Use of remote sensing to track changes to fish habitat in a modified wetland

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ABSTRACT

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Development and restoration works modify aquatic habitat and often require monitoring by proponents to ensure projects do not cause undue harm to fishes and their habitat. With traditional field surveys, areal cover of habitat can be difficult to ascertain and cannot be sampled retroactively. With remote sensing, analysts can easily identify changes in fish habitat using historic habitat imagery before projects are undertaken to assess pre-intervention conditions. In this document we show how remote sensing can be used to delineate changes to fish habitat following modification of a wetland in Lake Ontario. Even though our work started a decade after modification, we estimated both pre- and post-construction habitat area using historic, high resolution (<5m pixel) image archives. Created ponds see significantly more aquatic habitat after construction and no significant changes thereafter, though the composition of wetland species in these ponds is different than similar undisturbed ponds. Summer imagery requires a more complex workflow but can describe species within habitat types, while spring/fall workflows are rapid but can only identify broad land cover categories. Results between the two methods are difficult to compare so one method/seasonality should be maintained for consistent monitoring. These workflows can allow for rapid discrimination of aquatic habitat without requiring direct field observations and can be applied for historical and future monitoring.

RÉSUMÉ

Marcaccio, J.V., Gardner Costa J., and Midwood J.D. 2023. Use of remote sensing to track changes to fish habitat in a modified wetland. Can. Tech. Rep. Fish. Aquat. Sci. 3501: viii + 38 p.

Les travaux d’aménagement et de restauration modifient l’habitat aquatique et nécessitent souvent que les promoteurs effectuent un suivi pour de s’assurer que les projets ne nuisent pas aux poissons et à leur habitat. Avec les relevés sur le terrain traditionnels, il peut s’avérer difficile de déterminer la couverture de l’habitat et de l’échantillonner de manière rétroactive. Grâce à la télédétection, les analystes peuvent facilement déterminer les changements dans l’habitat des poissons en utilisant les anciennes images de l’habitat avant que les projets ne soient mis en œuvre, et ce, dans un souci d’évaluer les conditions préalables aux interventions. Dans ce document, nous montrons de quelle façon on peut utiliser la télédétection pour déterminer les changements dans l’habitat du poisson à la suite de modifications d’une zone humide dans le lac Ontario. Même si notre travail a commencé une décennie après les modifications, nous avons estimé la superficie de l’habitat avant et après la construction au moyen d’archives d’anciennes images à haute résolution (<5/m pixel). Les étangs créés présentent un habitat aquatique beaucoup plus important après la construction et aucun changement important par la suite, bien que la composition des espèces de zones humides dans ces étangs sont différentes de celle d’étangs similaires non perturbés. L’imagerie en été nécessite un flux de travail plus complexe, mais elle permet de décrire les espèces dans les types d’habitats; les flux de travail au printemps et en automne sont quant à eux rapides, mais ne permettent de déterminer que les grandes catégories de couverture terrestre. Il est difficile de comparer les résultats des deux méthodes — c’est pourquoi il est préférable de conserver une seule méthode et une seule saison pour assurer un suivi cohérent. Ces flux de travail peuvent permettre de distinguer rapidement l’habitat aquatique, sans que l’on ait à effectuer des observations directes sur le terrain. On peut également les appliquer aux fins des travaux de suivi passés et futurs.

INTRODUCTION

Diverse aquatic vegetation communities in coastal wetlands support a diverse fish community (Croft and Chow-Fraser 2007; Cvetkovic et al. 2010). Emergent, floating, and submerged aquatic vegetation within these systems provide ecosystem services by stabilizing sediment, limiting erosion, filtering nutrients from the surrounding watershed, producing oxygen, and providing essential habitat for a wide variety of aquatic organisms, including fish (Costanza et al. 1997; Wei et al. 2004; Lacoul and Freedman 2006; Kiviat 2013). Fish utilize aquatic vegetation throughout their life history for spawning, nursery, or foraging (Jude and Pappas 1992) and factors such as the morphology of the vegetation (Dibble et al. 1997; Cvetkovic 2008), its density (Jacobus and Webb 2005; Midwood and Chow-Fraser 2012), and dominance of a particular species (Trebitz et al. 2009) may all influence the community composition and abundance of fish. Despite the importance of aquatic vegetation for fishes, many wetlands in the Laurentian Great Lakes, particularly those in Lakes Ontario and Erie, are degraded due to anthropogenic disturbances (Chow-Fraser 2006; Trebitz et al. 2007), resulting in lower fish species richness and dominance of more degradation-tolerant fishes (Seilheimer and Chow-Fraser 2007; Bhagat et al. 2007). It is therefore important to ensure that remaining wetland habitats are maintained and, where possible, restored in such a way to provide sufficient habitat quality and quantity for fish and other aquatic species (Turko et al. 2021; Alofs and Jackson 2014).

The Fish and Fish Habitat Protection Program (FFHPP) at Fisheries and Oceans Canada is responsible for reviewing proposed works or activities that may impact fish and fish habitat to ensure any in-water activities are in compliance with the *Fisheries Act* and the *Species at Risk Act*. When a project may result in the harmful alteration, disruption, or destruction of fish habitat or the death of fish, there is often a requirement for implementing offsetting measures to counterbalance these impacts. Measures to offset may include: habitat restoration or enhancement, habitat creation, chemical or biological manipulations, or a limited contribution of elements that are complementary (e.g., data collection). Regardless of the approach undertaken, the offset should follow established guiding principles and thus should: support fisheries management objectives with a priority of restoring degraded habitat; be scaled to match the adverse effects of the activity; provide additional benefits beyond the works themselves; and be self-sustaining over the long term or at minimum comparable in duration to the adverse effects (Fisheries and Oceans Canada 2019). For habitat restoration, enhancement, or creation, the requirement for self-sustaining conditions necessitates repeated habitat surveys or assessments by either the project proponent or FFHPP to confirm that the capacity of the habitat to produce and sustain fish is maintained. Given its ability to yield repeatable and quantitative assessments of habitat, remote sensing can serve as a useful tool for supporting the ongoing assessment of the efficacy of habitat offsetting projects, particularly those related to the creation of new habitat.

Remote sensing refers to the collection of information using airborne or space-borne sensors; effectively, these are pictures of the Earth’s surface that contain information on the amount of electromagnetic radiation that is absorbed or reflected by a given surface feature (Marcaccio et al. 2021). These features can be classified using both manual and automated methods based on differences in their absorption or reflectance. Specifically for aquatic habitat, methods have been developed to classify different types of wetlands (Bourgeau-Chavez et al. 2015), different morphologies of aquatic vegetation (e.g., emergent and floating; Midwood and Chow-Fraser 2010), and even specific species (e.g., *Phragmites australis* [Marcaccio and Chow-Fraser 2018] or *Myriophyllum spicatum* [Brooks et al. 2019]). From these maps, information on the distribution, surface area, species composition, cover or density, height, and habitat heterogeneity can all be extracted and used to characterize aquatic habitat (Marcaccio et al. 2021). When mapping is conducted over multiple years of imagery, it can provide an indication of changes in the composition or amount of aquatic habitat (Zhao et al. 2013) and rates of expansion of species or patches of vegetation (Jung et al. 2017). Such changes in mapped aquatic habitat and vegetation have been further linked to changes in fish community composition (Midwood and Chow-Fraser 2012) or the abundance of specific species (e.g., Yellow Perch [*Perca flavescens*]; Massicotte et al. 2015). Consequently, the application of remote sensing to map aquatic vegetation and determine the extent of change in vegetation cover and the amount of aquatic habitat represents an important tool for effective management of fish habitat (Dauwalter et al. 2017).

