Miistakis Institute

Aquatic Condition Index Field Testing and Sensitivity Analysis Report

A component of the Urban Wetland Conservation project

Dr. Felix Nwaishi

Document prepared for The City of Calgary

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Aquatic Condition Index Field Testing and Sensitivity Analysis

Dr. Felix Nwaishi
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Miistakis Institute
EB3013, Mount Royal University
4825 Mount Royal Gate SW
Calgary, Alberta T3E 6K6

Phone: (403) 440-8444
Email: institute@rockies.ca
Web: www.rockies.ca

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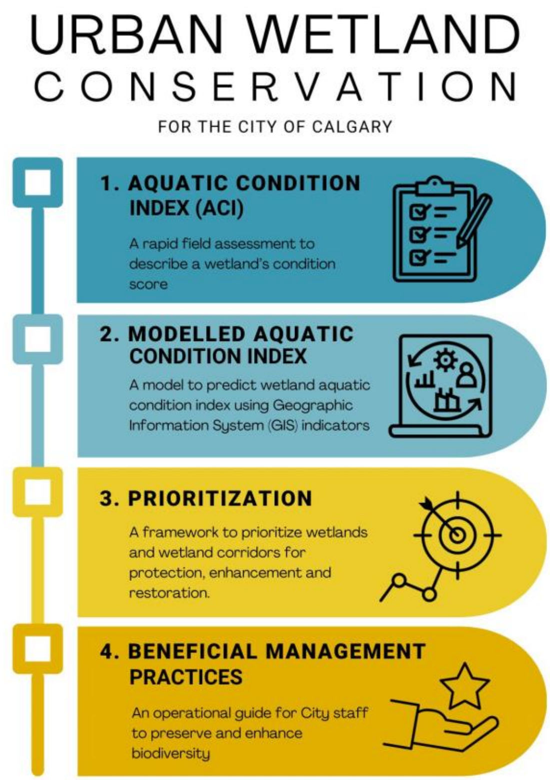


Executive Summary

This technical report provides an overview of the Aquatic Condition Index (ACI) framework, a rapid wetland assessment tool developed for evaluating the conditions of wetlands within the City of Calgary. The ACI tool was designed to incorporate functional indicators, including hydrologic, ecological, and water quality functions, that were selected by experts and together represent the condition of wetlands. In the summer of 2022, 74 wetland sites in Calgary were chosen for ACI assessment after which the ACI tool was tested to determine its effectiveness in predicting the condition of these wetland sites. The aquatic features covered in the field study were classified as follows: Constructed Stormwater Wetlands (CSW), Existing Modified Wetlands (EMW), Existing Retained Wetlands (ERW), Naturalized Wet Ponds (NWP) and Utility Wet Pond (UWP). A sensitivity analysis was performed on the indicators for each function to identify which indicators most influenced the wetland function in order to improve the operational efficiency of the tool. Of the 74 wetland sites sampled in Calgary, Wetland types designed for stormwater storage with limited ecological functions exhibited lower ACI scores, while existing modified wetlands displayed the highest ACI scores.

The sensitivity analysis of indicators for each function revealed that some indicators had a stronger influence on the function score. As a result, several indicators were removed, reducing the total number of indicators used in the assessment. This step significantly improved the operational efficiency of the ACI tool by streamlining data collection and analysis processes without compromising the accuracy of the assessment. Furthermore, the report highlights the relationships between the full and reduced indicator scores for ecological health, hydrologic and water quality functions. The operational efficiency of the tool was maintained between the full and reduced number of indicator scores. The strong correlations observed between the full and reduced indicator scores demonstrate the

reliability of the reduced indicator approach in estimating the overall condition of wetlands while offering improved practicality and accessibility for users.

The report concludes with recommendations for further research and advancement of the ACI tool. These include assessing more sites to generate sufficient data for validation and calibration of the ACI tool, establishment of a long-term monitoring program on some of the study sites to understand the impact of changing climate and environmental conditions on the effectiveness of the tool, integration of remote sensing and GIS-based model for predicting ACI scores across a wider geographical coverage, stakeholder engagement and capacity building, and continued improvement of the tool through collaboration and knowledge sharing.

In summary, the ACI framework provides a valuable tool for assessing the conditions of wetlands within The City of Calgary. The sensitivity of the ACI tool was evident in its ability to score wetlands in a manner that distinguishes wetland types and the key functions they were designed to support. With its functional indicators and streamlined approach, the ACI tool offers an effective and efficient means for evaluating wetland conditions, supporting informed decision-making, and promoting wetland conservation and management efforts.

Overview

Wetlands are highly valuable ecosystems that provide various ecological, hydrological, biogeochemical and socio-economic benefits. They serve as vital habitats for numerous plant and animal species, contribute to water purification and flood mitigation, and offer recreational opportunities for local communities (Gren et al. 1994; Novitski et al. 1996; Mitsch and Gosselink 2000). However, wetlands, face numerous threats, including habitat degradation, pollution, and climate change impacts, especially in urban environments. Further, the urban environment has significant impacts on natural wetland functions. Urbanization alters hydrological patterns, leading to changes in water flow, increased runoff, and reduced groundwater recharge (Brabec et al. 2002). Habitat loss and fragmentation occur as wetlands are drained, filled, or converted for development (Ehrenfeld 2000; Palta and Stander 2020). Consequently, water quality is degraded by urban runoff containing pollutants, leading to eutrophication and decreased water quality. Excessive nutrient inputs disrupt the biogeochemical cycling of major nutrients elements and exacerbate the pollution of downstream aquatic ecosystems (Paul and Meyer 2001; Walsh et al. 2005; Grimm et al. 2008). The introduction of invasive species is also common in urban environment, and these disrupts the ecological integrity of native ecosystems (Ehrenfeld 2008). Mitigating these urban impacts is crucial for the sustainability of wetland ecosystem functions and services (Naiman et al. 1993), thus, highlighting the need for effective management tools to assess these urban impacts. To address this need, the Urban Wetlands Conservation project was initiated to develop an Aquatic Condition Index (ACI) that complements the existing terrestrial-focused Habitat Condition Rating (HCR) tool used by The City of Calgary to assess the condition of urban natural areas.

As noted in the HCR manual, HCR is ineffective in predicting park condition for natural environment parks (NEPs) with greater than 10% aquatic features (Fiera Biological Consulting, 2015). Hence, the purpose of the ACI is to evaluate the overall condition of wetlands accurately and rapidly within The City of Calgary. The ACI focuses uses structural and functional indicators to evaluate the drivers of wetland condition, such as water flow and storage, soil substrate, vegetation, and landscape elements. The data collected on these indicators are scored on a scale of 0 to 15 and applied to assess three functional attributes of the wetlands, which include hydrologic, ecological, and water quality functions. This approach provides a quantitative assessment that facilitates comparison across different wetlands of the same type and across different wetland types as well as providing a baseline condition score for all city wetlands that can be re-assessed over time

The development of the ACI as a wetland rapid assessment tool marks a significant milestone in the assessment and monitoring of wetland conditions within The City of Calgary. By combining field assessments of both structural and functional indicators, the tool aims to provide a standardized and scientifically robust framework for wetland assessment. It also provides a comprehensive and efficient means of assessing and detecting change in wetland condition, which can be adapted for the same purpose in other municipalities. The ACI enables practitioners and policymakers to make informed decisions regarding wetland conservation, management, and restoration efforts, ultimately leading to improved wetland condition and ecosystem resilience.

The significance of functional and rapid wetland assessment tools has been highlighted in scientific research for environmental management. For instance, Craft and Casey (2000) emphasized the importance of functional indicators in evaluating wetland conditions and recommended their integration into assessment frameworks. Furthermore, numerous research studies have demonstrated the scientific foundation and practical relevance of employing rapid assessment tools, like the ACI , to evaluate wetland conditions (Spencer et al. 1998; Sutula et al. 2006; Fennessy et al. 2007; Stander and Ehrenfeld 2009) . Overall, by providing a rapid and functional assessment option for wetlands, the ACI enables a comprehensive evaluation of wetland condition in an efficient manner that provides the necessary information needed to prioritize actions for wetland conservation and restoration.

Field Testing of the ACI

During the summer of 2022, a field-testing campaign was conducted to evaluate the Aquatic Condition Indicator (ACI) as a wetland rapid assessment tool across 74 selected wetland sites within The City of Calgary. Field testing was undertaken as outlined in the ACI Field Manual (Nwaishi et al., 2023.). The field testing aimed to achieve several objectives related to establishing a methodology for site selection, determining the effectiveness of the ACI tool, conducting a sensitivity analysis of the ACI indicators, and improving the ACI operational efficiency.

Objective 1: Methodology Development for Site Selection

One of the primary objectives of the field testing was to develop a statistically robust and effective methodology for selecting the field testing sites across The City of Calgary. This methodology aimed to ensure representative coverage of wetland sites with varying degrees of support for key wetland functions, including hydrological, ecological, and water quality functions. By implementing a rigorous site selection process, the field testing aimed to provide a solid foundation for the subsequent evaluations of the ACI tool.

Objective 2: Effectiveness of the ACI Tool

The field testing aimed to determine the effectiveness of the ACI tool in predicting if a wetland is in good or bad ecological condition. By applying the ACI to the 74 selected wetland sites, the study sought to evaluate the tool's ability to accurately assess and predict the overall condition of wetland habitats. This assessment was essential in establishing the reliability and validity of the ACI as a rapid assessment tool for wetland condition evaluation in The City of Calgary.

Objective 3: Sensitivity Analysis of Subfunction Indicators

The field testing aimed to explore the field-collected ACI data to determine the indicators and/or function that were most influencing the overall ACI score, and if their inclusion improved model function or could be removed to streamline the data capture process without sacrificing score accuracy. Each function is derived from two to three sub-functions. By evaluating the performance and response of different indicators for each subfunction, the study sought to simplify the ACI by including only the most informative and responsive indicators for the subfunctions in the field ACI assessment methodology. This also improves the usability and applicability of the ACI tool for wetland management and decision-making purposes.

The significance of these objectives is evident in their potential to enhance the ACI's overall effectiveness for accurate wetland condition prediction. Using a statistically robust methodology for selecting field testing sites across The City of Calgary led to more accurate and representative data collection and optimized resource allocation by identifying the most efficient and effective sites for testing. Similarly, conducting a sensitivity analysis of the indicators for each subfunction to identify the most appropriate indicators of the ACI scores was considered necessary for improving the accuracy and reliability of the ACI tool. Using the most sensitive and easy-to-measure indicators in ACI score determination will reduce the time and resources required to complement ACI surveys while also making the tool more accessible and user-friendly. Overall, meeting these objectives enhanced the ACI's accuracy, reliability, and efficiency, making it a valuable resource for evaluating and monitoring wetland conditions in The City of Calgary, thereby supporting evidence-based decision-making for sustainable management of wetland ecosystems

Wetland Site Selection

We identified 80 candidate wetland sites for ACI field testing. Site selection protocol focused on wetlands within the city limits under management by The City of Calgary. Based on a The City's merged wetland inventory, 2,720 candidate wetlands within the urban landscape and 760 wetlands under The City's ownership or management jurisdiction were available for sampling. To select test sites the following decisions were made:

- Focused on wetland and lentic aquatic systems but did not including large rivers or streams, lakes, or reservoirs.
- Prioritize wetland sites within city landownership or under city management, removing wetland sites from private or provincial lands from the project's wetland inventory.
- Ensure a representative gradient of wetland naturalness across the city (including a range from constructed and utility retention ponds to near-natural wetlands).
- Ensure representation of catchment sizes (highly variable) for each wetland.
- Ensure geographic representation of wetlands across the city.

Data processing steps and R code used to derive wetland site selection are provided in Appendix A. The City of Calgary wetland inventory used for this project was generated from four layers, the Alberta merged wetland inventory (from GOA) and City of Calgary 2015 Fiera wetlands (Fiera Biological Consulting, 2015), City stormwater pond and natural area wetland assets. We determined that 62% of city-owned or managed wetlands include piped infrastructure, and 38% of the wetlands had no pipe infrastructure. Two datasets were developed based on this percentage split, resulting in the selection of 50 wetland sites with pipe infrastructure and 30 wetlands with no piped infrastructure to generate 80 wetlands sites. The wetland layer includes wetland that have now been developed or drained, prior to field assessment City staff reviewed randomly selected wetlands and removed wetlands from site selection that were no longer in existance. There were 283 catchments with wetland features varying in size from 5.2 to 18,000 acres. Figure 1 displays a histogram of the catchment size (acre) frequency for the total catchments with wetlands and ACI survey sites.

The following steps were taken to achieve the stated goals:

1. To facilitate permitting for fieldwork, wetlands under city jurisdiction (i.e., the City of Calgary is the landowner or manages the lands) were selected.
2. To achieve a representative sampling of wetland on a gradient of natural to constructed, we created two wetland layers in ArcGIS, with piped stormwater infrastructure and without. Of note the City has developed a new wetland typology that we applied to the survey site wetlands during the field season. At the time of site selection we did not have wetland type and used piped infrastructure as a syrogate to represent naturalness.
3. To achieve a representative sampling of hydrological function, bins were created for catchment size (based on percentiles), and an equal number of wetlands from each percentile bin for both wetlands with and without piped infrastructure were randomly selected. Outliers of catchments greater than 18,000 acres were removed from further analysis.
4. From the wetland dataset binned into different catchment sizes, 50 wetlands from the wetland piped infrastructure dataset and 30 wetlands from the non-piped wetland dataset were selected to make up the 80 wetland sites.

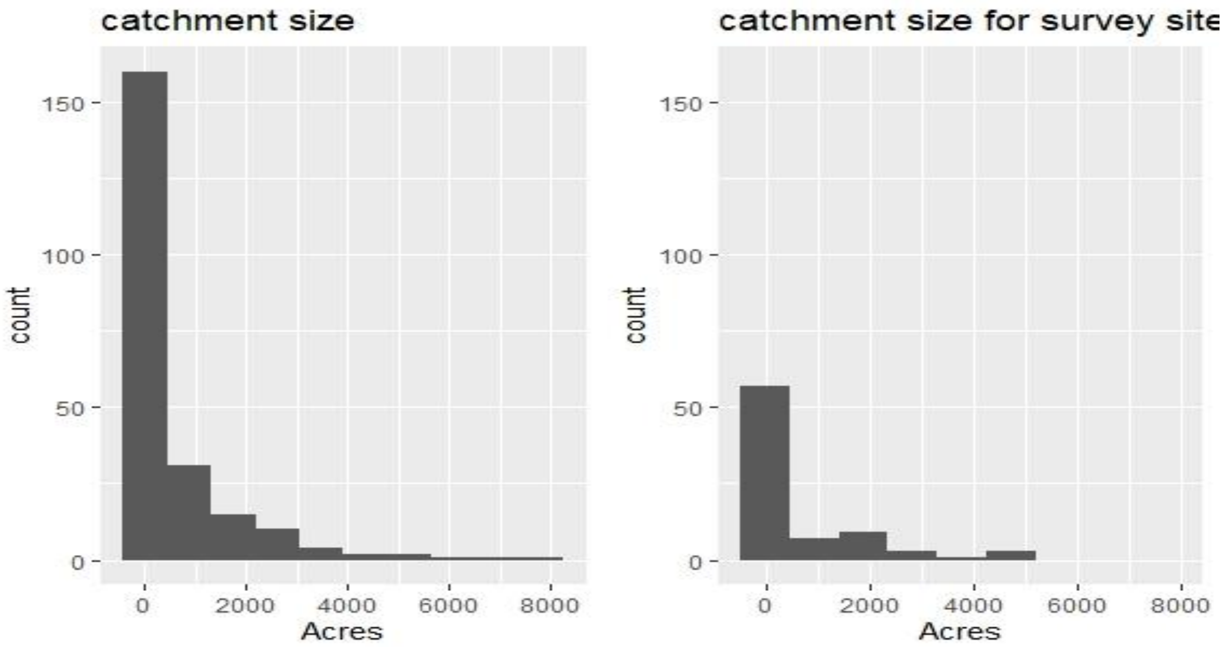


Figure 1: Catchment size (for all catchments with city-owned or managed wetlands) and catchment size for ACI survey sites based on ten percentile bins.

