4.5 are on the left and right respectively.

4.2.3 Response Curves and Significant Variables

For the SSP 5-8.5 scenario, shade had the largest contribution to the final Sword Fern MaxEnt model (Table 3). The response Curves for Shade, Temperature and Precipitation highlight that Sword Fern has a preference for shaded areas with higher precipitation and lower temperatures. Specifically, the shade response shows a stepped increase up to shade classification 5, while temperature exhibits a sharp increase in probability to a peak around 16.35 before dropping consistently. Precipitation follows a consistent linear increase before becoming hitting a plateau around 1375 millimeter (Figure 13).

Table 3: Contribution of Every Variable to the Final Sword Fern MaxEnt Model for the SSP 5-8.5 Scenario.

Variable	Percent Contribution
Shade	90
Mean Average Temperature	4.9
Mean Average Precipitation	2.3
Aspect	2.1
Slope	0.5
Relative Humidity	0.2

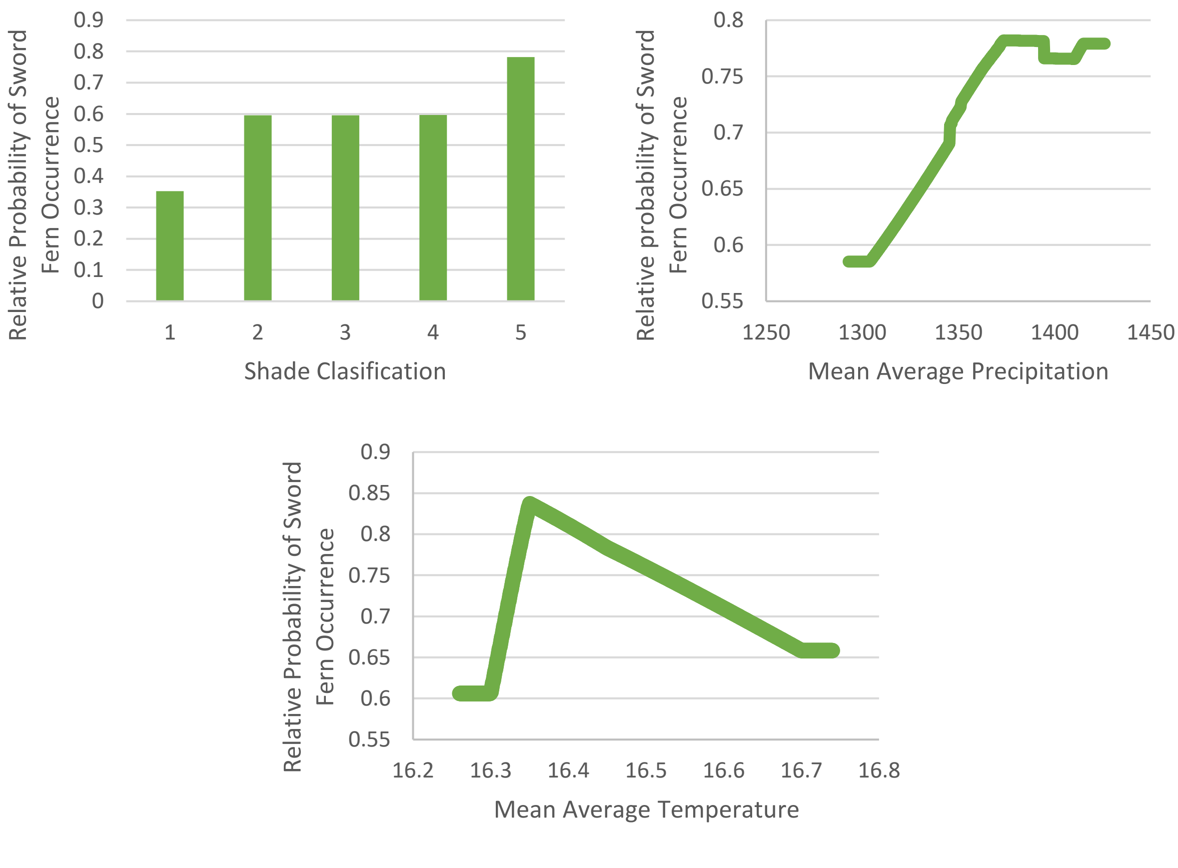
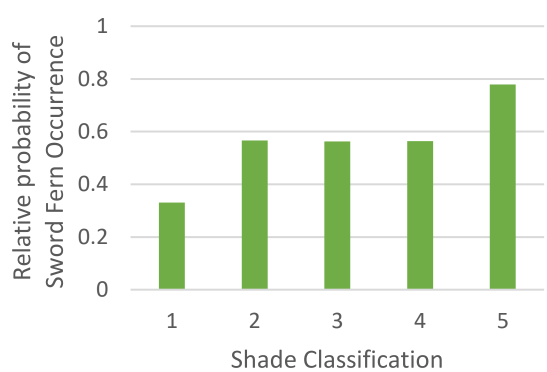