Given the importance of aquatic vegetation as habitat for fishes, considerable effort has gone into developing methods to quantify the extent, density, and composition of vegetation within an ecosystem. These efforts include traditional field sampling (Croft and Chow-Fraser 2009), the development of statistical models (Tang et al. 2020), as well as the noted application of remote sensing technology (Silva et al. 2008; Bourgeau-Chavez et al. 2015). While on-site monitoring allows for direct observation of fish species and their habitat, it is also labour-intensive and typically synoptic, meaning single snapshots are taken that can make it difficult to compare and characterize changes over time. Here we demonstrate a complementary tool to traditional assessments that uses remote sensing to map fish habitat and its change over time. There are numerous methods available to classify land cover types, which are outlined in Marcaccio et al. (2021), but the focus of this report is on how the results from a classification can be used by FFHPP or proponents to determine the efficacy and persistence of habitat creation efforts.

Using a habitat offsetting project that involved the creation of a new coastal wetland as a model site, we demonstrate how: high-resolution satellite imagery can be used to map water and aquatic vegetation; total area of potential fish habitat (i.e., wetted area and aquatic vegetation) can be estimated; and changes in the area of habitat and types of vegetation cover can be tracked over time. This approach could provide FFHPP with a faster, cheaper tool that can be used in conjunction with or as a replacement for traditional monitoring to provide information on the status of habitat over time; ensure continued compliance with offsetting targets; and can increase the number of projects that can be monitored by FFHPP with minimal additional effort. Specifically at our model site, our objectives are to: 1) classify land cover features in the spring, summer, and fall and validate the accuracy of the classification, 2) quantify the areal coverage of target land cover types at an ecotype and class-specific level, 3) quantify and describe changes in land cover, and 4) contrast changes at created ponds with those from local reference areas. For the discussion, we interpret the results in the context of how this approach and resulting output can be adapted to support FFHPP workflows.

METHODS

STUDY SITE

The study was conducted at a coastal wetland complex located in the Bay of Quinte (Lake Ontario; Figure 1), an area that allowed us to explore changes in habitat before and after a habitat restoration project was completed. Prior to habitat creation efforts, large portions of the wetland were dominated by mats of cattails (*Typha* spp.) that were inaccessible, semi-aquatic areas with limited utility as fish habitat. Starting in 2013 and continuing through 2014, three ponds were dug into the cattails to create fish and aquatic habitat as part of an offsetting agreement with Fisheries and Oceans Canada to provide compensatory fish habitat and production (Figure 2). For the present report, an additional five wetland areas situated within 0.3–5.0 km of the created ponds were included in the analyses to compare changes at the offsetting sites with proximate natural areas (herein all are referred to as “ponds”). Three of these reference ponds were similar to the created ponds since they were surrounded by *Typha*-dominated emergent vegetation, while the remaining two were distinct in that they were more coastal within the Bay of Quinte and contain a more traditional gradient of aquatic vegetation shifting from meadow dominated areas, then emergent, and finally submerged. Ponds were grouped into created, natural, and coastal categories and analyzed both as a group and individually. The boundaries of each pond were established prior to any analyses and were thus consistent within seasons. There were slight differences between the summer and spring/fall pond outlines and thus comparisons were not made between these two groups (reason for this are discussed in Appendix).

Water levels within lake systems can play a larger role in changing aquatic habitat area especially for coastal wetlands (Keddy and Reznicek 1986) and, for Lake Ontario, water levels are directly controlled by the Moses-Saunders Dam in the St. Lawrence River (IJC 2021). The image data used herein spanned nine years with a mean annual water level of 74.90 metres above sea level (MASL; range: 74.67–75.26 MASL). There was an increase in 2017, which brought water levels up 0.04–0.50 m above the long-term mean (Great Lakes Environmental Research Laboratory 2022). Monthly mean water level was typically lower in the spring and fall (mean 74.86 MASL, range 74.67–75.11 MASL) relative to the summer (mean 75.92 MASL, range 74.97–75.53 MASL).

IMAGE DATA ACQUISITION AND CLASSIFICATION

For this study, we required suitably high-resolution imagery that could delineate small differences (~5m or less) in land cover changes over the study site. For this reason, we chose to purchase image data from the SPOT satellite constellation from Planet Labs Geomatics Corporation (San Francisco, California). These were delivered via FTP download from Planet and are also available on the Earth Observation Data Management System (EODMS) for Government of Canada use. Details related to the preparation of the image data and the classification of the imagery are presented in the Appendix. Briefly, image data were acquired from the SPOT-6 satellite (resolution = 6.0 m in the red, green, blue, and near-infrared bands plus a 1.5 m resolution panchromatic band) except for one SPOT-5 image (resolution = 10.0 m in the red, green, and near infrared bands plus a 2.5 m panchromatic band). The specific years of image acquisition were dictated by the availability of clear sky imagery for our study region, which resulted in disparate dates for imagery among years. All remote sensing analyses were conducted in ArcGIS Pro (2.6.2, ESRI, Redlands, California).

Spring and fall were selected for dedicated water mapping since during these seasons only limited submerged or floating aquatic vegetation would be present and emergent vegetation would be growing or senescing leaving water more visible. No pre-construction spring/fall images were available, but post-construction spring (7 May 2015, 16 April 2016) and fall (23 October 2015, 28 November 2017) images were acquired. A simple binary thresholding procedure (i.e., split into areas with or without water) was applied to these images using the Otsu method (Liu and Yu 2009) on the infrared band. With this approach, we were only interested in mapping the extent of water so we could estimate a gain or loss of water within the ponds and their associated channels; an accuracy assessment was not undertaken since we manually edited the outputs to only include true water polygons (this is a well-established method that can be achieved quickly with minimal effort; Figure 3).

Summer imagery was acquired for more detailed classification of land cover types since aquatic vegetation would be at peak growth during this season. Imagery was acquired to provide one time period before pond construction (8 July 2010) and two post-construction (5 July 2014, 1 August 2019). A supervised classification using the Random Forest (“Random Trees” in ArcGIS Pro) method was conducted on this imagery using an object-based approach (see Marcaccio et al. 2022 for details). Briefly, Random Forest is a classification algorithm that builds multiple random “trees” or decision networks, using subsets of the input image data and samples, and then takes the majority vote of the trees to assign a class. The accuracy of the overall supervised classification and for each individual class was determined using a distinct dataset of manually classified objects. Target accuracy for the both the overall classification and for each land cover class of interest (i.e., aquatic habitat types) was set to 80% (after Aronoff 1985). After classification, land cover types were grouped at two levels: 1) ecotype (e.g., terrestrial, emergent vegetation, or aquatic) and 2) class (e.g., water, floating vegetation); a full list and description of each class presented in Table 1.