A t-test was conducted to determine the similarity of the means between catchment size for all catchments with wetlands and catchments for the survey sites, which was used to determine that the null hypothesis - means are similar was supported.

```
        Welch Two Sample t-test

data:  catchment$SUM_acres and random2$ctch_a
t = -0.6222, df = 135.13, p-value = 0.5349
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -398.6015  207.8166
sample estimates:
mean of x mean of y 
 662.7848  758.1772 
```

Of the 80 ACI sites (Figure 2), 50 occur in natural environment parks; the rest are under The City's jurisdictions or provincial lands managed by the City. The 80 sites represent 64 individual catchments and some me catchments contained both piped and non-piped wetlands, which is an example of complicated nature nature of urban catchements.

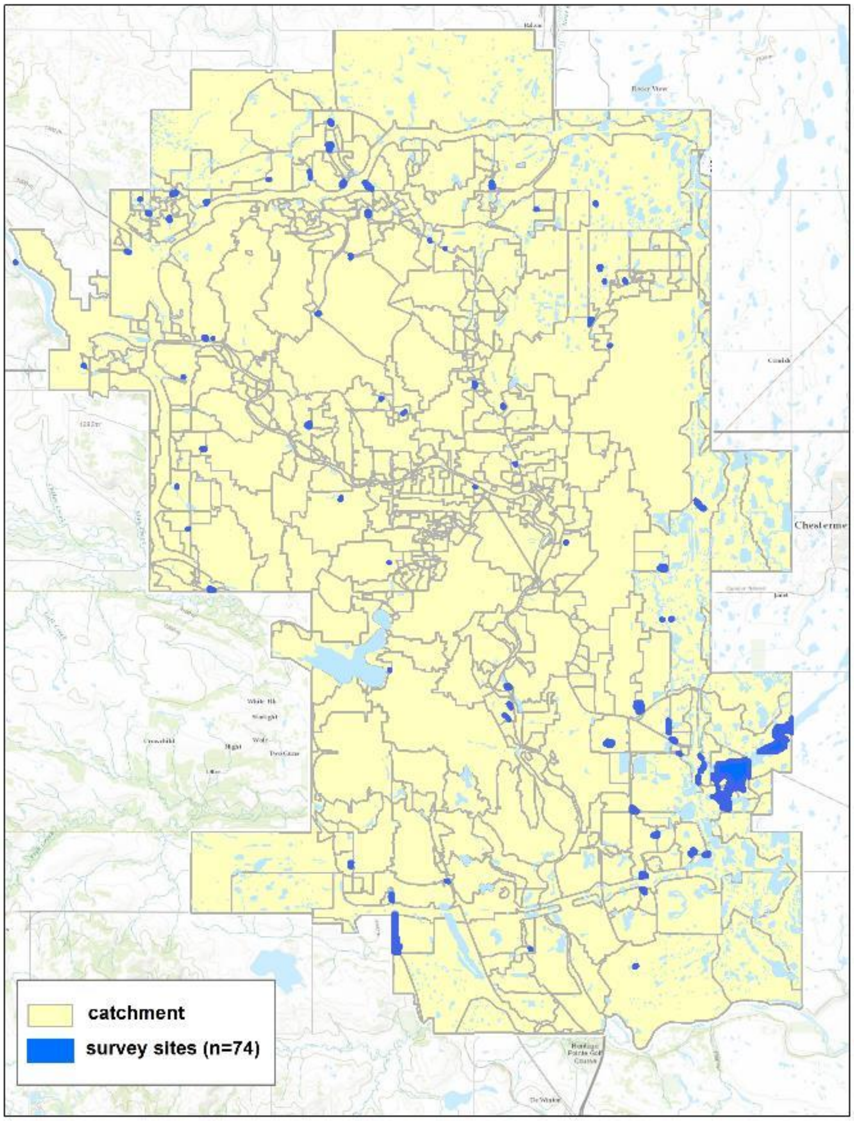


Figure 2: Site selection (in dark blue) for ACI field testing.

As this process proceeded, we determined the cathments to be problematic for our process due to piped infrastructure between catchments and catchments relating to roads represented as long stretches of roads indepdent of the surrounding landscape . We recommend for future site selection The City consider represenative samples from wetland typology. This will require assigning typology to wetland inventory (Nwaishi et al., 2023).

Survey Sites and Typology

A ground-truthing exercise revealed that a good portion of the originally selected sites from the merged wetland dataset were no longer on the landscapeon. Of the 80 sites selected for field testing during the desktop phase, some were inaccessible due to fences, gates, permit restrictions, etc. Some of the original sites also appeared dry during the pre-fieldwork site run-through. As a result, some of the candidate sites were moved to nearby existing wetland locations. Ultimately, only 74 of the 80 selected wetland sites were sampled for the field-testing exercise. The wetland sites were categorized using typologies that align with a new wetland naming convention in development by The City of Calgary to streamline the classification of wetlands and aquatic features across The City's departments. The aquatic features covered in the field study were classified as follows: Constructed Stormwater Wetlands (CSW), Existing Modified Wetlands (EMW), Existing Retained Wetlands (ERW), Naturalized Wet Ponds (NWP) and Utility Wet Pond (UWP). The ACI Field Manual provides a description of these wetland types, and their distribution in the study area is shown in Nwashi et al. 2023.

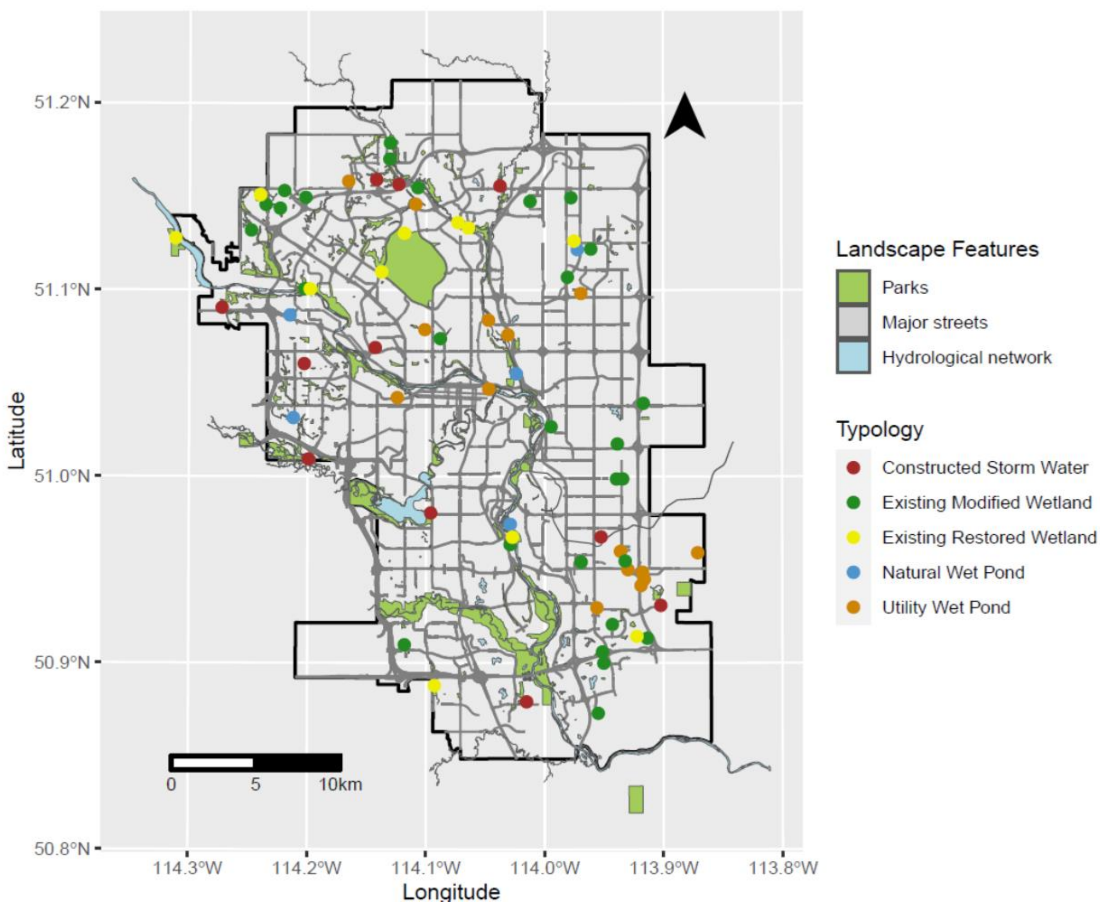


Figure 3: Map of The City of Calgary showing the distribution of wetland sample sites and highlighting the wetland types based on new typology developed in 2023.

Field Data Collection and Analysis Methods

The selected test sites were sampled twice over the growing season to assess the potential effect of seasonality on the performance of the ACI tool. However, there was no significant difference in the scores obtained for each site between the first and second rounds of field sampling with the ACI tool. The most notable change was flowering plants which made identifying vegetation significantly easier later in the growing seasons. This led to the recommendation that a single ACI Survey be conducted between late June to early August, which coincides with the peak to late growing season. The first field sampling campaign helped refine the ACI tool, which led to modifications that were added to the updated ACI Field Guide.

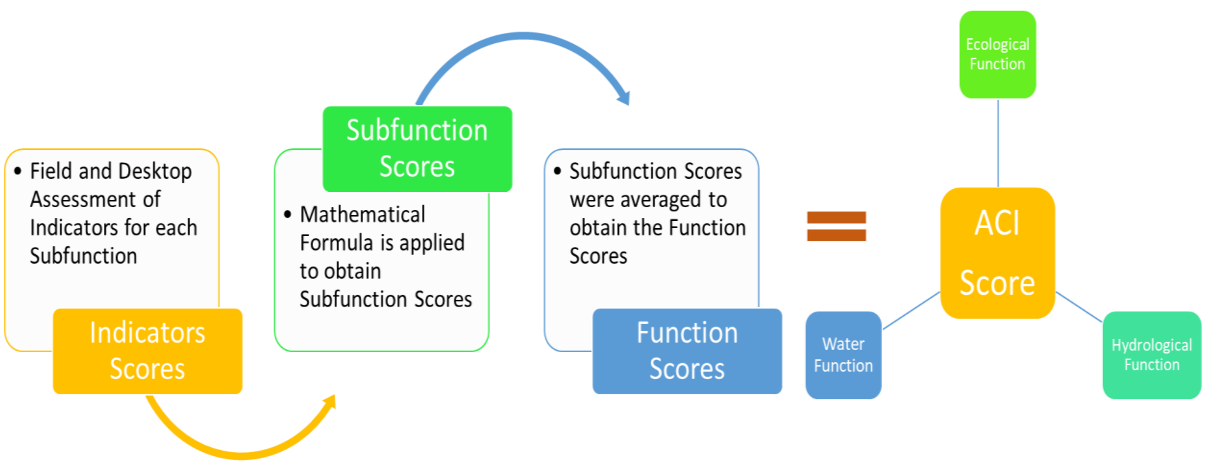


Figure 4: The process for obtaining the ACI score for each wetland site involves a series of steps, including indicator assessment, calculation of subfunction scores, and averaging to derive function and ACI scores

An Excel file named "ACI_FieldData_Analysis" was created to facilitate the entry and analysis of data collected from the field survey campaign. The Excel spreadsheet was programmed to calculate all the subfunction scores from relevant indicators; then, function scores were derived for each of the three functions (Water quality, Hydrology, and Ecological Health which were then averaged to obtain the ACI score. Formulae are outlined in the ACI manual (Nwaishi et al. 2023). It is worth noting that when calculating the subfunction scores, columns with indicator scores entered as “NA” are excluded from the formula. The possible maximum score is adjusted to reflect the number of columns removed.

Normalization and Categorization of ACI Scores

Data normalization was performed on the calculated functions and ACI scores to standardize the data format and to bring all the ACI score values to a range of 0 -1, being an index score, where 0 represents worst condition and 1 represents best condition (Figure 5). The Min-Max normalization technique was used to actualize this by applying the following formula:

X_norm = (X - X_min) / (X_max - X_min)

Where **X** is the original function or ACI score estimated for each site, **X_min** is the minimum score of the column, and **X_max** is the maximum score of the column.

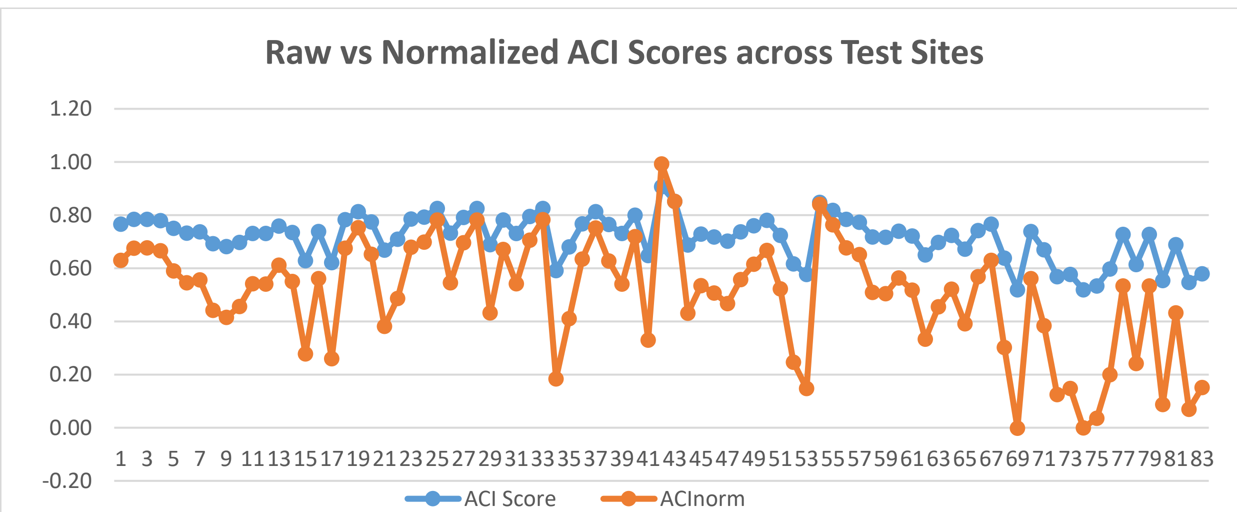


Figure 5: Comparison of normalized (Orange line) and non-normalized (Blue line) ACI scores for wetland assessment: Exploring trends and variations among wetland types.

Following normalization, the ACI and function scores were categorized into four categories (Very low, Low, Moderate and High) using the quartile formula, which calculates the variance from the scores by dividing the score distribution into four defined intervals. The Moore and McCabe method (Cangur et al. 2015; Samson 2015) for calculating quartiles divides the dataset into three points: a lower quartile, denoted by Q1, is the middle point betweent the smallest value and the median of the given data set; the median, denoted by Q2; and the upper quartile, denoted by Q3, is the middle point between the median and the highest number of the score distribution in the dataset. The Moore and McCabe method for calculating quartiles uses the following formula:

$$Q1 = x[(n+1)/4];\ Q2 = x[(n+1)/2];\ Q3 = x[3(n+1)/4]$$

Where "**x**" represents the sorted dataset, "**n**" represents the number of data points in the dataset.

Distribution of ACI Score across Wetland Types

The categorized ACI scores recorded across the study wetland sites are presented in the map below (Figure 6). The distribution of the wetland sites suggests there are still small pockets of high-scoring wetlands within the city, while a greater proportion of wetlands within Calgary fall within the very low to low scores. Most of the wetlands surveyed are in the Low ACI score category, followed by Moderate, then Very Low, with the least number of wetlands in the High score category. It is worthy to note that the categories are relative to the wetlands surveyed in this study, which might not be similar to wetlands outside city limits, which tend to be less altered.

The range of ACI scores obtained from the field survey highlights the sensitivity of ACI functions to the functional attributes of wetland types within the city. It was hypothesized that the wetlands designed specifically for stormwater management (e.g., Utility Wet Ponds and Naturalized Wet Ponds) would have little or no ecological functions and fall into lower ACI score categories.