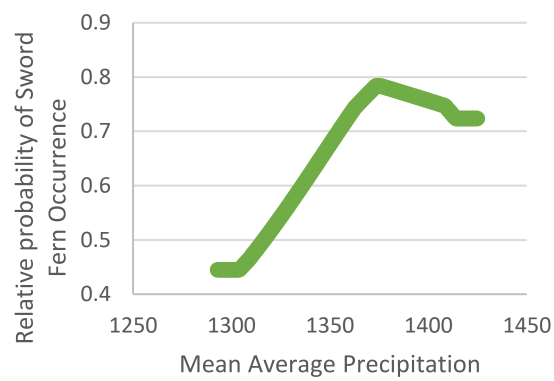
Figure 13: Response curves of the three most impactful variables (Shade, Mean Average Precipitation and Mean Average Temperature) on the MaxEnt model for Sword Fern using the SSP 2-4.5 scenario. Response curves show how each variable impacts the model's prediction. The curves show how the predicted probability of presence changes as each environmental variable is varied. The curves show the effect of changing a single variable.

For the SSP 2-4.5 scenario, shade had the largest contribution to the final Sword Fern MaxEnt model (Table 4). The response Curves for Shade, Temperature and Precipitation highlight that Sword Fern has a preference for shaded areas with higher precipitation and lower temperatures. Specifically, the shade response shows a stepped increase up to shade level 5, while temperature exhibits a sharp increase in probability to a peak around 16.35 then dropping slightly before plateauing. Precipitation follows a consistent linear increase until 1375 millimeter before slight dip (Figure 14).

Table 4: Contribution of Variables to the Final Sword Fern MaxEnt Model for the SSP2-4.5 Scenario.

Variable	Percent Contribution
Shade	92.7
Mean Average Precipitation	3
Mean Average Temperature	2.7
Aspect	1
Slope	0.6
Relative Humidity	0





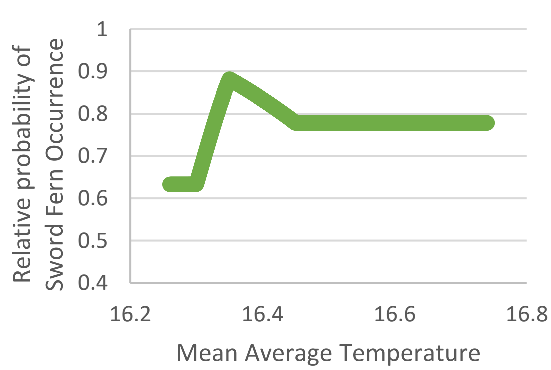


Figure 14: Response curves of the three most impactful variables (Shade, Mean Average Precipitation and Mean Average Temperature) on the MaxEnt model for Sword Fern using the SSP5-8.5 scenario. Response curves show how each variable impacts the model's prediction. The curves show how the predicted probability of presence changes as each environmental variable is varied. The curves show the effect of changing a single variable.