CLASSIFICATION INTERPRETATION

To demonstrate how multi-year image classification (thresholding or supervised) can be used to explore changes in land cover through time, the area of water and each land cover type was calculated for each imagery time period. In this study, we consider connecting channels to be a part of the associated pond (water) feature as disconnected ponds would not provide suitable habitat or access for larger adult fish. For the spring and fall imagery, area of water in the different pond types was compared using a two-way repeated measures ANOVA that was implemented in RStudio (version 1.2.1335, RStudio, Boston, Massachusetts). Area of water was set as the dependent variable with year, and pond type being factors with ponds within a type treated as replicates. A repeated mixed-measures ANOVA was also conducted that added season (fall vs. spring) as a factor. For the summer images, the mean proportional coverage within each pond type (e.g., created, natural, and coastal) for the ecotype and class-levels of land cover were determined and plotted for each time period. Similar to the changes in water, changes in the area of the ecotypes among pond types were compared using a two-way repeated measures ANOVA. To determine the type and amount of class conversion among years, the classification was converted to polygons and then the "Union" function in ArcGIS Pro was used to combine the classification from two years into distinct class conversion pairs (e.g., non-water to water or *Typha* to water to floating) and then the area and proportional area for each class conversion pair was calculated (see Appendix for further details). We focused our interpretation of changes on the aquatic ecotype classes since these are the most relevant for fish habitat.

RESULTS

CLASSIFICATION RESULTS – WATER MAPPING

In spring and fall, area of water in the created ponds ranged from a low of 16.8 ha (fall 2016) to a high of 17.4 ha (spring 2016; Table 2). No significant differences among created, natural, or coastal ponds per year were noted (two-way repeated measures ANOVA, $p>0.5$); pairwise t-test within pond types did not reveal any significant differences within ponds. In the mixed-effects model, seasonality was not a significant factor either. Water area within the created ponds increased slightly between the spring of 2015 and 2016 by 0.22 ha (gain of 1.3%) and was slightly higher in fall 2017 relative to 2015 (0.07 ha or 0.4%). The natural and coastal ponds showed the same pattern in the spring (increases of 0.8% and 0.4%, respectively), but in the fall, while the natural ponds similarly increased (1.2%), the coastal ponds showed a slight decrease (-1.1%; Table 2).

CLASSIFICATION RESULTS – SUMMER LAND COVER CHANGES

Classifications at both the ecotype and class levels exceeded the target of 80% for overall accuracy with ranges of 91–93% and 87–90%, respectively. For ecotypes, accuracies for both aquatic and low marsh ecotypes were consistently above 85%. Within the aquatic ecotype, the water class had consistently high classification accuracy (>90%), but floating and *Nitellopsis*-class accuracies were lower (75–92% and 53–77%, respectively), more variable among years, and most often confused with each other. A more detailed discussion of the accuracy of the classification can be found in the Appendix.

The surface area of each ecotype and class within the ponds among years are outlined in the Appendix; however, proportional cover of each ecotype or class is the primary focus of the interpretation of the results due to marked differences in the core area of each pond and among pond types. There were significant differences by pond type in the two way repeated measures ANOVA; only the created ponds showed a significant change in aquatic area between 2010 and 2014/2019 (pairwise t-test, $p<0.05$). For ecotypes, between 2010 and 2014, the created ponds produced a considerable amount of aquatic habitat (gain of 26.0 ha in 2014); however, following this gain there was a significant decrease in aquatic habitat between 2014–2019 . These gains primarily reflected the replacement of the emergent ecotype by aquatic habitat which was also significantly different (Figure 4). Similar changes were not observed at the natural or coastal ponds with total area of aquatic habitat at the natural (range across years 98.9–103.4 ha) and coastal (range across years 88.0–90.4 ha) remaining comparatively stable (i.e., no significant difference based on a two-way repeated measures ANOVA between 2010–2014 and 2014–2019 Figure 4; Appendix).

At the class level, aquatic habitat gains were primarily driven by the expansion of areas of open water (14.3 ha and 12.6 ha in 2014 and 2019, respectively) and to a lesser extent *Nitellopsis* and floating vegetation (7.4 ha and 0.4 ha, respectively by 2019; Appendix). The noted overall decrease in aquatic habitat between 2014 and 2019 was mostly driven by a decline in floating vegetation, with water and *Nitellopsis* classes remaining stable (Figure 5; Appendix). Similar reductions in floating vegetation between 2014 and 2019 were also evident in the natural and coastal wetlands, but here the floating vegetation was largely converted to *Nitellopsis* and thus there was no net decline in aquatic habitat (Figure 6). Without pond creation, the *Typha* class at the coastal and natural wetlands was stable through time with increasing areal coverage of *Phragmites* starting in 2014 and continuing into 2019; a similar increase in *Phragmites* was also evident at the created ponds. The proportional cover of aquatic classes in the created ponds was distinct with more open water areas and less floating vegetation than the natural and coastal ponds (Figure 5; Appendix).

From an ecotype conversion perspective, the gains in aquatic habitat from 2010–2014 are clear at the created ponds, driven by increases in the water and *Nitellopsis* classes and, to a lesser extent, the floating vegetation class. These gains were primarily at the expense of the emergent ecotype. The created ponds, however, had greater proportional losses at the class level between 2014–2019 than the coastal or natural systems where proportional gains or losses were comparatively stable during both time periods and represented changes of less than 10% of the total area (in contrast, created ponds saw 25–45% changes; Figure 6). Losses of aquatic habitat at the created ponds between 2014–2019 were apparent for all three aquatic classes, with the greatest proportional change in *Nitellopsis* shifting to both emergent and terrestrial ecotypes (Figure 6). While similar shifts among classes were also evident at the coastal and natural ponds, their individual proportional change was low (i.e., <1% of the area).

DISCUSSION

Remote sensing can provide a quick off-site alternative to field measurements of aquatic habitat area and composition. Here we demonstrate how a simple classification of water in the spring and fall can provide the amount of area available to fish in natural and created ponds. Additionally, using summer imagery and a slightly more complex classification method, information on the extent and composition of aquatic vegetation within these ponds can be determined. By applying these same approaches over multiple years, changes in the extent of fish habitat and changes in the composition of this habitat can be determined. For the discussion, we first provide a brief interpretation of the findings from the present study with particular focus on the accuracy of the classification, the observed land cover changes, and mapping of invasive aquatic plants. We then provide a more detailed discussion to provide guidance for habitat managers who may wish to request the use of image classification as an offsetting monitoring technique.