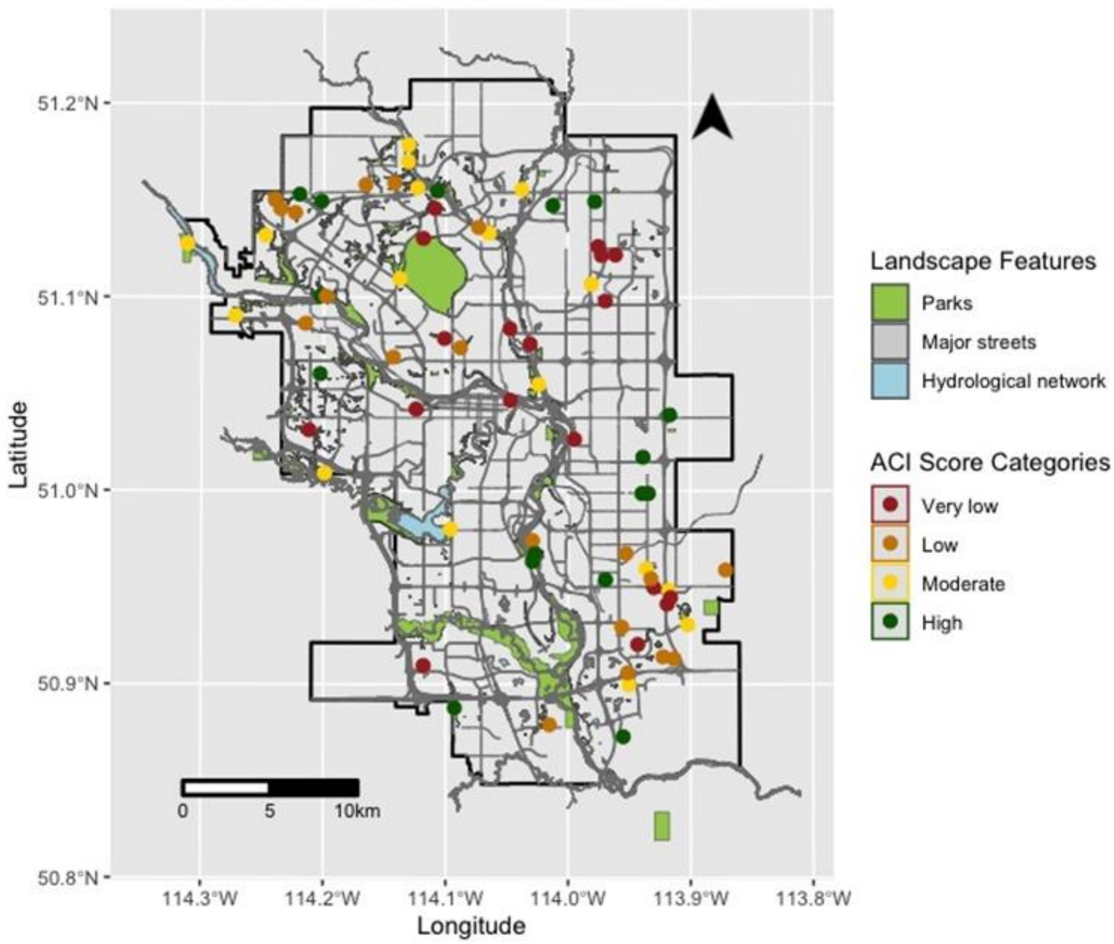


Figure 6: The distribution of categorized ACI scores recorded across the study sites within The City of Calgary

The results (Table 1) confirmed this, with about 80% of the Utility Wet Ponds and Naturalized Wet Ponds falling into the Very Low to Low score categories. In contrast, the Existing Modified Wetlands exhibited the highest proportion (46%) of high-scoring wetlands, indicating a greater presence of functional attributes and healthier wetland conditions. Most Existing Modified Wetlands (65%) also fell within the Moderate to High score categories, suggesting relatively better wetland health. Similarly, a significant proportion of Existing Retained Wetlands and Constructed Stormwater Wetlands were within the Low to Moderate score categories, with 64% and 91% of wetlands falling into these ranges, respectively.

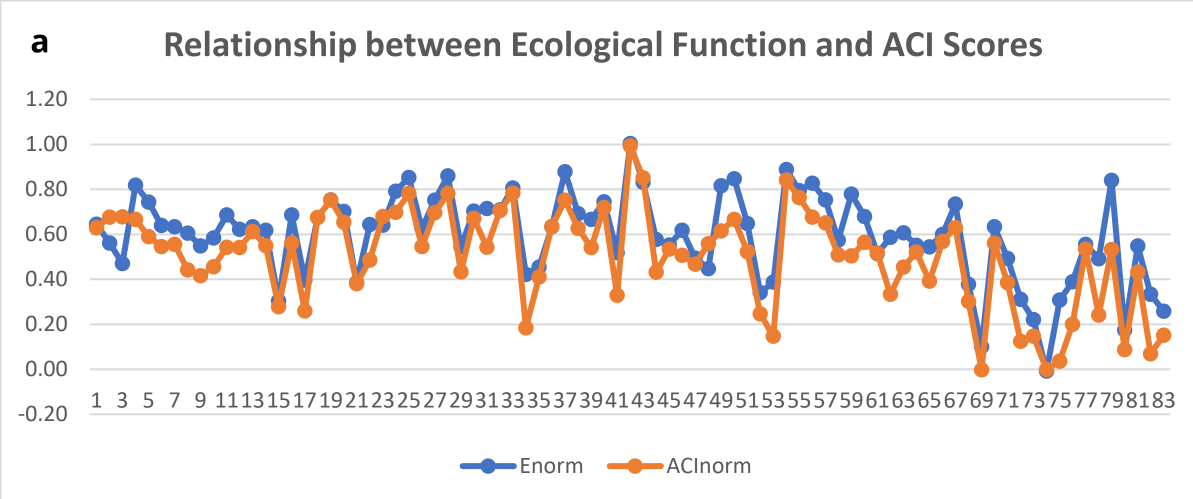
Table 1: Distributions of study sites across wetland types and the proportion of sites across the score categories, where CSW = constructed stormwater wetlands, EMW = existing modified wetlands, ERW = existing retained wetlands, NWP = natural wet ponds, UWP = utility wet pond

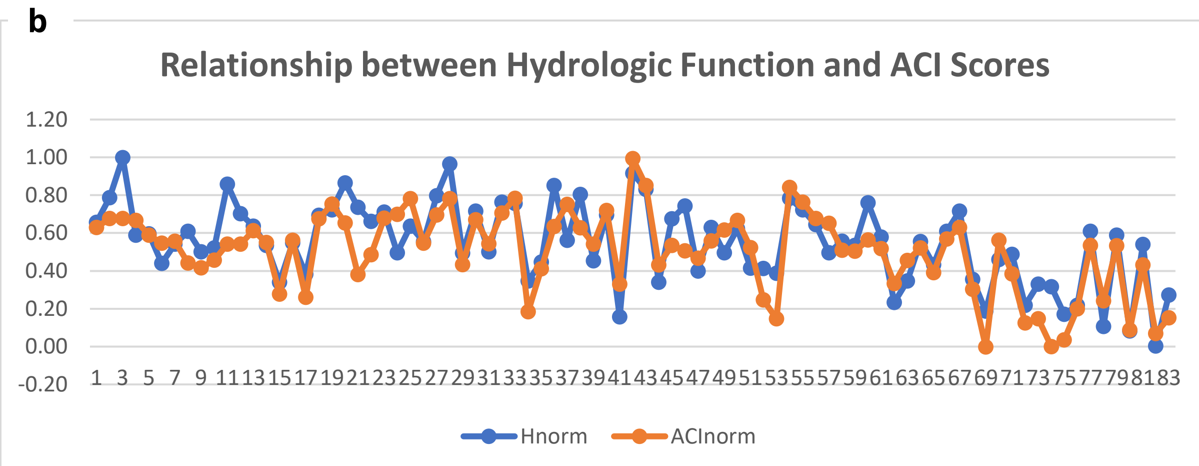
Site Typology	Total Sites	% Weighted Number of Sites per Score Category			
		Very Low	Low	Moderate	High
CSW	11	0	36	55	9
EMW	28	14	21	19	46
ERW	11	18	36	28	18
NWP	5	40	40	20	0
UWP	15	67	20	13	0

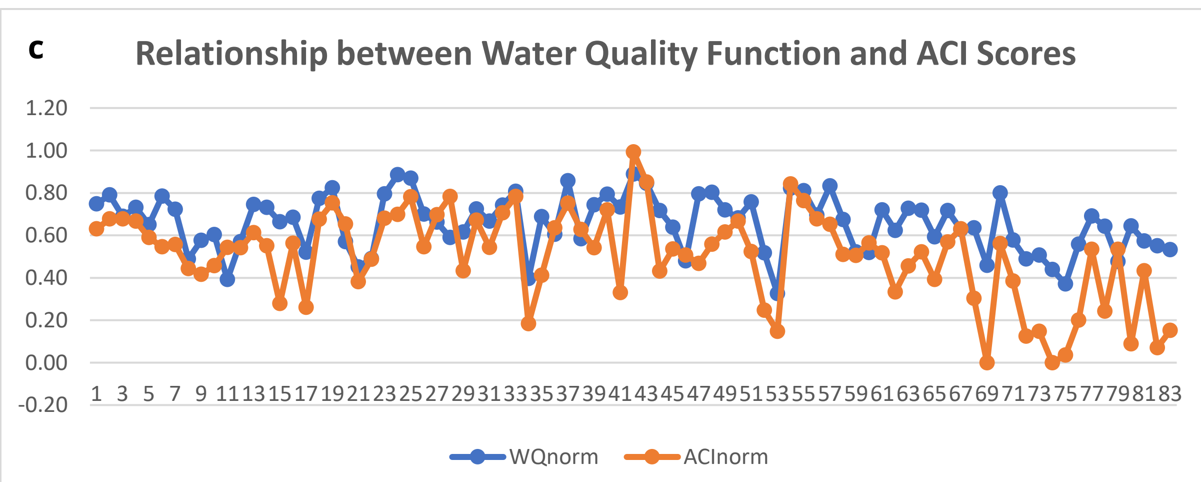
These findings underscore the varying levels of wetland functionality and highlight the importance of considering the specific wetland types when assessing their conditions. Future work would benefit from application of the new wetland typology to all wetlands occurring within city limits. By understanding the distribution of ACI scores across different wetland types, policymakers and practitioners can prioritize conservation and restoration efforts accordingly, focusing on Existing Modified Wetlands and Existing Retained Wetlands with lower scores, particularly those modified for stormwater management, to improve their functions and overall condition.

Relationship between Function Scores and ACI Scores

The relationship between function scores and ACI scores indicates that the ecological function is the dominant factor influencing the overall ACI score (Figure 7a). The variation observed in the function scores within and across different wetland types highlights the diverse range of wetland conditions and the importance of considering multiple functional aspects when assessing wetland condition.


a
Relationship between Ecological Function and ACI Scores
1.20
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 59 61 63 65 67 69 71 73 75 77 79 81 83
Enorm
ACInorm


b
Relationship between Hydrologic Function and ACI Scores
1.20
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 59 61 63 65 67 69 71 73 75 77 79 81 83
Hnorm
ACInorm


c
Relationship between Water Quality Function and ACI Scores
1.20
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 59 61 63 65 67 69 71 73 75 77 79 81 83
WQnorm
ACInorm

d

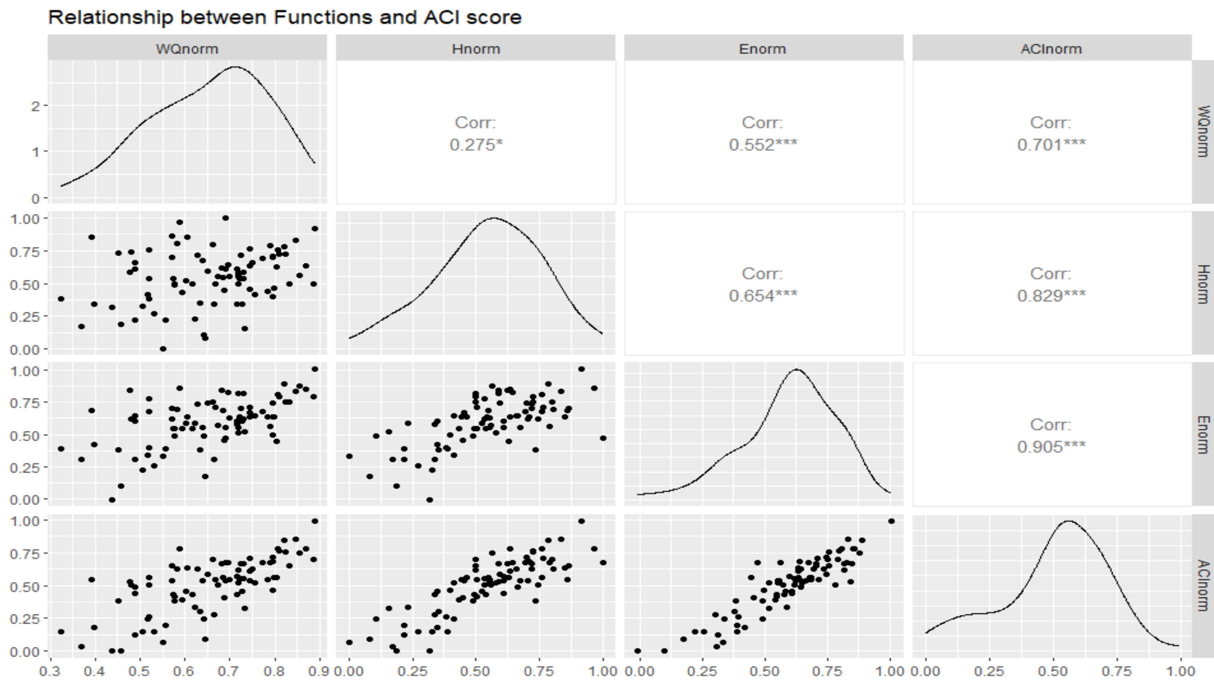


Figure 7: Graphical illustration of the relationships between the Normalized ACI Scores (ACInorm) and (a) Ecological Health (Enorm); b) Hydrologic Function (Hnorm) and c) Water Quality Function (WQnorm). The correlation analysis result (d) indicates that the strongest positive relationship exists between ACI and Ecological Health Function, followed by Hydrologic Function, with Water Quality Function having a lower but significant positive relationship with ACI scores.

The three function scores (hydrology, ecological health and water quality) do not exhibit strong interdependence. This means that the scores for each function (Figures 7a – 7c) are determined based on different indicators and considerations, reflecting the independent evaluation of these functional variables within the ACI framework. Furthermore, the correlation analysis between function scores and ACI score suggests that ecological health has a greater influence on the overall ACI scores compared to hydrology and water quality functions (Figure 7d). This implies that the ecological aspects of wetlands, such as biodiversity, habitat quality, and ecosystem functioning, play a dominant role in determining the overall condition of the wetland. This finding aligns with our understanding that ecological condition is a fundamental component of wetland conservation and management.

Sensitivity Analysis of Subfunction Indicators

A sensitivity analysis of ACI indicators was conducted to reduce the number of indicators and time required to collect the data needed for estimating the ACI scores. The approximation of the Full Penalized Model (Harrell 2017) was used to identify the most sensitive indicators for subfunctions within each of the three functions. The Full Penalized Model is set as the gold standard, and the backward step-down (which starts with an R^2 of 1.0) is done using Ordinary Least Squares (OLS) method (Harrell 2017). A Linear Predictor was computed from the Full Penalized Model. This modelling approach involves fitting the linear predictor model that incorporates all the selected indicators for a particular subfunction. The model is then penalized, meaning that it is adjusted to strike a balance between model complexity and the accuracy of the predictions. The penalized model is evaluated to assess the sensitivity of each indicator to changes in wetland conditions. The model then calculates the contribution and influence of each indicator in predicting the subfunction scores. Indicators with higher contributions are deemed more sensitive, as they have a stronger influence on the overall assessment of the subfunction. The most important predictors of subfunction scores in the full model are the ones with the smallest p-values. Based on the results of the sensitivity analysis, indicators with lower sensitivity or redundancy (indicator with R^2 value above 0.95) were eliminated from the final set of indicators used to estimate the ACI scores. This reduction process helps streamline the data collection efforts and improves the operational efficiency of the ACI tool.

Ecological Health Subfunction Indicators: Sensitivity Analysis

The ecological health function within the ACI tool consists of two subfunctions: ecological structure and ecological composition (Nwaishi et al., 2023). The sensitivity analysis was applied to the indicators under these two subfunctions to identify the most relevant and sensitive indicators for assessing wetland ecological health.

Initially, the ecological structure subfunction included 13 indicators. However, following the sensitivity analysis (as shown in Figure 8a), the number of indicators was reduced to seven. The indicators that were removed through the sensitivity analysis include “Outlet present”, “Ground cover native”, “Soil pH”, “Distance to industrial zone”, “Percentage riparian hard altered”, and “Distance to nearest residential zone”. Among these indicators, it is worth noting that the "Ground cover native" indicator was found to be sensitive to the structural subfunction score. However, to test the prospects of making the ACI tool more accessible to users without advanced plant identification skills, we tried a rerun of reduced indicators without the "Ground cover native" indicator and it didn’t have an evident impact on the result. This suggest that in cases where individuals without advanced plant identification skills are conducting the field survey for the ACI, the ecological structure subfunction can be estimated without including the "Ground cover native" indicator. By removing this indicator, the ACI tool becomes more user-friendly, allowing for easier and more efficient assessments of wetland ecological structures without relying on advanced plant identification skills. The decision to exclude the "Ground cover native" indicator should only be based on the practical considerations of data collection in the field.