5. Discussion

This study aimed to identify suitable planting locations for Salmonberry and Sword Fern on the University of British Columbia's Vancouver campus. To do so, a suitability analysis was conducted for each species using MaxEnt under two climate scenarios, incorporating both climate and categorical raster data. Suitability values varied widely, ranging from 0.008 to 0.933 depending on underlying conditions, with shade consistently emerging as the most influential variable across both models. The following discussion explores species-specific trends, assesses model performance, and reflects on the implications and limitations of modeling plant suitability within a small geographic area.

5.1 Salmonberry (*Rubus Spectabilis*) Results

The generated maps (Figure 7) and response curves (Figure 8, 9) suggest that Salmonberry's preferred conditions are moderate shade with higher precipitation and temperature. These findings are congruent with observed preferences for seedlings to establish in moderate shade with perennially moist soils (United State Forest Service, 2019b). Not observed in the results, is a preference for full sun and moist soils, one of the best growing conditions for mature Salmonberry plants (United State Forest Service, 2019b). The lack of preference for full sun may be due to several factors, including the study area's land use. Most open areas are designated for academic purposes such as farming, grass lawns, or sports fields, meaning occurrence data likely contained few, if any, mature plants growing in optimal full-sun conditions. Additionally, the absence of soil data as a variable in this study makes it difficult to account for differences in moisture levels, which are crucial for Salmonberry regardless of insolation levels (United State Forest Service, 2019b). While the study design might have inadvertently overestimated the importance of shade for Salmonberry's overall habitat suitability, this could be beneficial, as the stated goal of this research is to find planting locations, and Salmonberry seedlings may die in areas of high sun (United State Forest Service, 2019b).

5.2 Sword Fern (*Polystichum munitum*) Results

Predicted suitable conditions for Sword Fern differ slightly from Salmonberry with a preference for full shade and high precipitation (Figure 12, 13, 14). These conditions are in agreement with known preferences for the species, an abundant understory plant that thrives in mild wet coastal areas (United State Forest Service, 2019a). One unexplained trend of the predicted future habitat is the preference of Sword Fern for cooler temperatures, around 16.4 degrees Celsius, or the cooler spectrum of temperatures values in this study. This pattern may be driven by the concentration of occurrence data in forested, shaded areas, which are primarily located on the outer edges of the peninsula and tend to be cooler. In contrast, the warmer central region, occupied mainly by the university campus, has less shade and is less suitable for growth.

If similar forested conditions existed in these warmer areas, Sword Fern would likely grow there as well, given the minimal temperature variance across the study site.

5.3 Model Performance

While the resulting MaxEnt models, using the variables provided in this study, generated expected results for the two plants studied, the response curves, selected model metrics and variable importance suggest potential overfitting or spatial bias.

Firstly, for each studied permutation of the model in this study (Table 1, 2, 3, 4), shade represented over 74% of the contribution, nearing 92% in one case. While shade is a biologically relevant factor for each plant studied, and a high contribution is likely to result from this reality, a high value indicates the model might be over relying on the variable to predict habitat suitability, or that other variables fail to meaningfully impact the model.

Next, visible peaking and jagged values present throughout the temperature and precipitation response curves (Figure 8, 9, 13, 14) suggest that the model might be capturing noise rather than the relationship between the variable and occurrence data (Elith et al., 2011). Comparatively, unpredictable values are not present with a significant variable such as shade where the response curve is much smoother. This may indicate spatial bias, either from occurrence data being concentrated in easily accessible areas due to crowdsourcing or from the study area capturing only a limited range of environments, as discussed in the Salmonberry results.

Finally, as seen in Figure 5, 6, 10, 11, the reliance on complex relationships, such as Hinge, product, or threshold as well as low regularization multipliers, combined with the high importance of shade, is a sign that the model might be overfitting to the training data, making it less generalizable (Elith et al., 2011). Overfitting could be caused by low variance in environmental variables, which weakens their relationship with occurrence points and forces the model to increase parameter complexity to detect significance.