CLASSIFICATION ACCURACY

Consistent with previous satellite-based classification of aquatic habitat features, annual overall accuracies exceeded the target of 80% (Aronoff 1985; Shao et al. 2001). Greater variability in accuracy for non-aquatic land cover types is not surprising since: 1) these were not the focus of the classification and were thus often masked out of the area of interest, and 2) they were typically represented by fewer ground truth points, which would make them prone to greater variation in accuracy due to small sample sizes. Accuracy assessment of the spring and fall water classification was not possible as the data were manually selected after binary thresholding to exclude errors; however, this method is widely used and, given the binary nature of the classification, likely yields suitable output for a simple estimate of the surface area of water. While not the focus of the current works, results here confirm that aquatic habitat features including water and vegetation, can be accurately classified using satellite imagery and remote sensing techniques.

OBSERVED CHANGES – WATER MAPPING

The habitat creation project mapped herein is primarily linked to ensuring the surface area of open water in the system is maintained so that there is not major deviation (i.e., <3%) from the as-built conditions. The binary thresholding approach applied to the spring and fall imagery directly addresses this target, and found limited interannual variation (0.4–1.3%) in area of water among ponds. We explicitly did not compare the mapped values to the as-built conditions since these efforts are not meant to assess the project itself; rather this limited variation suggests the surface area of water is stable within the created ponds.

Based on the spring imagery, there was no apparent change in aquatic habitat within the ponds between 2015 and 2017. While individual ponds did show areal changes between image dates, when pooled by pond type these differences were not significant. The slight changes in area of aquatics among years and between spring and fall are to be expected given natural variations in water levels. Water level fluctuations, both seasonally and annually, are natural within the Great Lakes (Hanrahan et al. 2009). In the present study, water levels varied by up to 0.44 m during the spring and fall time periods (Great Lakes Environmental Research Laboratory 2022), but clearly did not result in a marked change in wetted area of the sheltered created ponds. This suggests that for these ponds spring and fall imagery can be used interchangeably for future comparisons of wetted area. This may not be the case in other systems where wetlands are more directly connected to the lake, or where water level fluctuations are not regulated as they are in Lake Ontario and can thus be much greater (e.g., Lake Michigan-Huron). Understanding the natural water level dynamics within the study system will therefore be critical when considering temporal changes in wetted area. Despite this caveat, given its relative ease of application and speed of processing of imagery data, binary thresholding of spring/fall data is clearly a suitable method for determining wetted area. By applying this technique over multiple years, it can serve as a useful tool for tracking changes in wetted area in aquatic ecosystems and for supporting the assessment of habitat creation projects.

OBSERVED CHANGES – SUMMER LAND COVER

The detailed land cover classification approach presented here expands on the more simplistic water mapping and provides greater context regarding the type of vegetation (and thus habitat conditions) that are present in a system. While not directly tied to the assessment of compliance with the terms of the offsetting agreement for these ponds, this extension provides more nuance on the potential benefits to the fish community from the pond creation work. Several of the land cover features mapped in the summer imagery represent functional groupings of vegetation that have been previously linked to distinct patterns of use by fishes (e.g., floating vegetation, *Typha* [emergent vegetation], and *Phragmites*; Jacobus and Webb 2006; Midwood and Chow-Fraser 2012; Croft-White et al. 2021). While not explored herein, mapping these distinct vegetation groups can be used to link the derived habitat maps with existing fish community composition data to determine whether mapped products can be used to predict fish assemblages. The relative dominance of different vegetation types can also indicate the quality of wetland habitat for fishes (Midwood and Chow-Fraser 2012), which can expand project offsetting beyond simple measures of the area of habitat and allow connections to be made between the heterogeneity of vegetation within a wetland and the richness or productivity of the fish communities it may support. Such a shift in focus from quantity of habitat to also the quality of that habitat would help improve offsetting efforts and support FFHPP in confirming that the capacity of the habitat to produce and sustain fish is being maintained.

The observed variation in proportional changes among pond types highlights the importance of including control ponds (both natural and coastal). By also classifying these areas we can explore whether annual changes in land cover type within the created ponds are linked to natural processes (i.e., phenology or water level fluctuations; Grabas and Rokitnicki-Wojcik 2015) or related to the creation of the ponds themselves (i.e., succession, planting; Keddy 2010). Any fluctuations due to Lake Ontario water level would be seen most dramatically in vegetation in the coastal ponds due to their high level of connectivity, while other natural changes in less-connected areas would be reflected in the natural ponds (i.e., changes in precipitation patterns or runoff from adjacent lands). These areas thus serve as a control against which to contrast patterns within the created ponds. In the present study, the summer classification data show a notable decrease in aquatic area at the created ponds from 2014–2019 that is not reflected in the natural or coastal ponds. This suggests that observed changes in aquatic habitat composition within the created ponds are linked more to processes such as succession than background natural variation (i.e., something distinct about the ponds being created is driving a change). While the overall aquatic area of the created ponds is less than the coastal and natural ponds, the observed decrease (9–14% of the area of aquatic classes) still represents a decline in the area of fish habitat and therefore continued monitoring is required to assess whether this variability stabilizes as the ponds age or if high rates of variation in aquatic habitat are to be expected in created ponds. Such a determination will inform expectations for future habitat creation projects as well as associated maintenance plans for these areas.

INVASIVE AQUATIC PLANTS

The establishment and spread of invasive aquatic plants (AIP) can potentially impact the quality of fish habitat in aquatic ecosystems (Schultz and Dibble 2012; Bradshaw et al. 2015). In the present study, the classification was able to map two AIP, *Nitellopsis* and *Phragmites*, with variable levels of accuracy; both AIP were present in the created, natural, and coastal ponds. *Nitellopsis* has been present in the Great Lakes region for over 40 years; however, no assessment of its potential impacts on fish and fish habitat has been undertaken, despite evidence for negative effects on both invertebrates and wetland water quality (Harrow-Lyle and Kirkwood 2020; Ginn et al. 2021). *Phragmites* has similarly been present in the Great Lakes region for decades, with documented high rates of expansion, particularly in areas of disturbance (Wilcox et al. 2003). The potential impact of *Phragmites* on fish and fish habitat has received some attention with both evidence for negative consequences for some fish species (e.g., mummichog [*Fundulus heteroclitus*]; Able and Hagan 2003) and use by some fishes when it is flooded (Croft-White et al. 2021). Due to uncertainty around impacts on fish and fish habitat from these species, further research is warranted, and remote sensing techniques can provide a complementary data source for such efforts.