On the other hand, the ecological composition subfunction initially consisted of seven indicators, but through the sensitivity analysis, the number of indicators was reduced to four (Figure 8b). The indicators that were found to be less sensitive include “Algae”, “Riparian non-native/undesirable species”, and “Percentage riparian soft altered”. Although the "Riparian non-native/undesirable species" indicator was found to be sensitive, it was removed for practical considerations, similar to the exclusion of "Ground cover native" in the ecological structure subfunction.

After conducting the sensitivity analysis and removing less sensitive and redundant indicators, the reduced set of indicators was utilized to recalculate the subfunction scores for ecological structure and composition. These revised subfunction scores were then used to derive a new "reduced indicator" ecological health value. To assess the relationship between the ecological health values obtained from the full set of indicators and the reduced set of indicators, the comparison is presented in (Figure 8c). The trendlines in the graph indicate a strong alignment between the outputs of the full indicator values and the reduced indicator values. This suggests that the reduced set of indicators can still capture and reflect the overall ecological health of the wetland sites. However, it is worth noting that for a few wetland sites, the reduced indicator value underestimated the ecological health value compared to the full indicator value. This implies that in these specific cases, excluding certain indicators may have resulted in a slightly lower ecological condition assessment than what would have been obtained using the full set of indicators.

The underestimation of ecological health values for some wetland sites could be due to the removed indicators providing additional information or capturing specific aspects of ecological health that were not adequately represented by the reduced set of indicators. These findings emphasize the importance of considering the potential limitations of using a reduced set of indicators and acknowledging that some nuances of ecological health assessment may be missed. Nonetheless, despite underestimating a few sites, the strong relationship between the full and reduced indicator values indicates that the reduced set of indicators still provides a reliable and effective means of assessing ecological health within the ACI framework. The reduced set allows for a more efficient data collection process while maintaining a robust evaluation of wetland ecological health across most sites.

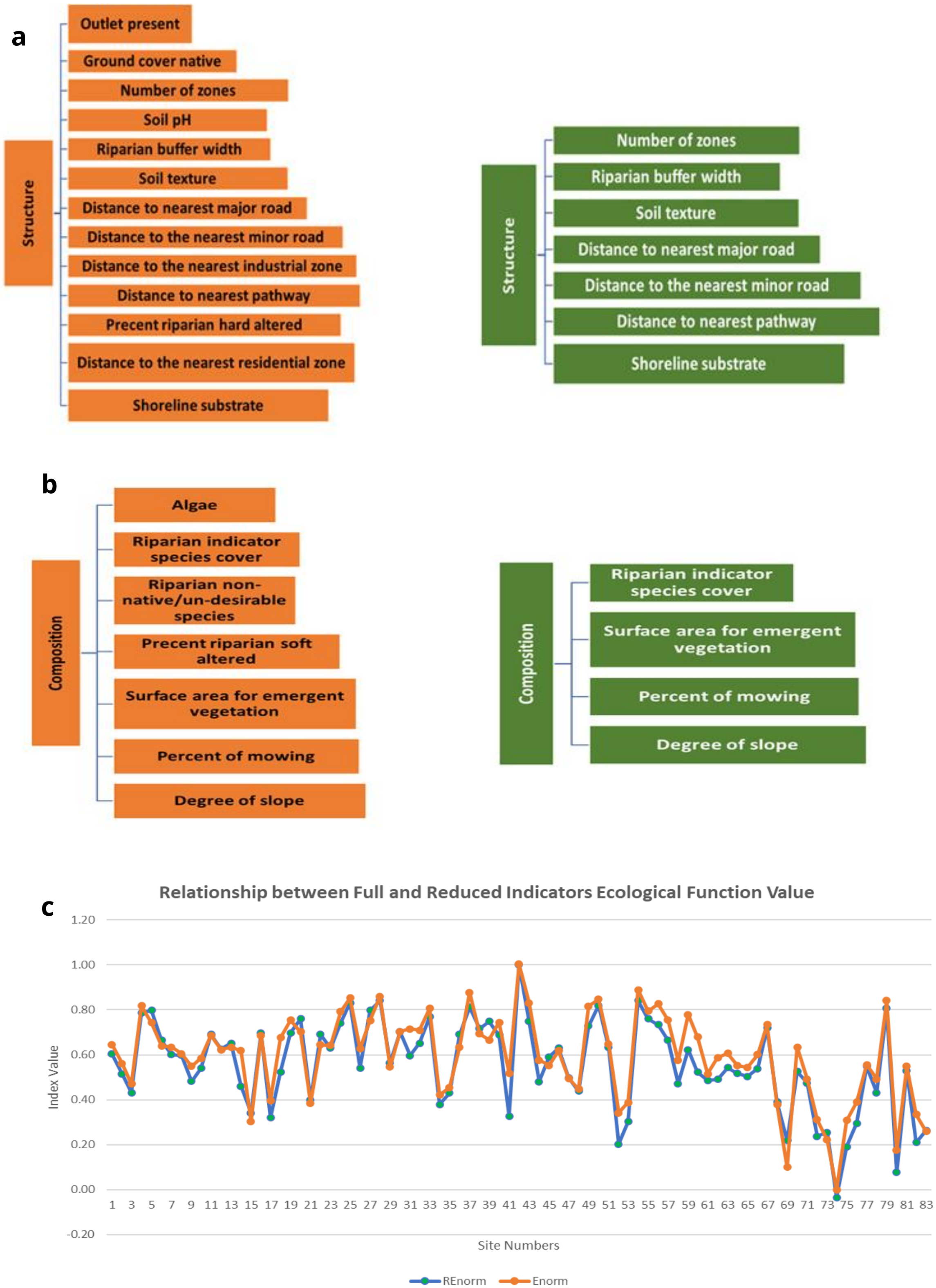


Figure 8: Results of the sensitivity analysis for Ecological function, indicating the full indicators in the Structure (a) and Composition (b) Subfunctions. Following the sensitivity analysis, (c) the Reduced Indicators were used to derive Reduced Indicators Ecological Function (REnorm), which strongly aligned with the Full Indicator Ecological Health Functions (Enorm).

Hydrological Subfunction Indicators: Sensitivity Analysis

The hydrological health function is divided into two subfunctions: water storage and water flow. The water storage subfunction consists of only three indicators, which were not included in the sensitivity analysis. On the other hand, the water flow subfunction comprises nine indicators, making it suitable for the sensitivity analysis process. Through the sensitivity analysis, the number of indicators for the water flow subfunction was reduced to four (Figure 9a). The five indicators removed through the sensitivity analysis included “Percent riparian soft altered”, “Percent riparian hard altered”, “Percent ponded water versus flowing”, “Presence of forebay” and “Shoreline Substrate”. Like the "Ground cover native" indicator in the ecological structure subfunction, the "Ground cover native" indicator under the water flow subfunction was sensitive but ultimately removed for practical considerations. indicator hydrological health function was examined.

The most sensitive indicators identified through the refinement of indicators within the water flow subfunctions were combined with the water storage subfunction to estimate the reduced indicator hydrological health function within the ACI framework. The relationship between the reduced indicator hydrological health function and the full indicator hydrological health function was examined. The analysis revealed a strong relationship between these two variables (Figure 9b) indicating that the reduced set of indicators effectively captures the overall hydrological health of the wetland sites. The strong relationship between the reduced and full indicator hydrological health functions further validates the effectiveness of the sensitivity analysis in identifying the most informative and sensitive indicators.

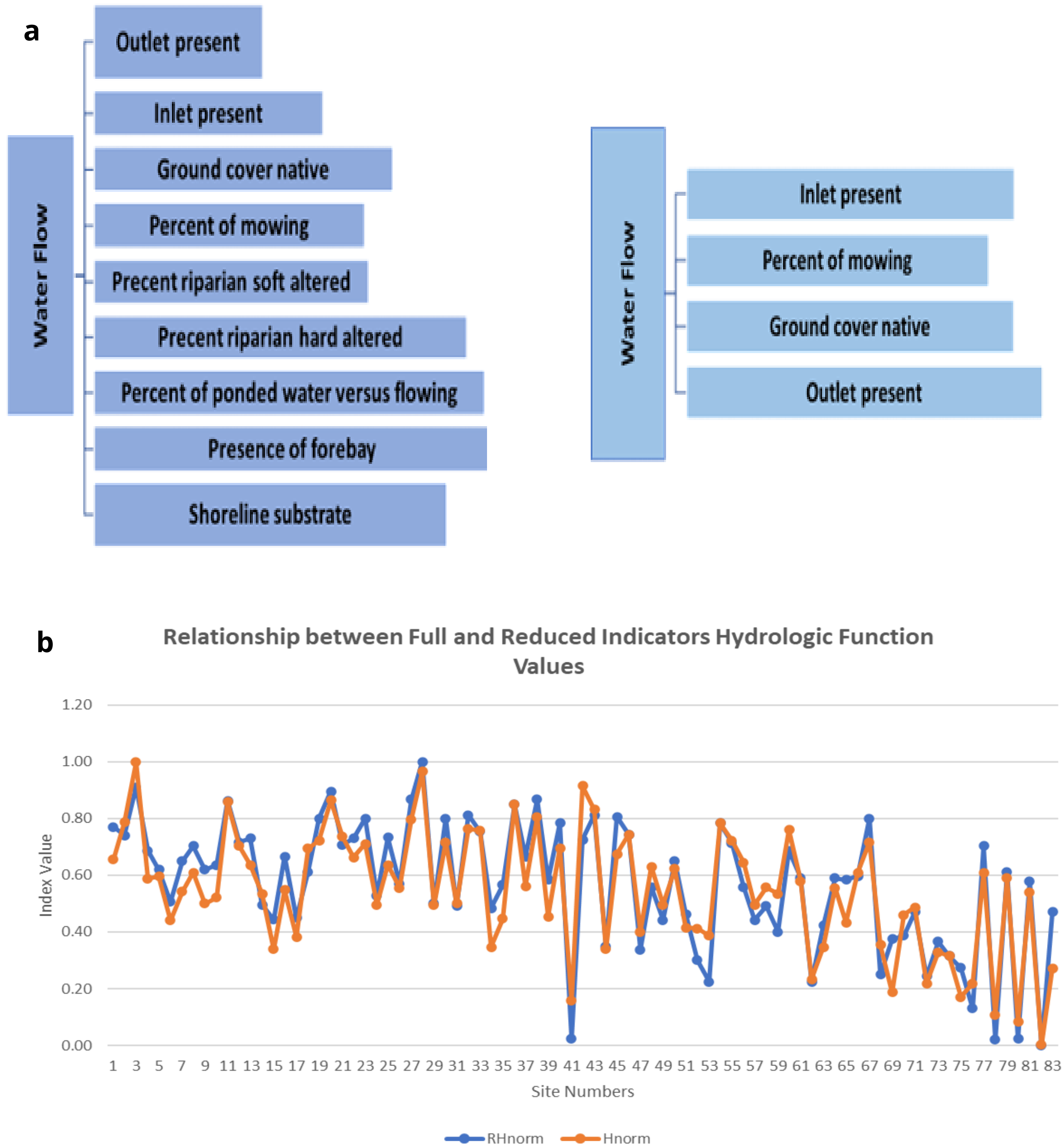
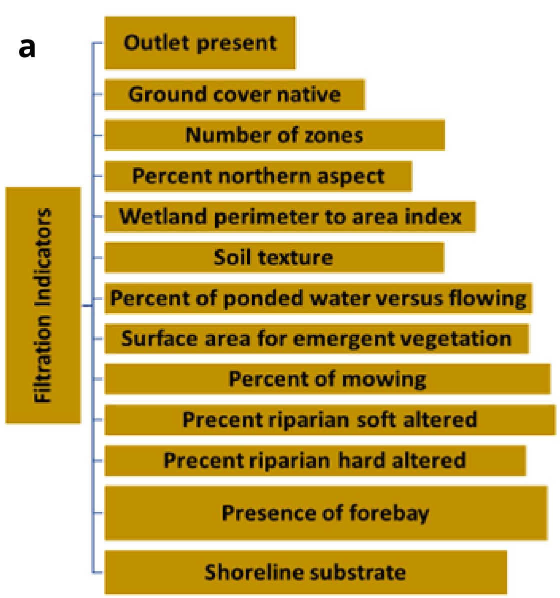


Figure 9: Results of the sensitivity analysis for Hydrologic function, indicating the full and reduced indicators in the Water flow Subfunctions (a), as well as the relationship between the Reduced Indicators Hydrologic Function (RHnorm in blue colour) and the Full Indicator Hydrologic Functions (Hnorm in orange colour).

Water Quality Subfunction Indicators: Sensitivity Analysis

The water quality function of the ACI is comprised of three subfunctions: source, filtration and bioindicator subfunctions. However, the bioindicator subfunction, consisting of only two indicators, was not considered for the sensitivity analysis. The filtration indicator consists of thirteen indicators, while the sources subfunction has eight indicators. As a result, the sensitivity analysis described previously was applied to these two subfunctions.

The sensitivity analysis removed seven indicators from the filtration subfunctions and three from the water source subfunctions. The seven indicators removed from the water filtration subfunction include: “Ground cover native”, “Percent northern aspect”, “Water perimeter to area index”, “Percent of ponded water versus flowing”, “Surface area of emergent vegetation”, “Percent riparian soft altered”, and “Percent riparian hard altered” (Figure 10a). On the other hand, the three indicators removed from the water source subfunction included: “Percent open ponded water”, “Water permanence probability” and “Distance to nearest minor road” (Figure 10b). Most of the indicators of water quality subfunction are not directly related to water quality, making them less sensitive to water quality.



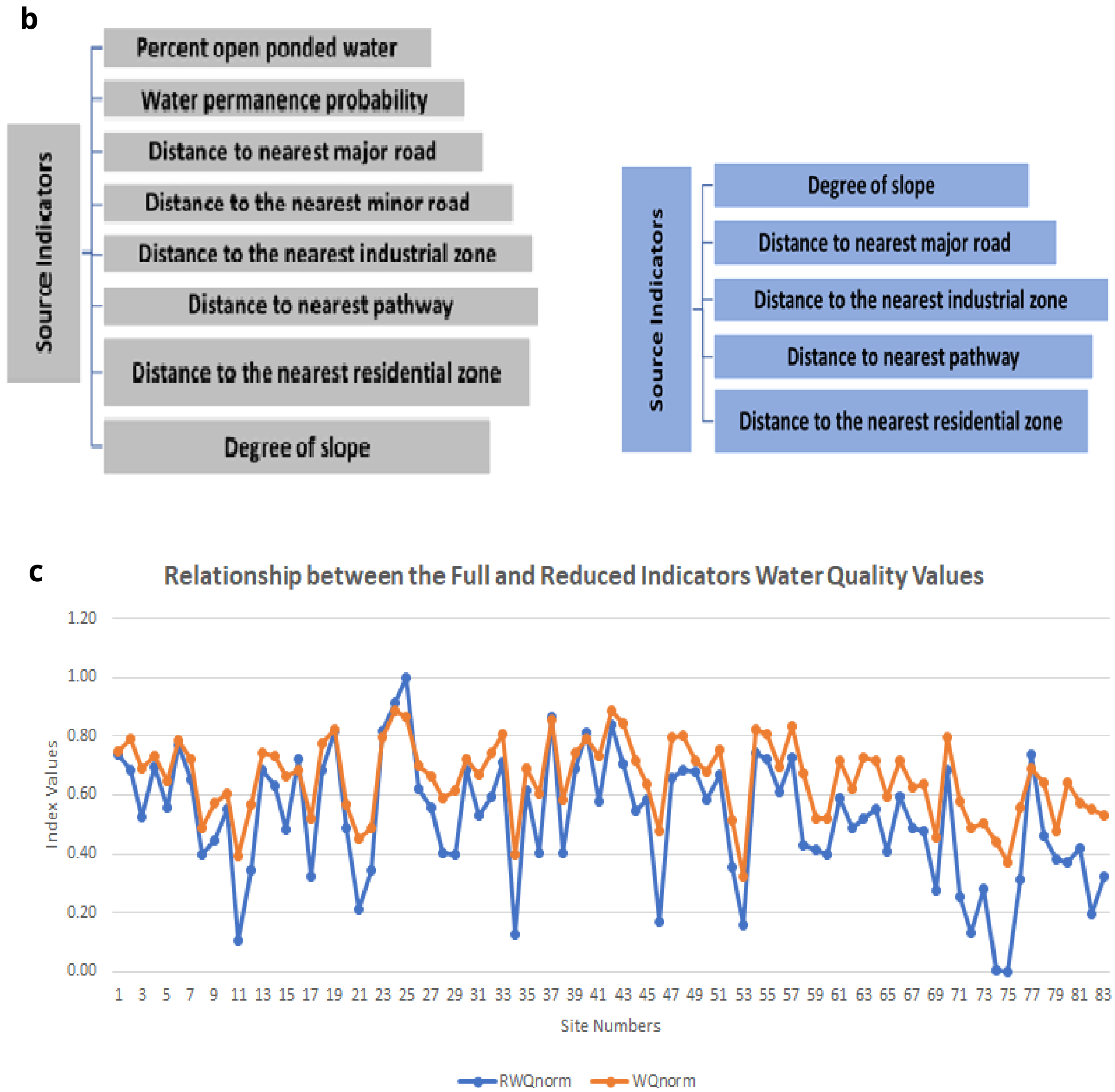


Figure 10: Results of the sensitivity analysis for Water Quality function, indicating the full indicators in the Water Filtration (a) and Water Source (b) Subfunctions. Following the sensitivity analysis, the Reduced Indicators were used to derive Reduced Indicators were used to derive Reduced Indicators Water Quality Function (RWQnorm in blue colour), which showed a consistent pattern (c) with the Full Indicator Water Quality Functions (WQnorm in orange colour).