5.4 Pitfalls of a Small Study Area for Plant Suitability Modelling

Concentrating on a small area for this study was done to obtain fine scale raster results needed to be able to effectively suggest planting locations at a very small scale. In doing so, the study area had to be limited for computational reasons. This limitation caused many of the issues that were discussed in the previous sections. The key challenge arising from using a small area is the limited variance in climate variables rasters. For example, the delta in the mean average temperature rasters used with the MaxEnt model was less than one degree Celsius. In contrast, suitability studies focusing on environmental factors, such as those for Oak Fern or Mountain Camellia, typically cover large study areas spanning multiple states, encompassing both suitable and unsuitable climate conditions. Including the full range of a plants viable climate allows effective modelling of changing climactic conditions and their impact on future changes (Hale et al., 2022; Hay et al., 2023). In this study, the limited climactic variance within the study area likely contributed to the counterintuitive result where future suitability maps indicated greater suitability under the more pessimistic climate model than the optimistic one. Given that climate variables were the only differing inputs between model implementations, this discrepancy suggests that low variance in the data may have led to an overrepresentation of shade in the model and the overfitting of noise in climactic variables.

5.5 Practitioners Recommendations

To improve the overall validity and usefulness of the model, two key steps are recommended: incorporating soil data and combining models of different spatial scales. Including soil variables such as depth and nutrient content could enhance the model's ability to capture local variability and more accurately identify suitable planting locations. This is particularly relevant for UBC’s Vancouver campus, where soil conditions likely differ from the surrounding forest, where most occurrence points are concentrated. Additionally, integrating models at both local and broader spatial scales would better capture climate variability and improve the model’s ability to project future climate suitability. This approach could also help address challenges such as overfitting and the overrepresentation of local variables (Olivero et al., 2016; Sun et al., 2021).

At present, it is recommended that practitioners continue planting species of interest in locations already known to be suitable.

Bibliography

Aram, F., García, E. H., Solgi, E., & Mansournia, S. (2019). Urban green space cooling effect in cities. *Heliyon*, *5*(4). https://doi.org/10.1016/j.heliyon.2019.e01339

Aronson, M. F., Lepczyk, C. A., Evans, K. L., Goddard, M. A., Lerman, S. B., MacIvor, J. S., Nilon, C. H., & Vargo, T. (2017). Biodiversity in the city: Key challenges for urban green space management. *Frontiers in Ecology and the Environment*, *15*(4), 189–196. https://doi.org/10.1002/fee.1480

Ball, M. (2023). Modelled Climate Change Impacts on Spring Canola Production Across British Columbia, Canada. *International Journal of Environment*, *12*(2), Article 2. https://doi.org/10.3126/ije.v12i2.65469

Bogati, K., & Walczak, M. (2022). The Impact of Drought Stress on Soil Microbial Community, Enzyme Activities and Plants. *Agronomy*, *12*(1), Article 1. https://doi.org/10.3390/agronomy12010189

Canadian Food Inspection Agency—Invasive Alien Plants in Canada—Summary Report. (n.d.). Retrieved September 20, 2024, from https://epe.lac-bac.gc.ca/100/206/301/cfia-acia/2011-09-21/www.inspection.gc.ca/english/plaveg/invenv/techrpt/summrese.shtml

CWH subzone maps. (n.d.). CFCG. Retrieved October 7, 2024, from https://cfcg.forestry.ubc.ca/resources/cataloguing-in-situ-genetic-resources/cwh-zone/cwh-subzone-maps/

Dickinson, D. C., & Hobbs, R. J. (2017). Cultural ecosystem services: Characteristics, challenges and lessons for urban green space research. *Ecosystem Services*, *25*, 179–194. https://doi.org/10.1016/j.ecoser.2017.04.014

El-Gabbas, A., & Dormann, C. (2018). Improved species-occurrence predictions in data-poor regions: Using large-scale data and bias correction with down-weighted Poisson regression and Maxent. *Ecography*, *41*, 1161–1172. https://doi.org/10.1111/ecog.03149