The temporal classification results presented herein offer insight into the expansion of *Nitellopsis* and *Phragmites* within the study area. *Nitellopsis* was noted to be expanding its areal extent in both the coastal and natural ponds, while *Phragmites* first appeared in the 2014 imagery and had increased by 2019. An outstanding question about *Phragmites* as it pertains to fish habitat relates to the extent to which it expands and converts aquatic areas to more terrestrial ecotypes (Croft-White et al. 2021; Gilbert et al. In Prep.). This may lead to a net reduction in fish habitat, and remote sensing approaches should be used to explore and quantify the extent and rate of this conversion. While *Phragmites* has been a frequent target of remote sensing-based mapping (Jung et al. 2017; Marcaccio and Chow-Fraser 2018), to our knowledge this is the first demonstration of the potential for summer imagery to be used to map *Nitellopsis*. As such, the spectral attributes of *Nitellopsis* are not described in the remote sensing literature and it appears to be most readily confused with other floating vegetation types (e.g., lilies). Summer imagery seems to hold promise for mapping this species, but more work is required to enhance separability of this non-native AIP; further analyses are also warranted given its noted expansion within the study area and in other freshwater systems (Ginn et al. 2021). Such mapping of *Nitellopsis* can help to inform not only its extent and rate of expansion, but also contribute to our understanding of its potential impacts on fish and fish habitat.

APPLICATION OF REMOTE SENSING FOR PROJECT MONITORING

Information on the extent of fish habitat is required to ensure habitat creation or offsetting works are in compliance with authorized area-based targets. While not all projects will require more detailed information on the composition of the habitat, those that include area-based targets for vegetation planting or removal of invasive aquatic plants as part of their authorization would benefit from this type of information. The workflows presented here as well as those outlined in Marcaccio et al. (2021) can be used by FFHPP to support the incorporation of image classification into the monitoring section of a *Fisheries Act* authorization offsetting plan. This could help to reduce the cost for proponents while also providing FFHPP with accurate and spatially comprehensive information on the compliance of these works.

One of the main benefits of using remote sensing techniques is that they can contribute to site observations without requiring field access. Habitat surveys for extent and composition have historically involved on-site mapping, which may require repeated site visits to validate findings or track changes through time. These types of surveys allow for the direct observation of the type of habitat present at a site (e.g., vegetation species, substrate composition, water chemistry) as well as observations of fish species that are associated with these habitats. Such surveys, however, can be costly and time-consuming, and access to a site may be limited due to its remote location or land ownership. When measuring the extent of habitat features in the field, estimates may be biased by limited GPS positional accuracy (particularly when tall buildings or trees are present; Kong 2011). Finally, field surveys cannot be done retrospectively and as such pre-modification information may be limited or may not capture historic changes and fluctuations to the natural system. Given these potential challenges, adopting a remote monitoring approach can reduce costs, simplify workflows, and allow for the establishment of longer-term records all while providing accurate information on composition and extent of aquatic habitat. Blending field-based surveys with remote sensing techniques is optimal since initial field work can provide more detailed site-based information on habitat and fish composition, which can then inform the development of more accurate image classifications (Millard and Richardson 2015). After a site-level survey has been completed, future works may only require remote monitoring of the habitat to note any significant changes to its extent or composition.

CONSIDERATION FOR IMPLEMENTING A REMOTE SENSING PROJECT

If remote monitoring of a project is deemed acceptable, there are some important technical considerations that should be resolved through a review of relevant publications (e.g., Daulwater et al. 2017; Marcaccio et al. 2021) or discussions with those familiar with remote sensing techniques. First, when selecting appropriate imagery for habitat monitoring it is important to acquire imagery at a sufficient resolution to allow mapping of the features of interest. For the present work, we used medium-high resolution imagery (1.5–6.0 m resolution), which allowed us to map features of interest but at a lower cost than imagery that has sub-meter resolution Depending on the project goals, lower-resolution imagery that is freely available (e.g., Landsat imagery, 30 m resolution) may be appropriate; however, most projects will require higher-resolution commercial image data like that used in the present works. While dependent on project specifications, the cost of this type of imagery is not necessarily prohibitive (as little as $200 for 25km^2) and if purchased by DFO can be freely transferable within the department through EODMS (eodms-sgdot.nrcan-rncan.gc.ca). By exploring image repositories such as EODMS, Planet Labs' web tools (planet.com/trial), and Maxar/DigitalGlobe's viewer (discover.digitalglobe.com), analysts can also identify pre-construction imagery, which, depending on the satellite system, may include 10–35 years of historical images. Much of these data are available under standing offer within the federal government and as such are relatively easy to acquire.

A second important consideration is the seasonal timing of image collection. The present study demonstrates that if only the area of water is required, then cloud- and ice-free image data from spring or fall will provide the best results since vegetation coverage is minimized. In contrast, projects interested in aquatic vegetation species should use late-summer imagery since growth will be close to its peak and thus allow the most accurate estimates of their peak areal cover. Separation among plant types may also be most accurate during the summer when at peak growth, although this can be species-specific (e.g., Bourgeau-Chavez et al. 2015, Rupasinghe and Chow-Fraser 2019). Given the potential for shifts in vegetation and other land cover types among seasons, collection of similarly timed imagery is essential for comparison of land cover among years.

WHAT TO REQUEST FOR REPORTING

From a reporting perspective, in addition to project-specific needs, which may include the extent or changes in the extent and composition of habitat, there are two key elements presented in this report that should also be included in any report. The first is an assessment of the accuracy of the classification using an independent dataset, which includes the *a priori* selection of accuracy targets for both the overall classification and, more importantly, the classification accuracy of the target land cover type. This assessment is essential since it ensures the resulting maps reflect the conditions on the ground. Here we used a minimum accuracy target of 80%, but a higher value may be desirable, particularly if the project is focused primarily on one land cover type (e.g., mapping *Phragmites* to measure control efforts, can likely increase this minimum accuracy to 85% after Chow-Fraser et al. 2018). High land cover-level classification accuracy is also essential since, when comparing the classifications from two different images or time periods, the accuracy of this comparison is the product of the accuracy of each individual classification (Tung and LeDrew 1988; Serra et al. 2003). So, if the classification of a land cover type in each of two time periods is 80%, the accuracy of any comparison between these time periods will only be 64%. Ensuring high initial accuracies is therefore essential for developing good-quality comparisons. For example, in the present work, we were willing to accept reduced accuracy of non-target classes (e.g., terrestrial land cover types) since our target ecotype had high accuracy (>90%). Without a presentation of the accuracy of any classification that is based on an independent dataset (i.e., distinct from the data used to train the classification), the results will be of unknown validity.

The second key reporting element is the inclusion of control areas, which is most important when a temporal comparison at a site is desirable. In these instances, including control areas provides an indication of the background variation in the focal system, which may be unrelated to any interventions at the site and more linked to natural processes or temporal misalignments in image acquisition. Since the goal of many habitat offsetting projects is to create functional aquatic habitat approximating natural conditions, comparing the created areas to control sites is essential. For example, in the present study, there was considerably more proportional class conversion in the created ponds compared to the coastal and natural ponds. This is most relevant for the period from 2014–2019 since changes at the created ponds in the previous time period were driven by the creation of the ponds themselves. Class changes in the coastal and natural systems were likely driven by a combination of natural water level variation, vegetation succession, and errors in the class-level classification. For the created ponds, while similar factors were likely at play, the stark difference in magnitude (i.e., <10% variation in the coastal and natural ponds vs >20% variation in the created ponds) suggests that vegetation composition in the created ponds was less stable and these systems may not be functioning like natural ponds yet. While we did not seek to determine the exact cause of the proportional differences, such discrepancies between the created and natural areas would not be apparent without the inclusion of control sites.