Water quality appears to be the least sensitive function of ACI, which can be attributed to the nature of the indicators used to derive the water quality subfunction scores, as many of them are indirect measures of water quality conditions within a wetland ecosystem. For example, indicators such as "Distance to nearest industrial zone" assume that wetlands closer to an industrial zone will have lower water quality relative to those located farther away. However, this assumption may not always hold true, as various factors can influence water quality and are not solely dependent on proximity to industrial zones. Using indirect measures for assessing water quality can introduce complexities and uncertainties into the evaluation process. While these indicators provide valuable information and insights into potential influences on water quality, they may not directly reflect the actual conditions of water quality within the wetland. As a result of these indirect measures and potential complexities, the relationship between the reduced and full indicators water quality scores (Figure 10c) did not exhibit as strong alignment compared to the relationships observed for the ecological and hydrologic functions. It is important to consider that the ACI tool aims to provide a comprehensive assessment of wetland health by considering multiple functions, including ecological, hydrological, and water quality. While water quality may exhibit a lower sensitivity within the ACI framework, it remains an important aspect to evaluate alongside other functions to gain a holistic understanding of wetland conditions.

In total, 50 indicators were assessed in the sensitivity analysis, and 24 were eliminated, which translates to almost a 50% reduction of indicators. It is worth noting that some indicators were removed in one subfunction but retained in another subfunction. For instance, the “Presence of forebay” was selected as a sensitive indicator for the Water Filtration subfunction but was less sensitive to the Water Flow subfunction for the hydrological Function. This example demonstrates that certain indicators may have different levels of sensitivity or relevance across subfunctions within the ACI framework. The removal or retention of indicators is determined based on their individual performance in relation to the specific subfunction they are associated with.

Effectiveness of Sensitivity Analysis in Improving the ACI

The sensitivity analysis ensured that the selected indicators could provide meaningful insights into wetland conditions while considering the feasibility and accessibility of data collection in the field. Indeed, the sensitivity analysis achieved the objective of improving the operational efficiency of the ACI tool by identifying the most sensitive and easy-to-measure indicators. This optimization of the indicator selection enhances the practicality and effectiveness of the ACI tool for assessing and monitoring wetland conditions within The City of Calgary. It also streamlined data collection efforts, simplified analysis processes, and increased the accessibility of the tool, ultimately enhancing ACI's effectiveness in assessing and monitoring wetland conditions. The effectiveness of the sensitivity analysis was also evident in the strong positive relationship between the ACI scores derived from the reduced indicator subfunctions and the ACI scores obtained with the full set of indicators (Figure 11).

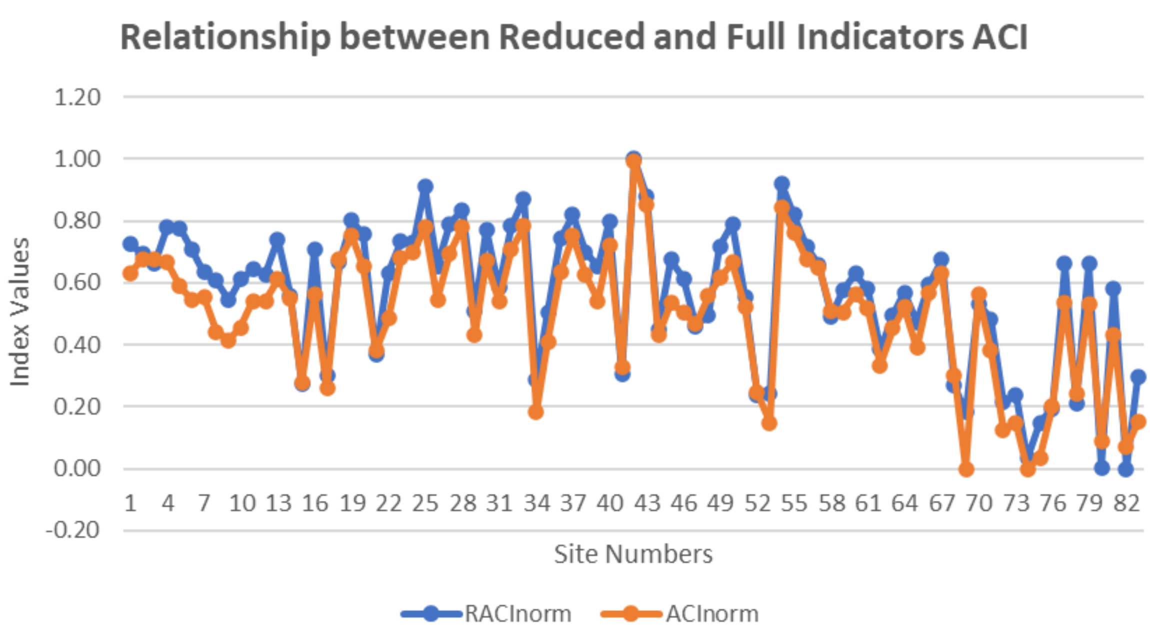


Figure 11: Comparison between Reduced Indicator ACI (RACInorm in blue colour) and Full Indicators-ACI (ACInorm in orange colour).

When the reduced set of indicators is used to calculate the subfunction scores and, subsequently, the ACI scores, the resulting values closely align with the ACI scores obtained using the full set of indicators. This indicates that the selected reduced indicators have retained the key information necessary for assessing the functional attributes of wetlands. The strong relationship between the reduced and full indicator ACI scores also suggests that the reduced set of indicators can provide a reliable and representative assessment of wetland conditions. This is important for practical purposes, as it allows for a more streamlined and efficient assessment process by focusing on fewer indicators without compromising the overall accuracy and validity of the ACI scores. Furthermore, the strong relationship between the reduced and full indicator ACI scores validates the sensitivity analysis approach. By identifying and selecting the most sensitive indicators, the analysis ensured that the reduced set of indicators captured the essential information needed to assess the health and functionality of wetlands.

The ACI and function scores derived through the reduced indicator analysis slightly modified the distribution of score categories within each wetland type. The modification of the score categories resulted in the reclassification of some wetland sites that were situated at the boundary between the two score categories (Table 2). Specifically, the sensitivity analysis led to an increase in the number of Constructed Stormwater Wetland (CSW) sites categorized as "high" in the ACI score, with one additional site moving up to this category (Figure 12). Similarly, in the case of Existing Modified Wetlands (EMW), two sites were reclassified as "moderate" due to the improvement observed in their ACI scores.

Table 2: Showing the effect of sensitivity analysis and application of the reduced indicators on the distribution of ACI score categories among wetland types.

Site Typology	Total Sites	ACI Score Category							
		Very Low		Low		Moderate		High	
		Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced
CSW	11	0	0	4	4	6	5	1	2
EMW	28	4	5	6	3	5	7	13	13
ERW	11	2	2	4	4	3	4	2	1
NWP	5	1	2	2	4	1	0	0	0
UWP	15	10	10	2	3	2	3	0	0

Conversely, the sensitivity analysis also resulted in the downgrading of certain sites to the immediate lower score category. This downgrading primarily affected low-performing wetland sites, such as Existing Retained Wetlands (ERW), Naturalized Wet Ponds (NWP), and Utility Wet Ponds (UWP). These wetland sites were shifted to the lower score categories based on the outcomes of the sensitivity analysis. This pattern of score categories upgrading for high-performing sites (i.e., CSW and EMW) and downgrading of low-performing sites (i.e., ERW, NWP, and UWP) was also consistent across the function scores and became apparent when assessing differences in score categories derived with the reduced and full indicators (Appendix B).

The modification of score categories within each wetland type demonstrates the importance of conducting sensitivity analysis to refine the assessment and ensure accurate classification of wetland health. Incorporating the reduced indicator approach made the ACI tool more sensitive to variations in wetland conditions, allowing for a more precise evaluation and categorization of wetland sites based on their functional health.

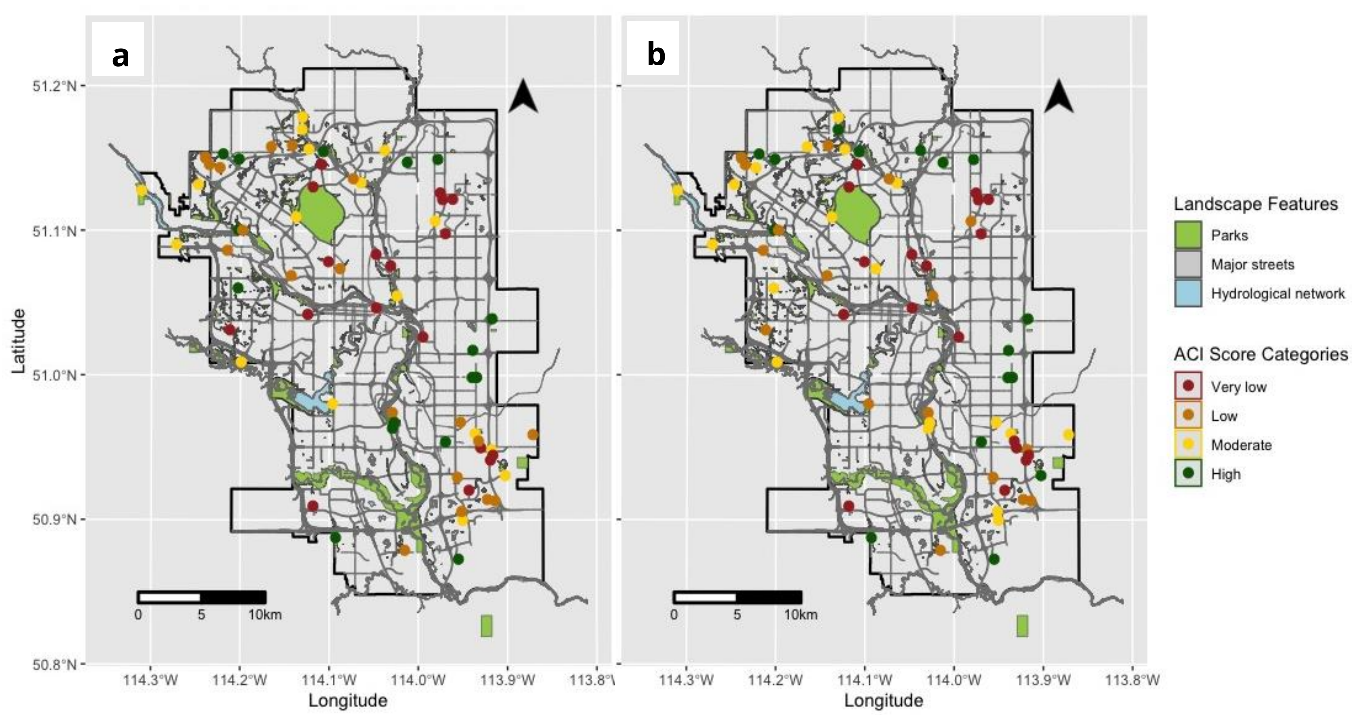


Figure 12: Maps of the study area showing slight changes in ACI score categories between the full indicators ACI (a) and reduced indicator ACI scores (b).

Conclusion

The Aquatic Condition Indicator (ACI) framework provides a comprehensive and robust tool for assessing the conditions of wetlands within The City of Calgary. Through the field testing and sensitivity analysis conducted, several key findings and insights have emerged, demonstrating the effectiveness and practicality of the ACI in evaluating wetland condition.

The ACI tool incorporates functional indicators related to hydrologic function, ecological function, and water quality functions, allowing for a holistic assessment of wetland conditions. The field-testing phase successfully identified statistically robust and effective methodologies for selecting field-testing sites across the city, enabling a representative assessment of various wetland types. The sensitivity analysis of the indicators assessed through the field testing further refined the ACI tool by identifying the most sensitive and easy-to-measure indicators for each subfunction. This process resulted in the reduction of indicators, streamlining data collection efforts, and improving operational efficiency. Furthermore, the analysis led to the removal of redundant and less sensitive indicators while maintaining the overall integrity and accuracy of the ACI scores.

The results obtained from the field testing and sensitivity analysis demonstrated the sensitivity of the ACI functions to the functional attributes of wetland types. Wetland types designed for stormwater storage with limited ecological health functions showed lower ACI scores, while wetlands with more natural and diverse ecological attributes exhibited higher scores, with the exception of some Existing Retained Wetlands in highly disturebed land uses. Additionally, the strong relationships observed between the full and reduced indicator values for ecological health and hydrological health indicate the reliability and validity of the reduced indicator approach. The ACI scores derived from the reduced indicators maintained a strong association with the original ACI scores, further validating the effectiveness of the sensitivity analysis in capturing key aspects of wetland health. However, it is important to note that the water quality function of the ACI showed relatively lower sensitivity, primarily due to the indirect nature of the indicators used. Further research and refinement of the water quality indicators are recommended to enhance the accuracy and sensitivity of this function.

In conclusion, the ACI framework provides a valuable and practical tool for assessing the conditions of urban wetlands in Calgary. The field testing and sensitivity analysis have improved the accuracy, efficiency, and applicability of the ACI, enabling more precise evaluations and categorizations of wetland condition. The findings and insights gained from this research will contribute to effective wetland management, conservation, and restoration efforts in the city, facilitating the protection and enhancement of these valuable ecosystems in The City's natural environment parks.

Recommendations

Based on the information obtained from the field testing of the ACI framework and sensitivity analysis of the subfunction indicators, the following recommendations are provided for advancing research and development of this wetland rapid assessment tool:

Survey timing: During the 2022 field survey season each survey site was visited twice (May/June and June/July) to provide recommendations on survey timing. The most notable change was flowering plants which made identifying vegetation significantly easier later in the growing seasons. This led to the recommendation that the ACI Survey should be conducted once between Late June to Early August, which coincides with the peak to late growing season. If indicators based on flowering plants are removed in future iterations of the ACI tool, the results indicate that the surveys could take place between May and August.

Application of wetland types: Our findings identified various levels of wetland functionality and highlight the importance of considering the specific wetland types when assessing wetland conditions. We recommend The City of Calgary apply the new typology developed for wetlands to all wetlands occurring within the city limits. By understanding the distribution of ACI scores across different wetland types, policymakers and practitioners can prioritize conservation and restoration efforts, accordingly, focusing on Existing Modified Wetlands and Existing Retained Wetlands with lower scores, particularly those modified for stormwater management, to improve their ecological functions and overall condition.