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, *17*(1), 43–57. https://doi.org/10.1111/j.1472-4642.2010.00725.x

ENMevaluate function—RDocumentation. (n.d.). Retrieved March 1, 2025, from https://www.rdocumentation.org/packages/ENMeval/versions/0.3.0/topics/ENMevaluate

Environment and Climate Change Canada. (2023, October 3). *CMIP6 and Shared Socio-economic Pathways overview*. https://climate-scenarios.canada.ca/?page=cmip6-overview-notes

Europe, W. H. O. R. O. for. (2016). *Urban green spaces and health* (No. WHO/EURO:2016-3352-43111-60341). Article WHO/EURO:2016-3352-43111-60341. https://iris.who.int/handle/10665/345751

Export Observations · iNaturalist. (n.d.). iNaturalist. Retrieved October 8, 2024, from https://www.inaturalist.org/observations/export

Faeth, S. H., Bang, C., & Saari, S. (2011). Urban biodiversity: Patterns and mechanisms. *Annals of the New York Academy of Sciences*, *1223*(1), 69–81. https://doi.org/10.1111/j.1749-6632.2010.05925.x

Geurts, E. (2023). *Examining spatial biases in the community science platform, iNaturalist, using British Columbia, Canada, as a case study*. http://hdl.handle.net/1828/15061

Gill, S. E., Handley, J. F., Ennos, A. R., & Pauleit, S. (2007). Adapting Cities for Climate Change: The Role of the Green Infrastructure. *Built Environment*, *33*(1), 115–133. https://doi.org/10.2148/benv.33.1.115

Guth, P. L. (2006). Geomorphometry from SRTM. *Photogrammetric Engineering & Remote Sensing*, *72*(3), 269–277. https://doi.org/10.14358/PERS.72.3.269

Haaland, C., & van den Bosch, C. K. (2015). Challenges and strategies for urban green-space planning in cities undergoing densification: A review. *Urban Forestry & Urban Greening*, *14*(4), 760–771. https://doi.org/10.1016/j.ufug.2015.07.009

Hale, C. W., Granger, J. J., Paulson, A. K., Ramirez-Reyes, C., Ma, Q., & Yang, J. (2022). Modeling Habitat Suitability for Stewartia ovata Across the Southeastern United States. *Castanea*, *86*(2), 173–184. https://doi.org/10.2179/0008-7475.86.2.173

Hamann, A., & Wang, T. (2006). Potential Effects of Climate Change on Ecosystem and Tree Species Distribution in British Columbia. *Ecology*, *87*(11), 2773–2786. https://doi.org/10.1890/0012-9658(2006)87[2773:PEOCCO]2.0.CO;2

Hay, N. M., Akinwuntan, J. V., Cai, V., Windham, M. D., & Pryer, K. M. (2023). Exploring Past and Future Distributions of the Rare Appalachian Oak Fern Using MaxEnt Modeling. *American Fern Journal*, *113*(2), 109–125. https://doi.org/10.1640/0002-8444-113.2.109

Holland, P. G., & Steyn, D. G. (1975). Vegetational Responses to Latitudinal Variations in Slope Angle and Aspect. *Journal of Biogeography*, *2*(3), 179–183. https://doi.org/10.2307/3037989

Liu, X. (2008). Airborne LiDAR for DEM generation: Some critical issues. *Progress in Physical Geography: Earth and Environment*, *32*(1), 31–49. https://doi.org/10.1177/0309133308089496

Mair, L., & Ruete, A. (2016). Explaining Spatial Variation in the Recording Effort of Citizen Science Data across Multiple Taxa. *PLOS ONE*, *11*(1), e0147796. https://doi.org/10.1371/journal.pone.0147796

Majidian, M. (2011, April 5). *Potential for migration of coastal redwood to British Columbia*. https://doi.org/10.14288/1.0075523