CONCLUSIONS

Remote sensing can be a key tool in describing changes to aquatic habitat features that are relevant to fish species. With adequate imagery and historic image archives projects can be observed well before any works are conducted even if prior field observations were not made. The methods can be continuously applied when new imagery is available without repeated site visits to track the evolution of aquatic habitat within the project area. Based on the present study, summer image data can be used to delineate wetland plant species if these are of interest to a project. In situations where only aquatic habitat area (i.e., wetted area) is required, spring or fall image data can be leveraged using a faster binary thresholding approach. For future projects assessed by FFHPP, we encourage the use of remote sensing as a complementary component of monitoring programs given the type of information that can be extracted (e.g., habitat area) and relative ease with which it can be implemented. These works can be requested for the proponent to undertake (i.e., via a consulting company or internally) or, in the case of large projects and/or those with related works and goals within DFO Science, could be conducted within DFO collaboratively between science and regulatory members.

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Table 1: Descriptions of land cover classes and how they were grouped into higher-levels. The delineated class represents the features that were identified during the creation and validation of the classification. These are further grouped into the class level, which reflects species or functional forms that may reflect fish habitat. Finally, the classes are grouped into distinct ecotypes to distinguish overall area of fish habitat (aquatic) from emergent marsh and terrestrial ecotypes.

Ecotype	Description	Class	Description	Delineated Class	Description
Aquatic	Land cover classes that are potential fish habitat	Water		Water	Water with a flat surface
				Wavy Water	Water with waves that may break up the surface
		Floating	Same as delineated	Floating	Vegetation with leaves primarily floating on the surface (e.g., *Nymphaea* spp., *Nuphar* spp., etc.)
		Nitellopsis	Same as delineated	*Nitellopsis*	Starry stonewort (*Nitellopsis obtusa*); invasive submerged species that can breach the surface in shallow water areas
Emergent	Transitional land cover classes between aquatic and terrestrial	*Phragmites*		*Phragmites*	Common reed (*Phragmites australis*); invasive species
		Typha		*Typha*	Cattails with lighter colours
				“Dark” *Typha*	Cattails with darker appearance – some variability in the spectral signature of this species are to be expected
Terrestrial	Natural/anthropogenic terrestrial land cover classes	Forest		Trees	
				Shrubs	
		Grass		Grass	
		Urban	Anthropogenic land cover classes	Road	

Table 2: Areal cover of water (ha) as defined by the water threshold maps from spring or fall, and the areal changes between image dates. Spring images represent any growth/expansion of vegetation from the previous year, while fall images will represent conditions from the same year. The percent change (both for each and for all ponds of the same types when combined) are shown.

		Area (ha)				**Change (ha)**		**Change (%)**	
Pond Num.	**Pond Type**	Spring 2015 (May)	Fall 2015 (Oct.)	Spring 2016 (Apr.)	Fall 2017 (Nov.)	Spring 2015 – Spring 2016	Fall 2015 – Fall 2017	Spring 2015 – Spring 2016	Fall 2015 – Fall 2017
1	Created	6.02	5.89	6.12	5.94	0.10	0.05	1.7	0.8
2	Created	4.86	4.27	4.94	4.69	0.08	0.42	1.9	9.0
3	Created	6.35	6.63	6.39	6.23	0.04	-0.40	0.6	-6.4
4	Natural	4.36	5.03	4.94	4.64	0.58	-0.39	11.5	-8.4
5	Coastal	65.21	66.60	65.38	65.66	0.17	-0.94	0.3	-1.4
6	Natural	52.40	51.68	52.54	52.02	0.14	0.34	0.3	0.7
7	Natural	44.15	43.41	44.26	45.25	0.11	1.84	0.3	4.1
8	Coastal	35.02	35.65	35.25	35.50	0.23	-0.15	0.6	-0.4
Overall	Created	17.23	16.79	17.45	16.86	0.22	0.07	1.3	0.4
	Natural	100.91	100.12	101.74	101.91	0.83	1.79	0.8	1.8
	Coastal	100.23	102.25	100.63	101.16	0.40	-1.09	0.4	-1.1

Figure 1: Location of study area (red) within Lake Ontario.