Increasing the number of test sites: To ensure a statistically robust sensitivity analysis process, a statistically significant number of wetland sites that is suitable for the number of indicators of interest should be surveyed. Generally, for ecological modelling exercises, such as the sensitivity analysis conducted in this study, the "10:1 rule" in ecology is applied as a guideline for deciding the ideal number of wetland sites (Magurran, 1988). The rule suggests having a minimum of 10 wetland sites per indicator of interest. Given that the highest number of indicators per subfunction in the ACI framework is 13, it implies that a minimum of 130 wetland sites is required to improve the robustness of the sensitivity analysis. It is also important to ensure that the 130 wetland sites are evenly distributed across the five wetland types surveyed in this study, which translates to 26 replicates for each wetland type. Achieving equal replication will improve the statistical power, robustness, precision, and reliability of the sensitivity analysis results. It will also allow for more accurate estimation, better assumption testing, and increased generalizability of the findings.

Validation and calibration: To further enhance the ACI framework and ensure its robustness and accuracy, it is recommended to conduct validation and calibration analyses. Validation involves comparing the ACI scores with independent data or reference conditions to assess the reliability and validity of the tool. For instance, empirical measurement of water quality parameters can be used to validate the sensitivity of water quality scores obtained with the ACI. Calibration, on the other hand, will help to fine-tune the ACI by adjusting the scoring system or thresholds based on empirical data obtained from the validation exercise. This process ensures that the ACI scores accurately reflect the specific conditions and characteristics of wetlands within The City of Calgary. Calibration may involve adjusting the weights assigned to different indicators or revising the scoring criteria to better align with local ecological and hydrological contexts.

Integration of remote sensing and GIS: Explore the integration of remote sensing and geographic information system (GIS) data to enhance the efficiency and accuracy of data collection for the ACI tool. The combination of remote sensing, GIS and modelling to the ACI tool provides valuable information on wetland characteristics and conditions over large spatial extents, complementing field-based assessments.

Long-term monitoring: Implement long-term monitoring programs using the predictive ACI model (in development) to track changes in wetland conditions over time and validate the impacts of the change using the ACI field assessment tool discussed in this report. This will provide valuable data to inform wetland interventions such as conservation and restoration efforts and help identify trends and patterns in wetland conditions.

Expand geographical coverage: Extend the application of the ACI tool beyond The City of Calgary to assess wetland conditions in other (e.g., Cochrane, Airdrie, and Okotoks) municipalities within the regions. This will allow for better improvement of the ACI's effectiveness and a broader understanding of wetland health and contribute to developing regional wetland monitoring programs.

Continuous improvement: Regularly review and update the ACI tool, incorporating new indicators or refining existing ones based on scientific advancement to ensure the tool remains up-to-date and effective in assessing wetland condition. The continuous improvement process should be iterative and data-driven, involving collaboration among wetland experts, ecologists, and stakeholders. It is crucial to consider the feedback and input from field practitioners and local experts who have direct experience and knowledge of the wetland systems in The City of Calgary.

By implementing these recommendations, The City's Park Ecologists can further enhance the applicability and effectiveness of the ACI tool, contributing to improved wetland conservation, management, and decision-making processes.

References

Brabec E, Schulte S, Richards PL (2002) Impervious surfaces and water quality: a review of current literature and its implications for watershed planning. J Plan Lit 16:499–514

Cangur S, Pasin O, Ankarali H (2015) Comparison of Sampling Distributions and Performances of Minitab And Freund & Perles Quartiles. Pakistan J Stat 31:

Ehrenfeld JG (2000) Evaluating wetlands within an urban context. Urban Ecosyst 4:69–85

Ehrenfeld JG (2008) Exotic invasive species in urban wetlands: environmental correlates and implications for wetland management. J Appl Ecol 45:1160–1169

Fiera Biological Consulting. 2015. City of Calgary Habitat Condition Rating Tool: Final Report. Prepared for City of Calgary. 75 pp.

Gren I-M, Folke C, Turner K, Batemen I (1994) Primary and secondary values of wetland ecosystems. Environ Resour Econ 4:55–74

Grimm NB, Faeth SH, Golubiewski NE, et al (2008) Global change and the ecology of cities. Science (80-) 319:756–760

Harrell FE (2017) Regression modeling strategies. Bios 330:14

Magurran AE (1988) Ecological diversity and its measurements. Princet Univ Press New Jersey 177pp.

Mitsch WJ, Gosselink JG (2000) The value of wetlands: importance of scale and landscape setting. Ecol Econ 35:25–33

Naiman RJ, Decamps H, Pollock M (1993) The role of riparian corridors in maintaining regional biodiversity. Ecol Appl 3:209–212

Novitski RP, Smith RD, Fretwell JD (1996) Wetland functions, values, and assessment. Natl Summ Wetl Resour USGS Water Supply Pap 2425:79–86

Nwaishi F, Dennett J, Lee TS, et al (2023) Aquatic Health Indicator Manual for the City of Calgary. 75

Palta MM, Stander EK (2020) Wetlands in urban environments. In: The Routledge handbook of urban ecology. Routledge, pp 371–382

Paul MJ, Meyer JL (2001) Streams in the urban landscape. Annu Rev Ecol Syst 32:333–365

Samson D (2015) Calculating quartiles for box-and-whisker plots. Learn Teach Math 2015:35–38

Walsh CJ, Roy AH, Feminella JW, et al (2005) The urban stream syndrome: current knowledge and the search for a cure. J North Am Benthol Soc 24:706–723

Appendix A: GIS Methods and R code for Survey Site Selection

Spatial layers provided by City of Calgary

- Merged wetland dataset derived from GOA and Fierra Biological Consulting wetland layer developed in 2015
- Stormponds
- Natural_area

GIS steps to prepare for R script site selection:

- MOPT (that is city land or TUC yes, exclude if private = yes) + storm pond, then see if any are missing from the natural area (asset type of wetland or wetland environment) and life_cycle_status = active use, add anything missing back to the MOPT+storm pond
- selected MOPT data that are city_land or TUC yes and private = NULL, clipped to city boundary -> MOPT_city_owned
- erase MOPT_city_owned with Storm_pond_existing -> MOPT_city_owned_Erased
- merge MOPT_city_owned_Erased with Storm_pond_existing -> MOPT_Storm_merged
- selected from Natural_area life_cycle_status = active and Asset_type = wetland or wetland environment save to new dataset -> Natural_area_wetlands
- spatial selection of Natural_area_wetlands with MOPT_storm_merged for interesection to see how many are missing (8)
- merge selected Natural_area_wetlands with MOPT_Storm_merged -> Complete Wetlands
- disolve complete_wetlands -> complete_wetlands_dissolved
- spatial select wetlands that intersect with storm_pipes_usethis with a 10m range
- assign these records a 1 in the withPipe field, rest will be 0
- feature to point, selecting incide to create centriods dataset -> complete_wetlands_points
- intersect wetlands with catchments (not sub catchments) to see how many have wetlands - give number of catchments with wetland
- clip catchment by the city boundary -> catchment (didnt use catchment within city limit dataset as it doesnt extend to city boundary, leaving wetlands outside, plus the catchment data is already disolved to catchment, doesnt include subcatchment
- dissolved to CTCH_NM -> catchment_disolved
- select catchments that intersect with complete_wetland_points and save to new dataset -> catchment_disolved_withwetland, 228 catchments of 492 of have wetlands

- calcaulated acres, then broke acres into 10 quantiles and created a sizecat field on catchment_disolved_withwetland

  1 - 22 <39.360322
  2 - 24 <73.538871
  3 - 22 <97.841918
  4 - 24 <150.844071
  5 - 22 <221.162712
  6 - 24 <318.483282
  7 - 22 <454.430015
  8 - 23 <891.607270
  9 - 23 <2164.130199
  10 - 22 <= 18048.453991

- joined catchment_disolved_withwetland to complete_wetlands_points_catchment on CTCH_NM and transfer over acres and sizecat to ctch_a and ctch_sc fields

Create random points using R script.

R code for survey site selection

```
# Script for selecting Actual-ACI survey sites
# Developed by Miistakis Institute
# April 29 2022
# R version:

library(sf)
library(rgdal)
library(sp)
library(dplyr)

# import shapefile
thepoints <- read_sf("P:/Current Projects/PRJ 934 YYC Wetland
Conservation/ACI/ACI_site_selection/wetland_pnts_catchment.shp")

#break points into pipe and no pipe groups
pipepoints <- thepoints[thepoints$withPipe ==2,]
nopipepoints <- thepoints[thepoints$withPipe ==1,]

#selects one of each point type from every catchment if available
randompipepoints <- pipepoints %>% group_by(ctch_sc) %>% slice_sample(n = 8)
```

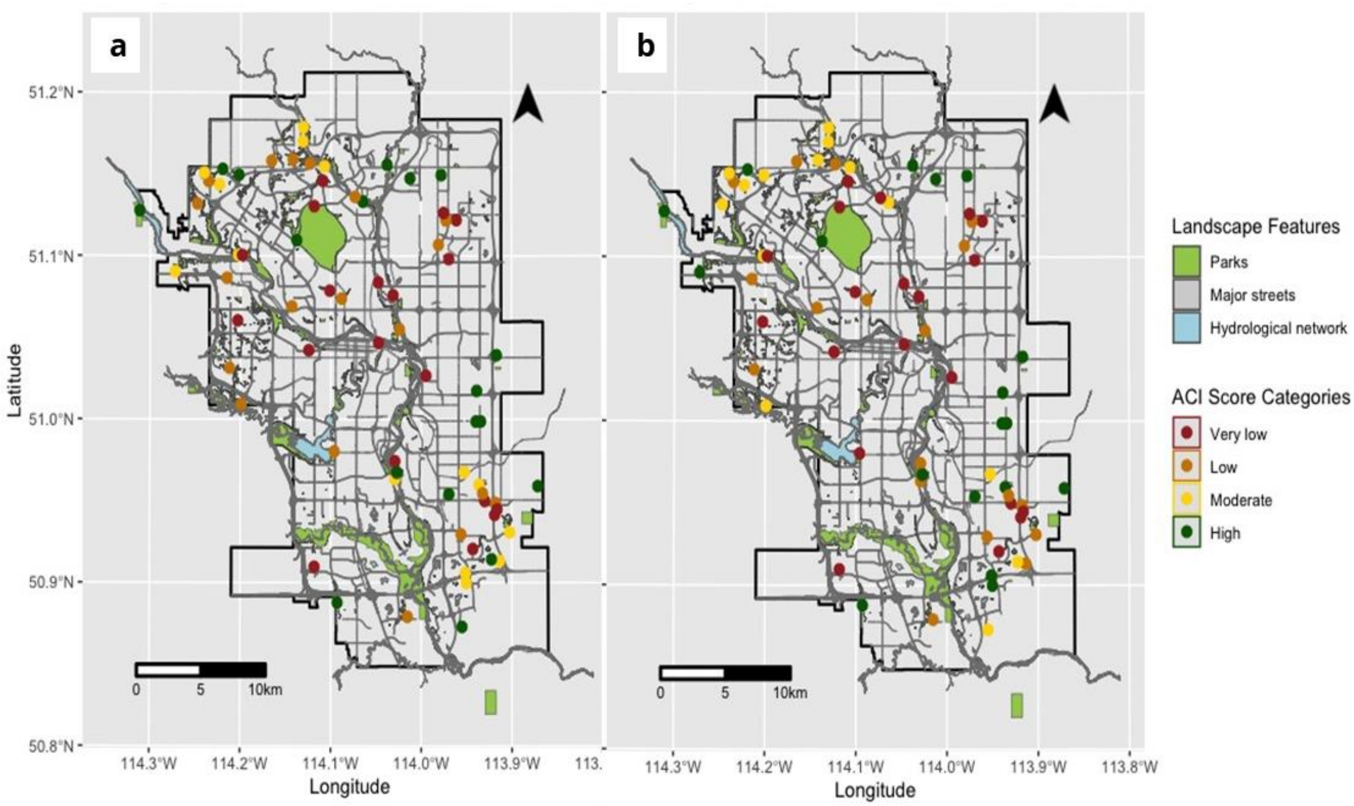
```
randomnopipepoints <- nopipepoints %>% group_by(ctch_sc) %>% slice_sample(n = 8)

#need to upgroup data, above process leaves them all as groups of 1
randompipepoints <- ungroup(randompipepoints)
randomnopipepoints <- ungroup(randomnopipepoints)

#piped wetlands make up 0.62, 0.38 have no pipes, so 49.6 of the 80 points need to have
pipes, 30.4 with no pipes. so 50/30
randompipes <- slice_sample(randompipepoints,n=50)
randomnopipes <- slice_sample(randomnopipepoints,n=30)

#create datasets of the points not selected at random
norandompipes <- setdiff(randompipepoints,randompipes)
norandomnopipes <- setdiff(randomnopipepoints,randomnopipes)

#join the two datasets together, for both the random points and the points not selected for
random
random <- rbind(randompipes,randomnopipes)
random

min(random$ctch_a)

#see how many catchments covered from the 80 points
numcatch <- length(unique(random$CTCH_NM))
numcatch

#=================================================================
# Histogram - frequency of size (acres to 10 percentiles)of catchments
library("ggplot2")
library("ggpubr")
install.packages("gridExtra")             # Install gridExtra package
library("gridExtra")                      # Load gridExtra package

catchment_w_wetland <- read.csv("P:/Current Projects/PRJ 934 YYC Wetland
Conservation/ACI/ACI_site_selection/catchment_w_wetlands.csv")

catchment <- catchment_w_wetland %>%
  subset(SUM_acres < 8000)

random2 <- random %>%
```

```
  subset(ctch_a < 8000)

# ggplot size by size plots 10 bins
catchment_size_h10 <- ggplot(
  catchment, aes(SUM_acres)) +
  geom_histogram(bins=10)+
  ggtitle("catchment size") +
  ylim(0,160)+
  xlab("Acres")

random_h10 <- ggplot(
  random2, aes(ctch_a))+
  geom_histogram(bins=10)+
  ylim(0,160)+
  xlim(-500,8000)+
  ggtitle("catchment size for survey sites") +
  xlab("Acres")

grid.arrange(catchment_size_h10, random_h10, ncol = 2)

# test if frequency distributions are similar

catchment_t.test <- t.test(x = catchment$SUM_acres,
                           y = random2$ctch_a)
catchment_t.test

#save random points
randomSP <- as_Spatial(random2)
writeOGR(randomSP,"P:/Current Projects/PRJ 934 YYC Wetland
Conservation/ACI/ACI_site_selection","ACI_survey_sites_v2", driver = "ESRI Shapefile",
overwrite_layer = T)
```

Appendix B: Differences in Score Categories Derived with the Full and Reduced Indicators

ST 1: Showing the effect of sensitivity analysis and application of the reduced indicators on the distribution of Ecological Health score categories among wetland types.

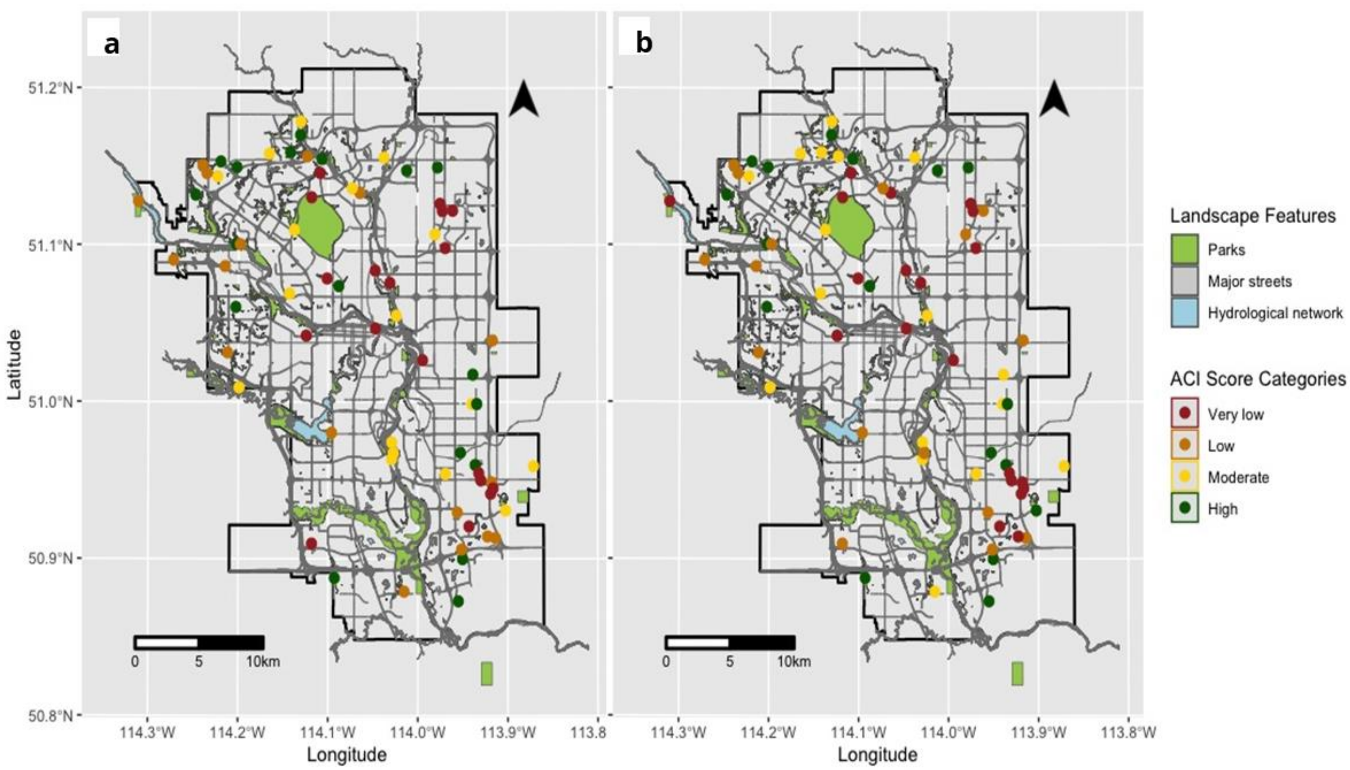
		Score Categories							
Site Typology	**Total Sites**	**Very Low**		**Low**		**Moderate**		**High**	
		Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced
CSW	11	1	2	6	4	3	3	1	2
EMW	28	4	4	5	6	9	8	10	10
ERW	11	3	4	1	0	1	3	6	4
NWP	5	1	0	4	5	0	0	0	0
UWP	15	10	10	3	3	1	0	1	2



SF1: Maps of the study area showing slight changes in Ecological Health score categories between the full indicators (a) and reduced indicator Ecological scores (b)

ST 2: Showing the effect of sensitivity analysis and application of the reduced indicators on the distribution of Hydrologic Function score categories among wetland types.