Mesaglio, T., & Callaghan, C. T. (2021). An overview of the history, current contributions and future outlook of iNaturalist in Australia. *Wildlife Research*, *48*(4), 289–303. https://doi.org/10.1071/WR20154

Mielcarek, M., Stereńczak, K., & Khosravipour, A. (2018). Testing and evaluating different LiDAR-derived canopy height model generation methods for tree height estimation. *International Journal of Applied Earth Observation and Geoinformation*, *71*, 132–143. https://doi.org/10.1016/j.jag.2018.05.002

Morales, N. S., Fernández, I. C., & Baca-González, V. (2017). MaxEnt's parameter configuration and small samples: Are we paying attention to recommendations? A systematic review. *PeerJ*, *5*, e3093. https://doi.org/10.7717/peerj.3093

Mukherjee, S., Joshi, P. K., Mukherjee, S., Ghosh, A., Garg, R. D., & Mukhopadhyay, A. (2013). Evaluation of vertical accuracy of open source Digital Elevation Model (DEM). *International Journal of Applied Earth Observation and Geoinformation*, *21*, 205–217. https://doi.org/10.1016/j.jag.2012.09.004

Nielsen, A. B., van den Bosch, M., Maruthaveeran, S., & van den Bosch, C. K. (2014). Species richness in urban parks and its drivers: A review of empirical evidence. *Urban Ecosystems*, *17*(1), 305–327. Scopus. https://doi.org/10.1007/s11252-013-0316-1

Observations. (n.d.). iNaturalist. Retrieved October 8, 2024, from https://www.inaturalist.org/observations?place_id=any&view=species

Omann, I., Stocker, A., & Jäger, J. (2009). Climate change as a threat to biodiversity: An application of the DPSIR approach. *Ecological Economics*, *69*(1), 24–31. https://doi.org/10.1016/j.ecolecon.2009.01.003

Planning, U. of B. C. C. and C. (2022). *[University of British Columbia Vancouver Campus Lidar], 2021* [Dataset]. Abacus Data Network. https://abacus.library.ubc.ca/dataset.xhtml?persistentId=hdl:11272.1/AB2/Y5KQNB

Prevéy, J. S., Parker, L. E., Harrington, C. A., Lamb, C. T., & Proctor, M. F. (2020). Climate change shifts in habitat suitability and phenology of huckleberry (*Vaccinium membranaceum*). *Agricultural and Forest Meteorology*, *280*, 107803. https://doi.org/10.1016/j.agrformet.2019.107803

Priestnall, G., Jaafar, J., & Duncan, A. (2000). Extracting urban features from LiDAR digital surface models. *Computers, Environment and Urban Systems*, *24*(2), 65–78. https://doi.org/10.1016/S0198-9715(99)00047-2

Qin, Y. (2020). Urban Flooding Mitigation Techniques: A Systematic Review and Future Studies. *Water*, *12*(12), Article 12. https://doi.org/10.3390/w12123579

Rainey, J. L., Brody, S. D., Galloway, G. E., & Highfield, W. E. (2021). Assessment of the growing threat of urban flooding: A case study of a national survey. *Urban Water Journal*, *18*(5), 375–381. https://doi.org/10.1080/1573062X.2021.1893356

Rocchini, D., Hortal, J., Lengyel, S., Lobo, J. M., Jiménez-Valverde, A., Ricotta, C., Bacaro, G., & Chiarucci, A. (2011). Accounting for uncertainty when mapping species distributions: The need for maps of ignorance. *Progress in Physical Geography: Earth and Environment*, *35*(2), 211–226. https://doi.org/10.1177/0309133311399491

Rose, N.-A., & Burton, P. J. (2009). Using bioclimatic envelopes to identify temporal corridors in support of conservation planning in a changing climate. *Forest Ecology and Management*, *258*, S64–S74. https://doi.org/10.1016/j.foreco.2009.07.053

Sack, L., & Grubb, P. J. (2002). The combined impacts of deep shade and drought on the growth and biomass allocation of shade-tolerant woody seedlings. *Oecologia*, *131*(2), 175–185. https://doi.org/10.1007/s00442-002-0873-0