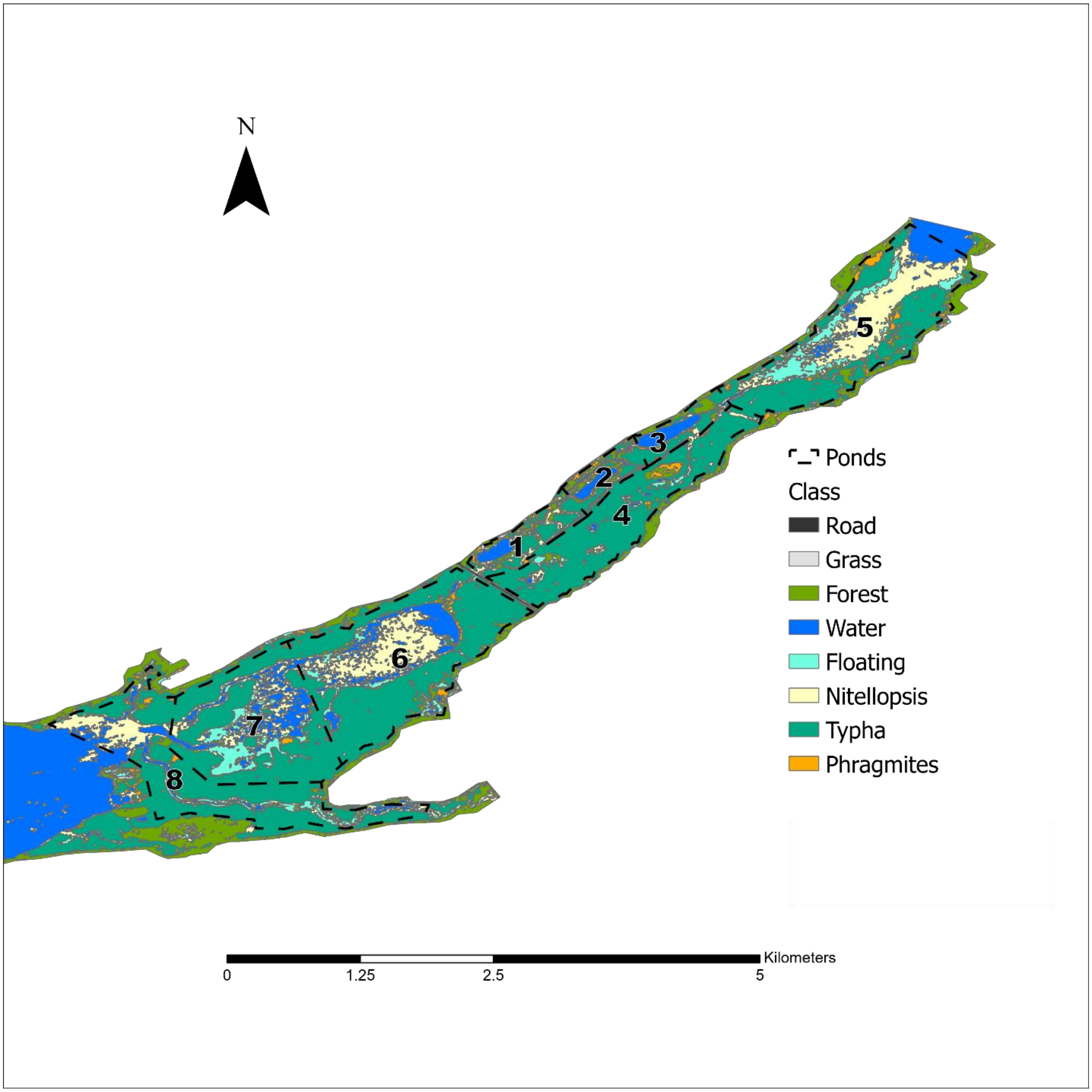

Figure 2: Land cover map from 2019 summer image data acquired by SPOT-5 satellite. Ponds are numbered, with created ponds (1, 2, 3), natural ponds (4, 6, 7), and coastal ponds (5, 8).

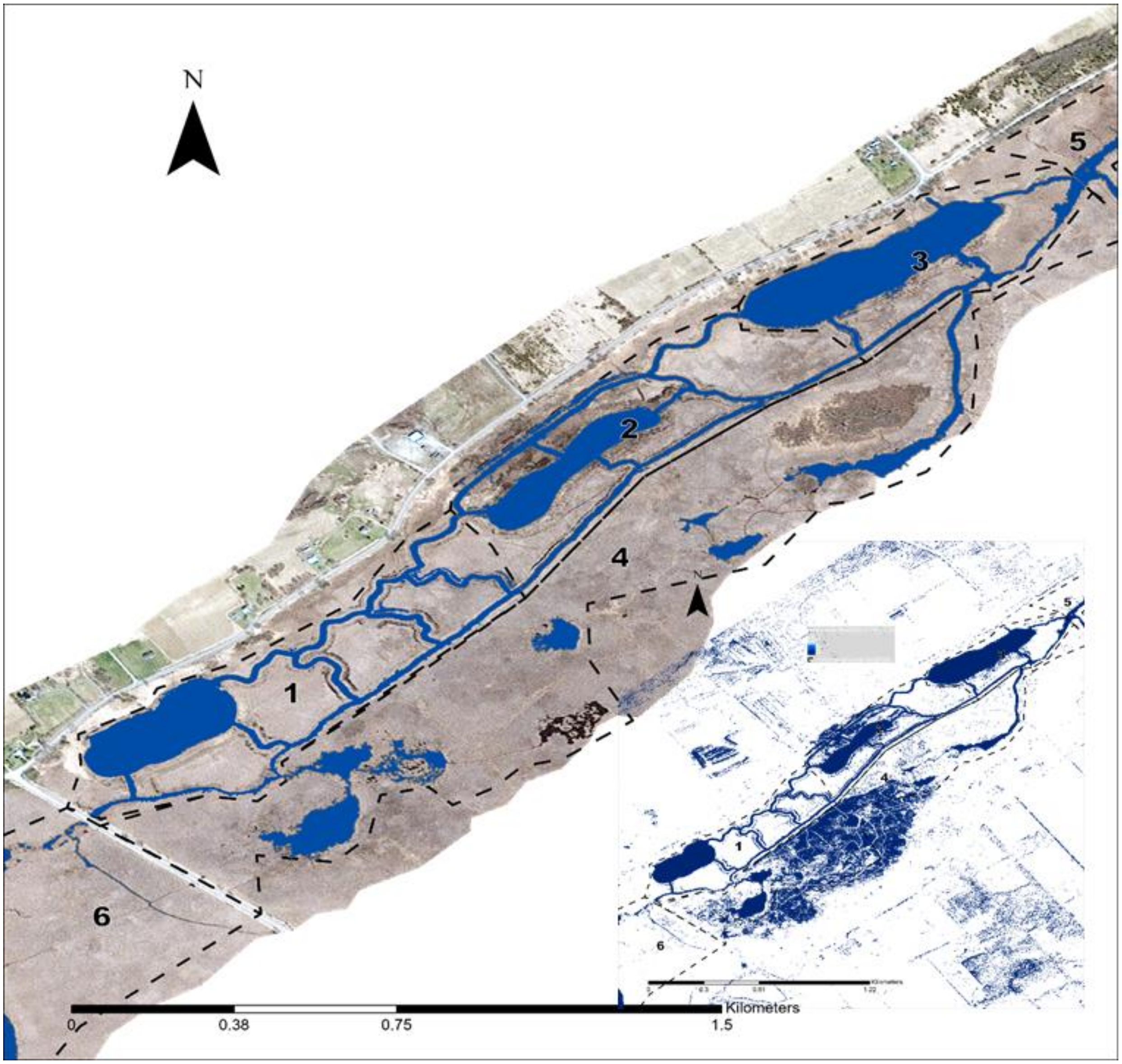

Figure 3: Binary water threshold map from 07 May 2015 using the near-infrared band of a SPOT-6 image. As a spring image, this represents any potential overgrowth of vegetation from the 2014 season. Considerable speckling (i.e., classification of water when shadow is a more likely feature being mapped) is evident in areas outside of the delineated ponds (black dashed line) in bottom-right image. Selecting for only large, continuous areas of water shows the true water coverage in the right image.