Site Typology	Total Sites	Very Low		Low		Moderate		High	
		Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced
CSW	11	0	0	4	2	4	6	3	3
EMW	28	5	3	4	7	6	6	13	12
ERW	11	2	5	5	4	3	1	1	1
NWP	5	1	1	2	2	2	2	0	0
UWP	15	10	11	2	1	2	2	1	1

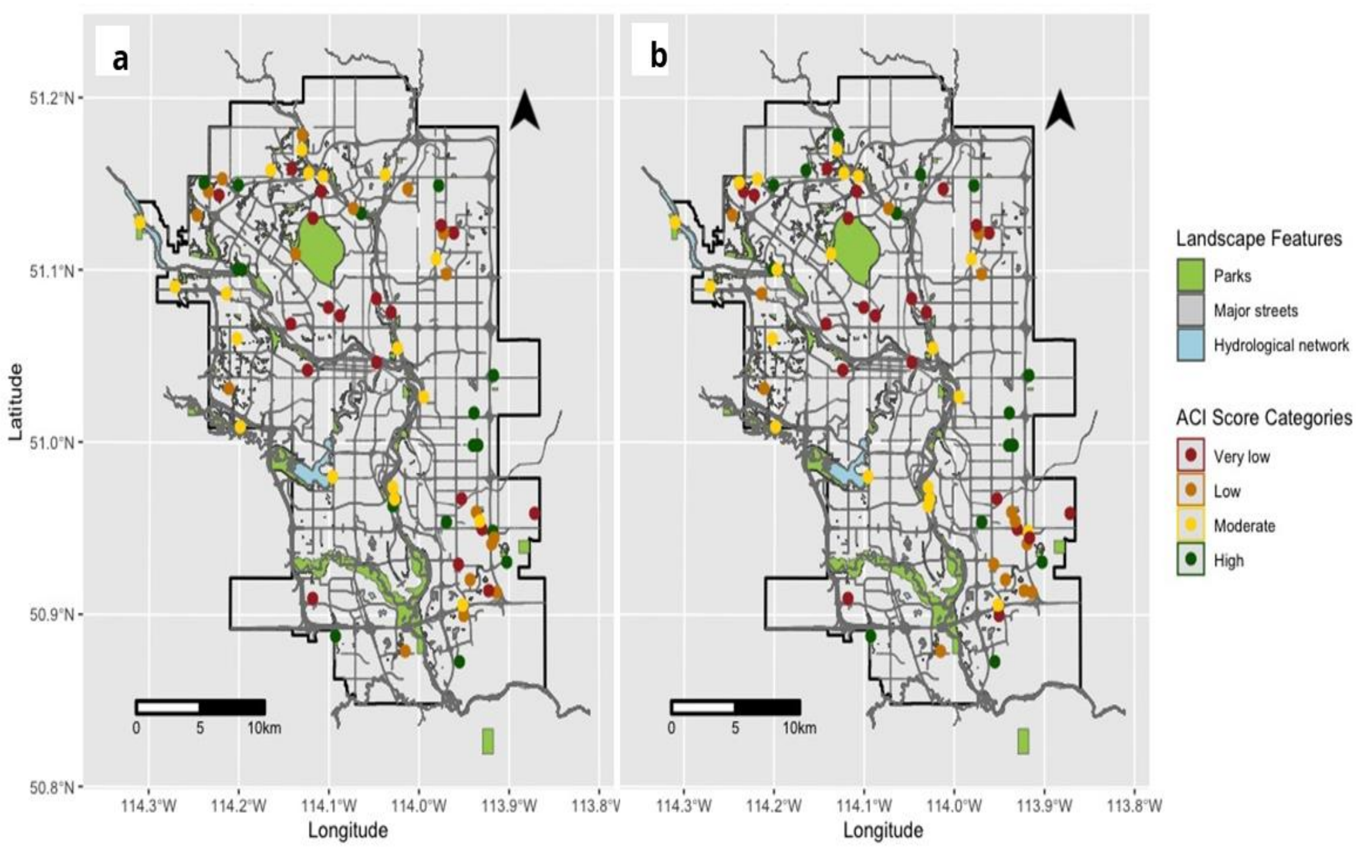


SF2: Maps of the study area showing slight changes in Hydrologic Function score categories between the full indicators (a) and reduced indicator Hydrologic scores (b)

ST 3: Showing the effect of sensitivity analysis and application of the reduced indicators on the distribution of Water Quality Function score categories among wetland types.

Site Typology	Total Sites	Very Low		Low		Moderate		High	
		Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced
CSW	11	3	3	1	1	6	5	1	2
EMW	28	4	7	8	4	6	7	10	10
ERW	11	3	2	2	2	2	5	4	2
NWP	5	0	0	2	3	3	2	0	0
UWP	15	9	9	4	4	1	1	1	1

(Score Categories spans Very Low, Low, Moderate, High.)



SF3: Maps of the study area showing slight changes in Water Quality Function score categories between the full indicators (a) and reduced indicator Water Quality scores (b)