Salgado, V. G., Viera Barreto, J. N., Rodríguez-Cravero, J. F., Grossi, M. A., & Gutiérrez, D. G. (2024). Factors influencing the global invasion of the South American weedy species Praxelis clematidea (Asteraceae): A niche shift and modelling-based approach. *Botanical Journal of the Linnean Society*, boae079. https://doi.org/10.1093/botlinnean/boae079

Savard, J.-P. L., Clergeau, P., & Mennechez, G. (2000). Biodiversity concepts and urban ecosystems. *Landscape and Urban Planning*, *48*(3–4), 131–142. Scopus. https://doi.org/10.1016/S0169-2046(00)00037-2

Spittlehouse, D. L. (with British Columbia, British Columbia, & British Columbia). (2008). *Climate change, impacts and adaptation scenarios: Climate change and forest and range management in British Columbia*. British Columbia, Ministry of Forests and Range, Forest Science Program.

Steven J. Phillips, Miroslav Dudík, Robert E. Schapire. (n.d.). *Maxent software for modeling species niches and distributions (Version 3.4.1)* [Computer software]. http://biodiversityinformatics.amnh.org/open_source/maxent/

Subzone/variant climate data. (n.d.). CFCG. Retrieved October 7, 2024, from https://cfcg.forestry.ubc.ca/resources/cataloguing-in-situ-genetic-resources/subzonevariant-climate-data/

Taylor, A., Sigona, A., & Kelly, M. (2023). Modeling spatial distributions of Amah Mutsun priority cultural plants to support Indigenous cultural revitalization. *Ecosphere*, *14*(1), e4374. https://doi.org/10.1002/ecs2.4374

Ummenhofer, C. C., & Meehl, G. A. (2017). Extreme weather and climate events with ecological relevance: A review. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *372*(1723), 20160135. https://doi.org/10.1098/rstb.2016.0135

United State Forest Service. (2019a). *Polystichum munitum*. https://www.fs.usda.gov/database/feis/plants/fern/polmun/all.html

United State Forest Service. (2019b). *Rubus spectabilis*. https://www.fs.usda.gov/database/feis/plants/shrub/rubspe/all.html

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S. J., & Rose, S. K. (2011). The representative concentration pathways: An overview. *Climatic Change*, *109*(1), 5. https://doi.org/10.1007/s10584-011-0148-z

Vancouver—UBC Campuses | The University of British Columbia. (n.d.). Retrieved October 8, 2024, from https://www.ubc.ca/our-campuses/vancouver/

Wang, J., Zhou, W., & Jiao, M. (2022). Location matters: Planting urban trees in the right places improves cooling. *Frontiers in Ecology and the Environment*, *20*(3), 147–151. https://doi.org/10.1002/fee.2455

Wang, T., Hamann, A., Spittlehouse, D., & Carroll, C. (2016). Locally Downscaled and Spatially Customizable Climate Data for Historical and Future Periods for North America. *PLOS ONE*, *11*(6), e0156720. https://doi.org/10.1371/journal.pone.0156720

Warren, D. L., & Seifert, S. N. (2011). Ecological niche modeling in Maxent: The importance of model complexity and the performance of model selection criteria. *Ecological Applications*, *21*(2), 335–342. https://doi.org/10.1890/10-1171.1

Zhang, Y., Li, Z., Ge, W., Wang, J., Guo, X., Wang, T., & Li, W. (2022). Assessment of the impact of floods on terrestrial plant biodiversity. *Journal of Cleaner Production*, *339*, 130722. https://doi.org/10.1016/j.jclepro.2022.130722

Zhao, Y., Deng, X., Xiang, W., Chen, L., & Ouyang, S. (2021). Predicting potential suitable habitats of Chinese fir under current and future climatic scenarios based on Maxent model. *Ecological Informatics*, *64*, 101393. https://doi.org/10.1016/j.ecoinf.2021.101393