Appendix C: R Code for Sensitivity Analysis

```
## Set work directory
setwd("C:/Users/fnwai/Documents/R Project Directory/ACI/")

# Load the required libraries
install.packages("rlang")
install.packages("ggplot2")
install.packages("rio")
library(rio)
library(GGally)
library(scatterplot3d)
library(ggplot2)
library(ggpmisc)
library(car)
install.packages("rms")
install.packages("performance")
library(performance)
library(rms)
new_data<-
import_list("./ACI_RawData_Current_21102022_scoring_FN_JDUpdate.xlsx")

#selecting the last four values
new_names<- c("WQnorm", "Hnorm", "Enorm", "ACInorm")

# select the first named list
selected_data<- new_data[["Raw_Data"]]

#selecting the last four values
new_names<- c("WQnorm", "Hnorm", "Enorm", "ACInorm")

subset_data<- selected_data[, (names(selected_data) %in% new_names)]

lapply(subset_data, function(x) shapiro.test(x))
# fit linear model
fit <- lm(`ACInorm` ~ `Enorm`+`Hnorm`+`WQnorm`, data = subset_data)
summary(fit)
```

```
ggpairs(data = subset_data, columns = 1:4, title = "Relationship between predictor
variables and ACI score")

ggplot(data = subset_data, aes(x = `Enorm`, y = `ACInorm`)) +
  stat_poly_line()+
  stat_poly_eq(aes(label= paste(after_stat(eq.label),
                              after_stat(rr.label), sep = "*\",\"*")))+
  geom_point() +
  theme(panel.background = element_rect(fill = "white"),
        axis.line.x=element_line(),
        axis.line.y=element_line()) +
  ggtitle("Linear Model for Normalized Ecosystem value and Normalized ACI score
Fitted to Data")

ggplot(data = subset_data, aes(x = `Hnorm`, y = `ACInorm`)) +
  stat_poly_line()+
  stat_poly_eq(aes(label= paste(after_stat(eq.label),
                              after_stat(rr.label), sep = "*\",\"*")))+
  geom_point() +
  theme(panel.background = element_rect(fill = "white"),
        axis.line.x=element_line(),
        axis.line.y=element_line()) +
  ggtitle("Linear Model for Normalized Hydrology value and Normalized ACI score
Fitted to Data")

ggplot(data = subset_data, aes(x = `WQnorm`, y = `ACInorm`)) +
  stat_poly_line()+
  stat_poly_eq(aes(label= paste(after_stat(eq.label),
                              after_stat(rr.label), sep = "*\",\"*")))+
  geom_point() +
  theme(panel.background = element_rect(fill = "white"),
        axis.line.x=element_line(),
        axis.line.y=element_line()) +
  ggtitle("Linear Model for Normalized water quality value and Normalized ACI score
Fitted to Data")

#Water Quality Indicators Sensitivity Analysis
# Listings all the water quality indicators and subfunctions
names_water<- c("algae_wq", "dist_residential_wq", "percent_northern_aspect_wq",
```

```
             "outlet_pipe_channel_connection_wq","turbidity_wq",
"dist_major_road_wq",
             "percent_mowing_wq", "dist_industrial_wq", "percent_ponded_water_wq",
             "percent_open_ponded_water_wq", "number_zones_wq",
"dist_minor_road_wq",
             "percent_riparian_altered_soft_wq", "percent_riparian_altered_hard_wq",
             "forebay_wq","dist_pathway_wq", "slope_wq","water_permanence_wq",
"ground_cover_native_cover_wq",
             "surface_area_emergent_veg_wq", "score_perimeter_area_ratio",
"soil_texture_wq", "shoreline_substrate_wq",
             "WQ SF-Source", "WQ SF - bio-indicator", "WQ SF - Filtration/ mitigation",
"Water Quality value average")

raw_data<- new_data$Raw_Data
## Sub-setting raw_data based on water quality indicator
# extracting only required columns based on the col_nam vector
selected_data<- raw_data[, (names(raw_data) %in% names_water)]


## Replace "NA" with NA

selected_data <- selected_data %>% naniar::replace_with_na_all(~.x == "NA")
selected_data[is.na(selected_data)]<- "0"

# drops rows with DNC
selected_data<- selected_data[c(1:10,12:51,53:58,60:83), ]

# convert all columns to numeric values

selected_data[names(selected_data)]<-
sapply(selected_data[names(selected_data)], as.numeric)

## replace the additional NA created on conversion to numeric
selected_data[is.na(selected_data)]<- 0

# plot to ensure no missing values
visdat::vis_miss(selected_data, sort_miss = T)

#Sensitivity of Analysis of Indicators for WQ SF-Source
```

```
#See Section 17.1 of Frank Harrell's Regression Modelling Strategy Book (2nd Edition)
library(rms)
names(selected_data)
SF_Source <- selected_data[, c (5,7:8,15:18,20,24),]
dd = datadist(as.data.frame(SF_Source))
options(datadist="dd")
fS <- ols( `WQ SF-Source` ~., data = SF_Source)
summary(fS)

#You can logit-transform your WQ subfunction scores using the logit() function
#in the car package and then fit your models to the logit-transformed scores,
#which are no longer bounded between 0 and 1.

range(SF_Source$`WQ SF-Source`)

lp <- predict(fS) # compute linear predictor from
# full penalized model

# insert sigma = 1 as otherwise sigma = 0 will cause problems

a <- ols(lp ~.,data = SF_Source, sigma = 1)

ffS <-lm(`WQ SF-Source` ~., data = SF_Source)

#check_model(ffS)
avPlots(ffS)

# specify silly stopping criterion to remove all predictor variables
#===> this allows you to find out the order in which predictors
#     should be removed from the full penalized model

s <- fastbw(a, aics = 10000)
s

betas <- s$Coefficients # matrix, rows = iterations
#X <- cbind(1, fS$x)     # design matrix
ap <- X %*% t(betas)
ap
X <-model.matrix(fS)
```

```
model.matrix(fS)[, 1]
model.matrix(fS)


# compute the series of approximations to lp
ap <- X %*% t(betas)
ap

# for each approximation, compute approximation R-squared and
# ratio of likelihood ratio chi-square for approximate model
# to that of original model
m <- ncol(ap) - 1 # all but intercept-only model
r2 <- frac <- numeric(m)
fullchisq <- f$stats['Model L.R.']
for (i in 1:m){
  lpa <- ap[,i]
  r2[i] <- cor(lpa, lp)^2
  fapprox <- ols(`WQ SF-Source` ~ lpa, data = SF_Source)
  frac[i] <- fapprox$stats['Model L.R.']/fullchisq
}


r2
frac

round(r2,4)
round(frac,4)

rownames(s$result)
rio::export(data.frame(predictor = rownames(s$result),
                       s$result), "s.result.WQ.subfunction.score.xlsx")
browseURL("s.result.WQ.subfunction.score.xlsx")

windows(height = 7, width = 7)
par(mar=c(5,5,2,2))
plot(r2, frac, type='b',
     xlab = expression(paste('Approximation ', R^2)),
     ylab = expression(paste('Fraction of ', chi^2, ' Preserved')),
     xlim = c(0.2,1), ylim=c(0.2,1), cex=1.3)
# abline(h = 0.80, col=grey(0.83), lwd=1.3)
```

```
abline(v = 0.80, col=grey(0.83), lwd=1.3)
abline(a = 0, b = 1, col = grey(0.83), lwd=1.3)

names (SF_Source)
fapprox.3.deletions <- ols(lp ~ `dist_industrial_wq` + `slope_wq`+
                        `dist_pathway_wq` + `dist_residential_wq` +
`dist_major_road_wq`,
                      data = SF_Source,
                      x = TRUE)
round(fapprox.3.deletions$stats['R2'],5)

ffS2 <-lm(`WQ SF-Source` ~ `dist_major_road_wq`+`dist_pathway_wq`
      +       + `dist_residential_wq` + `dist_industrial_wq` + `slope_wq`, data =
SF_Source)

avPlots(ffS2)


#subsetting by Filtration subfunctions
names(selected_data)
SF_filtration <- selected_data[, c (2:4,6,10:14,19,21:23,25),]
dd = datadist(as.data.frame(SF_filtration))
options(datadist="dd")
f2 <- ols( `WQ SF - Filtration/ mitigation` ~., data = SF_filtration)
summary(f2)
lp <- predict(f2)
a <- ols(lp ~.,data = SF_filtration,sigma = 1)

ffF <-lm(`WQ SF - Filtration/ mitigation` ~., data = SF_filtration)
avPlots(ffF)

# specify silly stopping criterion to remove all predictor variables
#===> this allows you to find out the order in which predictors
#     should be removed from the full penalized model

s <- fastbw(a, aics = 10000)
s

betas <- s$Coefficients # matrix, rows = iterations
#X <- cbind(1, f$x)      # design matrix
```

```
X <-model.matrix(f2)

# compute the series of approximations to lp
ap <- X %*% t(betas)
ap

# for each approximation, compute approximation R-squared and
# ratio of likelihood ratio chi-square for approximate model
# to that of original model
m <- ncol(ap) - 1 # all but intercept-only model
r2 <- frac <- numeric(m)
fullchisq <- f$stats['Model L.R.']
for (i in 1:m){
  lpa <- ap[,i]
  r2[i] <- cor(lpa, lp)^2
  fapprox <- ols(`WQ SF - Filtration/ mitigation` ~ lpa, data = SF_filtration)
  frac[i] <- fapprox$stats['Model L.R.']/fullchisq
}


r2
frac

round(r2,4)
round(frac,4)

rownames(s$result)
rio::export(data.frame(predictor = rownames(s$result),
                       s$result), "s.result.WQ.filtrationSF.score.xlsx")
browseURL("s.result.WQ.filtrationSF.score.xlsx")

windows(height = 7, width = 7)
par(mar=c(5,5,2,2))
plot(r2, frac, type='b',
     xlab = expression(paste('Approximation ', R^2)),
     ylab = expression(paste('Fraction of ', chi^2, ' Preserved')),
     xlim = c(0.2,1), ylim=c(0.2,1), cex=1.3)
# abline(h = 0.80, col=grey(0.83), lwd=1.3)
abline(v = 0.80, col=grey(0.83), lwd=1.3)
abline(a = 0, b = 1, col = grey(0.83), lwd=1.3)
```

```
names (SF_filtration)
fapprox.8.deletions <- ols(lp ~ `outlet_pipe_channel_connection_wq` +
`number_zones_wq` + `percent_mowing_wq`+
                    `soil_texture_wq` + `forebay_wq` + `shoreline_substrate_wq`,
                  data = SF_filtration,
                  x = TRUE)
round(fapprox.8.deletions$stats['R2'],5)

ffF2 <-lm(`WQ SF - Filtration/ mitigation` ~ `outlet_pipe_channel_connection_wq` +
`number_zones_wq` + `percent_mowing_wq`+
        `soil_texture_wq` + `forebay_wq` + `shoreline_substrate_wq`, data =
SF_filtration)

avPlots(ffF2)


####Sensitivity Analysis, Hydrology Subfunction
new_data<-
import_list("./ACI_RawData_Current_21102022_scoring_FN_JDUpdate.xlsx")

names_hydro<- c("outlet_pipe_channel_connection_h", "inlet_pipe_h",
           "percent_ponded_water_h", "forebay_h", "percent_open_ponded_water_h",
           "water_permanence_h", "ground_cover_native_cover_h", "soil_texture_h",
           "percent_mowing_h", "percent_riparian_altered_soft_h",
           "percent_riparian_altered_hard_h", "shoreline_substrate_h",
           "H SF - water storage", "H SF - water flow", "Hydrology value")
raw_data<- new_data$Raw_Data
hydro_data<- raw_data[, (names(raw_data) %in% names_hydro)]

## Replace "NA" with NA

hydro_data <- hydro_data %>% naniar::replace_with_na_all(~.x == "NA")
hydro_data[is.na(hydro_data)]<- "0"
# drops rows with DNC
hydro_data<- hydro_data[c(1:10,12:51,53:58,60:83), ]

# convert all columns to numeric values
```

```
hydro_data[names(hydro_data)]<- sapply(hydro_data[names(hydro_data)],
as.numeric)

## replace the additional NA created on conversion to numeric
hydro_data[is.na(hydro_data)]<- 0

# plot to ensure no missing values
visdat::vis_miss(hydro_data, sort_miss = T)

#Sensitivity of Analysis of Indicators for HQ SF-FLOW

names(hydro_data)
SF_Hflow <- hydro_data[, c (1:3,5,7,9:12,14),]
dd = datadist(as.data.frame(SF_Hflow))
options(datadist="dd")
fHF <- ols( `H SF - water flow` ~., data = SF_Hflow)
summary(fHF)

range(SF_Hflow$`H SF - water flow`)

lp <- predict(fHF) # compute linear predictor from
# full penalized model

# insert sigma = 1 as otherwise sigma = 0 will cause problems

a <- ols(lp ~.,data = SF_Hflow, sigma = 1)

ffH <-lm(`H SF - water flow` ~., data = SF_Hflow)

#check_model(ffS)
avPlots(ffH)

# specify silly stopping criterion to remove all predictor variables
#===> this allows you to find out the order in which predictors
#     should be removed from the full penalized model

s <- fastbw(a, aics = 10000)
s

betas <- s$Coefficients # matrix, rows = iterations
```

```
#X <- cbind(1, fS$x)      # design matrix

# compute the series of approximations to lp
ap <- X %*% t(betas)
ap
X <-model.matrix(fHF)
model.matrix(fHF)[, 1]
model.matrix(fHF)




ap <- X %*% t(betas)
ap

# for each approximation, compute approximation R-squared and
# ratio of likelihood ratio chi-square for approximate model
# to that of original model
m <- ncol(ap) - 1 # all but intercept-only model
r2 <- frac <- numeric(m)
fullchisq <- f$stats['Model L.R.']
for (i in 1:m){
  lpa <- ap[,i]
  r2[i] <- cor(lpa, lp)^2
  fapprox <- ols(`H SF - water flow` ~ lpa, data = SF_Hflow)
  frac[i] <- fapprox$stats['Model L.R.']/fullchisq
}


r2
frac

round(r2,4)
round(frac,4)

rownames(s$result)
rio::export(data.frame(predictor = rownames(s$result),
                       s$result), "s.result.HF.subfunction.score.xlsx")
browseURL("s.result.HF.subfunction.score.xlsx")
```

```
windows(height = 7, width = 7)
par(mar=c(5,5,2,2))
plot(r2, frac, type='b',
    xlab = expression(paste('Approximation ', R^2)),
    ylab = expression(paste('Fraction of ', chi^2, ' Preserved')),
    xlim = c(0.2,1), ylim=c(0.2,1), cex=1.3)
# abline(h = 0.80, col=grey(0.83), lwd=1.3)
abline(v = 0.80, col=grey(0.83), lwd=1.3)
abline(a = 0, b = 1, col = grey(0.83), lwd=1.3)

names (SF_Hflow)
fapprox.5.deletions <- ols(lp ~ `forebay_h` + `inlet_pipe_h` +
`percent_mowing_h`+
                        `ground_cover_native_cover_h` +
                        `outlet_pipe_channel_connection_h`, data = SF_Hflow,
                      x = TRUE)
round(fapprox.3.deletions$stats['R2'],5)

ffH2 <-lm(`H SF - water flow` ~ `inlet_pipe_h` + `percent_mowing_h`+
          `ground_cover_native_cover_h` + `outlet_pipe_channel_connection_h`, data
= SF_Hflow)
avPlots(ffH2)

########Sensitivity Analysis for Ecological Health Indicators###


names_eco<- c("algae_ec", "outlet_pipe_channel_connection_ec","dredging_ec" ,
          "slope_ec", "number_zones_ec", "riparian_buffer_width_ec",
          "ground_cover_native_cover_ec", "surface_area_emergent_veg_ec",
"soil_texture_ec",
          "soil_ph_ec", "dist_major_road_ec", "dist_minor_road_ec" ,
          "dist_pathway_ec", "dist_residential_ec", "percent_mowing_ec",
          "percent_riparian_altered_soft_ec", "percent_riparian_altered_hard_ec",
          "shoreline_substrate_ec", "Riparian indicator species cover - ec" ,
          "Riparian non-native underisrable species - ec", "E - SF Species structure" ,
          "E - SF Species composition")
raw_data<- new_data$Raw_Data
eco_data<- raw_data[, (names(raw_data) %in% names_eco)]

## Replace "NA" with NA
```

```
eco_data <- eco_data %>% naniar::replace_with_na_all(~.x == "NA")
eco_data[is.na(eco_data)]<- "0"
# drops rows with DNC
eco_data<- eco_data[c(1:10,12:51,53:58,60:83), ]

# convert all columns to numeric values

eco_data[names(eco_data)]<- sapply(eco_data[names(eco_data)], as.numeric)

## replace the additional NA created on conversion to numeric
eco_data[is.na(eco_data)]<- 0

# plot to ensure no missing values
visdat::vis_miss(eco_data, sort_miss = T)

#Sensitivity Analysis of Indicators for EH SF-ECOSTRUCTURE

names(eco_data)
SF_ecostrucuture <- eco_data[, c (3,5:7,9:14,16:18,21),]
SF_ecocomposition <- eco_data[, c (1:2,4,8,15,19:20,22),]
dd = datadist(as.data.frame(SF_ecostrucuture))
options(datadist="dd")
fES <- ols( `E - SF Species structure` ~., data = SF_ecostrucuture)
summary(fES)

range(SF_ecostrucuture$`E - SF Species structure`)

lp <- predict(fES) # compute linear predictor from
# full penalized model

# insert sigma = 1 as otherwise sigma = 0 will cause problems

a <- ols(lp ~.,data = SF_ecostrucuture, sigma = 1)

fES <-lm(`E - SF Species structure` ~., data = SF_ecostrucuture)

#check_model(fES)
avPlots(fES)
```

```
# specify silly stopping criterion to remove all predictor variables
#===> this allows you to find out the order in which predictors
#     should be removed from the full penalized model

s <- fastbw(a, aics = 10000)
s

betas <- s$Coefficients # matrix, rows = iterations
#X <- cbind(1, fS$x)      # design matrix

# compute the series of approximations to lp
ap <- X %*% t(betas)
ap
X <-model.matrix(fES)
model.matrix(fES)[, 1]
model.matrix(fES)


# for each approximation, compute approximation R-squared and
# ratio of likelihood ratio chi-square for approximate model
# to that of original model
m <- ncol(ap) - 1 # all but intercept-only model
r2 <- frac <- numeric(m)
fullchisq <- f$stats['Model L.R.']
for (i in 1:m){
  lpa <- ap[,i]
  r2[i] <- cor(lpa, lp)^2
  fapprox <- ols(`E - SF Species structure` ~ lpa, data = SF_ecostrucuture)
  frac[i] <- fapprox$stats['Model L.R.']/fullchisq
}


r2
frac

round(r2,4)
round(frac,4)

rownames(s$result)
rio::export(data.frame(predictor = rownames(s$result),
```

```
                s$result), "s.result.ES.subfunction.score.xlsx")
browseURL("s.result.ES.subfunction.score.xlsx")

windows(height = 7, width = 7)
par(mar=c(5,5,2,2))
plot(r2, frac, type='b',
   xlab = expression(paste('Approximation ', R^2)),
   ylab = expression(paste('Fraction of ', chi^2, ' Preserved')),
   xlim = c(0.2,1), ylim=c(0.2,1), cex=1.3)
# abline(h = 0.80, col=grey(0.83), lwd=1.3)
abline(v = 0.80, col=grey(0.83), lwd=1.3)
abline(a = 0, b = 1, col = grey(0.83), lwd=1.3)

names (SF_ecostrucuture)
fapprox.6.deletions <- ols(lp ~ `riparian_buffer_width_ec` + `dist_major_road_ec`+
                    `shoreline_substrate_ec` + `soil_texture_ec` +
                    `number_zones_ec` + `dist_pathway_ec` +
                    dist_minor_road_ec, data = SF_ecostrucuture, x = TRUE)
round(fapprox.6.deletions$stats['R2'],5)

fES2 <-lm(`E - SF Species structure` ~ `riparian_buffer_width_ec` +
`dist_major_road_ec`+
        `shoreline_substrate_ec` + `soil_texture_ec` +
        `number_zones_ec` + `dist_pathway_ec` +
        dist_minor_road_ec, data = SF_ecostrucuture,)
avPlots(fES2)

#Sensitivity Analysis of Indicators for EH SF-ECOSYSTEM Composition

names(eco_data)
SF_ecocomposition <- eco_data[, c (1:2,4,8,15,19:20,22),]
dd = datadist(as.data.frame(SF_ecocomposition))
options(datadist="dd")
fEC <- ols( `E - SF Species composition` ~., data = SF_ecocomposition)
summary(fEC)

range(SF_ecocomposition$`E - SF Species composition`)

lp <- predict(fEC) # compute linear predictor from
# full penalized model
```

```
# insert sigma = 1 as otherwise sigma = 0 will cause problems

a <- ols(lp ~.,data = SF_ecocomposition, sigma = 1)

fEC <-lm(`E - SF Species composition` ~., data = SF_ecocomposition)

#check_model(fEC)
avPlots(fEC)

# specify silly stopping criterion to remove all predictor variables
#===> this allows you to find out the order in which predictors
#     should be removed from the full penalized model

s <- fastbw(a, aics = 10000)
s

betas <- s$Coefficients # matrix, rows = iterations
#X <- cbind(1, fS$x)      # design matrix

# compute the series of approximations to lp
ap <- X %*% t(betas)
ap
X <-model.matrix(fEC)
model.matrix(fEC)[, 1]
model.matrix(fEC)


# for each approximation, compute approximation R-squared and
# ratio of likelihood ratio chi-square for approximate model
# to that of original model
m <- ncol(ap) - 1 # all but intercept-only model
r2 <- frac <- numeric(m)
fullchisq <- f$stats['Model L.R.']
for (i in 1:m){
  lpa <- ap[,i]
  r2[i] <- cor(lpa, lp)^2
  fapprox <- ols(`E - SF Species composition` ~ lpa, data = SF_ecocomposition)
  frac[i] <- fapprox$stats['Model L.R.']/fullchisq
}
```

```
r2
frac

round(r2,4)
round(frac,4)

rownames(s$result)
rio::export(data.frame(predictor = rownames(s$result),
                  s$result), "s.result.EC.subfunction.score.xlsx")
browseURL("s.result.EC.subfunction.score.xlsx")

windows(height = 7, width = 7)
par(mar=c(5,5,2,2))
plot(r2, frac, type='b',
   xlab = expression(paste('Approximation ', R^2)),
   ylab = expression(paste('Fraction of ', chi^2, ' Preserved')),
   xlim = c(0.2,1), ylim=c(0.2,1), cex=1.3)
# abline(h = 0.80, col=grey(0.83), lwd=1.3)
abline(v = 0.80, col=grey(0.83), lwd=1.3)
abline(a = 0, b = 1, col = grey(0.83), lwd=1.3)

names (SF_ecocomposition)
fapprox.3.deletions <- ols(lp ~ `outlet_pipe_channel_connection_ec` + `algae_ec` +
`slope_ec`
                     + `percent_mowing_ec` + `surface_area_emergent_veg_ec`, data =
SF_ecocomposition,x = TRUE)
round(fapprox.3.deletions$stats['R2'],5)

fEC2 <-lm(`E - SF Species composition` ~ `outlet_pipe_channel_connection_ec` +
`slope_ec` +
          `slope_ec` + `percent_mowing_ec` + `surface_area_emergent_veg_ec`,
data = SF_ecocomposition,)
avPlots(fEC2)


#####Reduced Indicators ACI  Analysis
#selecting the last four values
new_names<- c("RWQnorm", "RHnorm", "REnorm", "RACInorm")
```

```
# select the first named list
selected_data<- new_data[["Raw_Data"]]

#selecting the last four values
new_names<- c("RWQnorm", "RHnorm", "REnorm", "RACInorm")

Rsubset_data<- selected_data[, (names(selected_data) %in% new_names)]

lapply(Rsubset_data, function(x) shapiro.test(x))
# fit linear model
Rfit <- lm(`RACInorm` ~ `REnorm`+`RHnorm`+`RWQnorm`, data = Rsubset_data)
summary(Rfit)

ggpairs(data = Rsubset_data, columns = 1:4, title = "Relationship between functions
and ACI score")

ggplot(data = Rsubset_data, aes(x = `REnorm`, y = `RACInorm`)) +
  stat_poly_line()+
  stat_poly_eq(aes(label= paste(after_stat(eq.label),
                              after_stat(rr.label), sep = "*\",\"*")))+
  geom_point() +
  theme(panel.background = element_rect(fill = "white"),
        axis.line.x=element_line(),
        axis.line.y=element_line()) +
  ggtitle("Linear Model for R_Normalized Ecosystem value and R_Normalized ACI
score Fitted to Data")

ggplot(data = Rsubset_data, aes(x = `RHnorm`, y = `RACInorm`)) +
  stat_poly_line()+
  stat_poly_eq(aes(label= paste(after_stat(eq.label),
                              after_stat(rr.label), sep = "*\",\"*")))+
  geom_point() +
  theme(panel.background = element_rect(fill = "white"),
        axis.line.x=element_line(),
        axis.line.y=element_line()) +
  ggtitle("Linear Model for R_Normalized Hydrology value and R_Normalized ACI
score Fitted to Data")
```

```
ggplot(data = Rsubset_data, aes(x = `RWQnorm`, y = `RACInorm`)) +
  stat_poly_line()+
  stat_poly_eq(aes(label= paste(after_stat(eq.label),
                              after_stat(rr.label), sep = "*\",\"*")))+
  geom_point() +
  theme(panel.background = element_rect(fill = "white"),
        axis.line.x=element_line(),
        axis.line.y=element_line()) +
  ggtitle("Linear Model for R_Normalized water quality value and R_Normalized ACI
score Fitted to Data")
```

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Miistakis Institute
EB3013, Mount Royal University
4825 Mount Royal Gate SW
Calgary, Alberta T3E 6K6

www.rockies.ca

Miistakis Institute