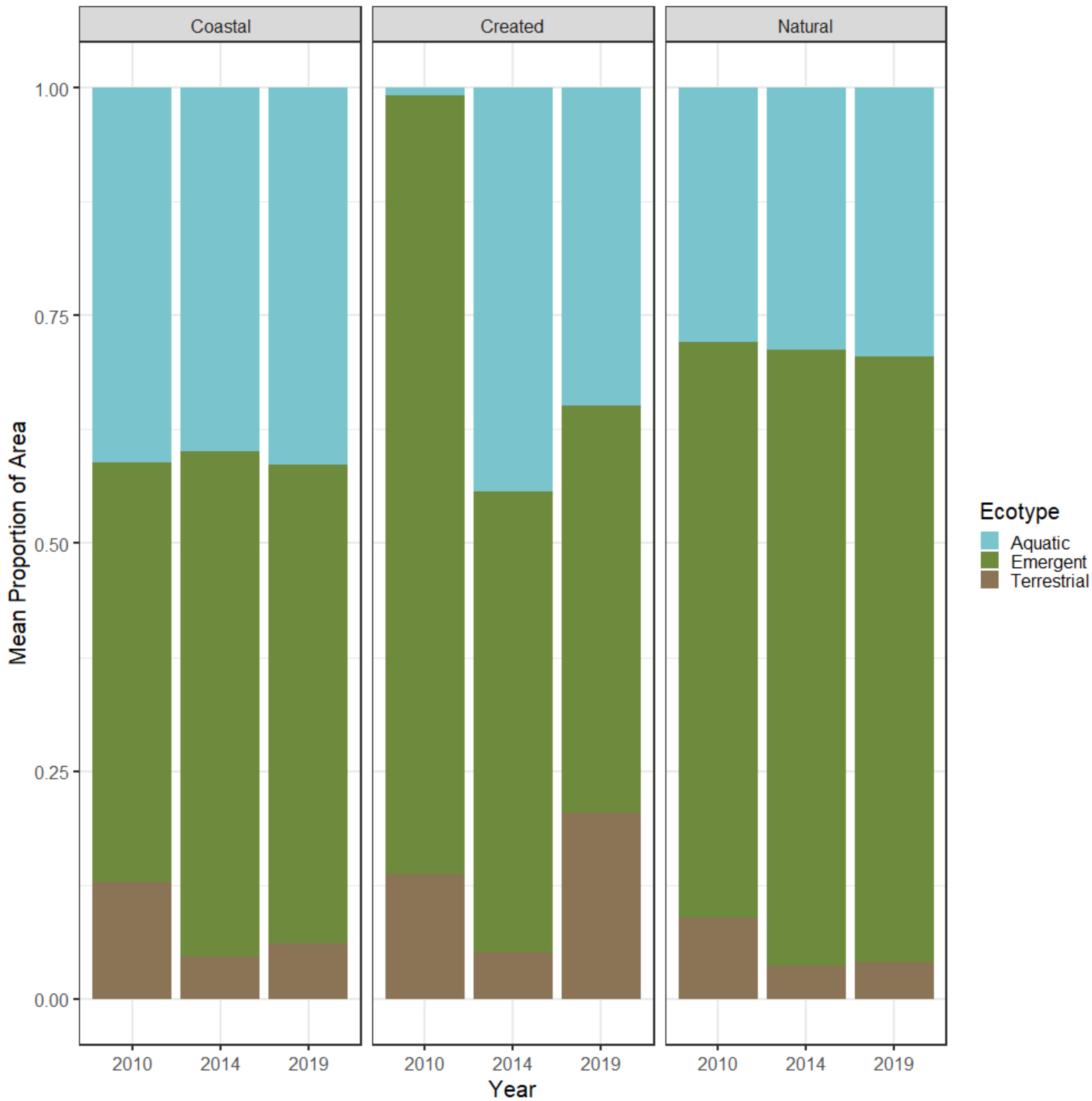

Figure 4: Mean proportion of land cover that was classified for each ecotype per pond type for the summer images. Created ponds were constructed from 2012–2014 leading to little aquatic land cover in the 2010 image for this pond type.

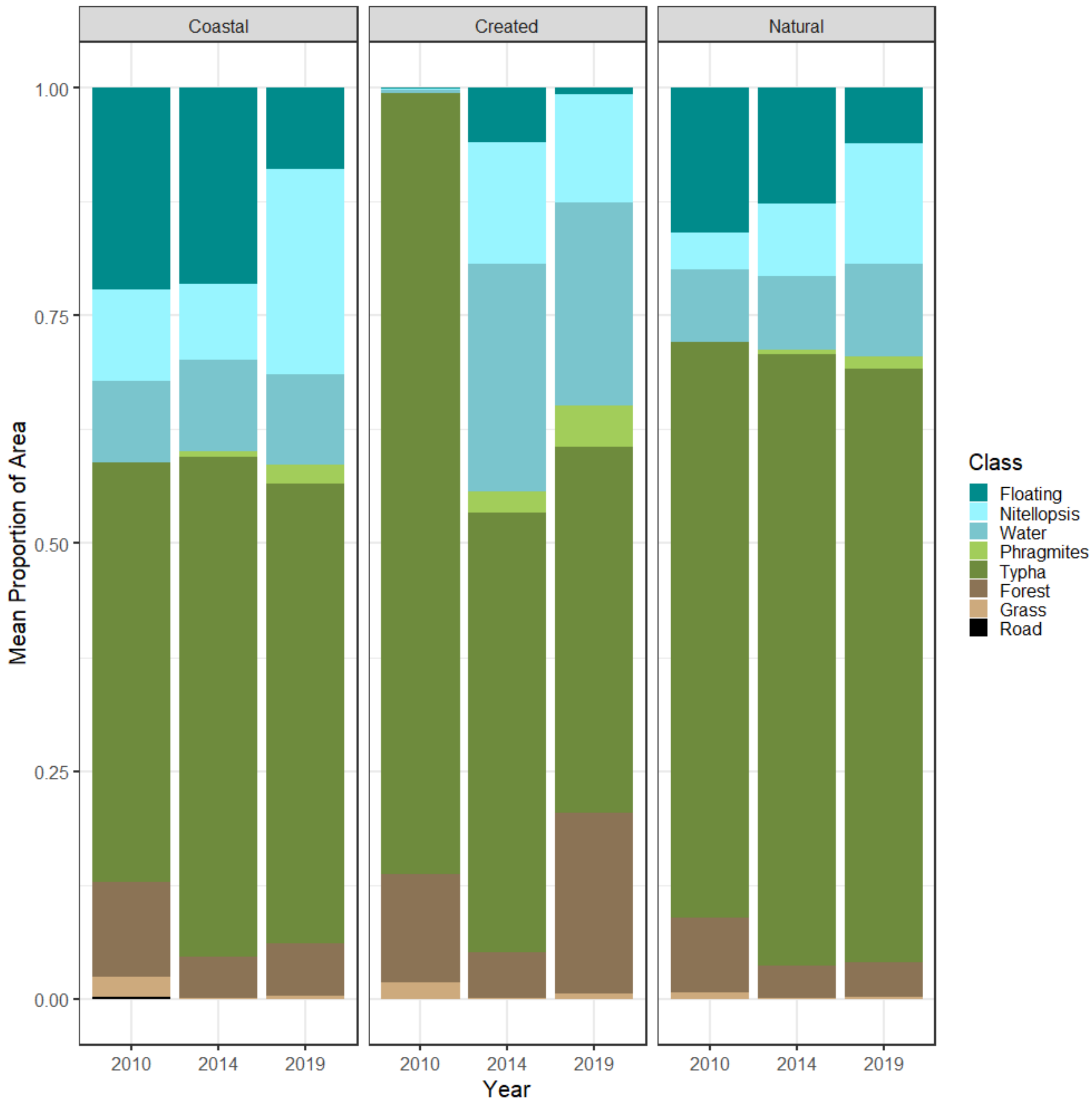

Figure 5: Mean proportion of land cover that was classified for each class per pond type for each summer image. Created ponds were constructed from 2012–2014, hence the dominance of the *Typha* vegetation class. *Phragmites* was not detected in the 2010 summer imagery, but was present in 2014 and had expanded in all pond types by 2019.

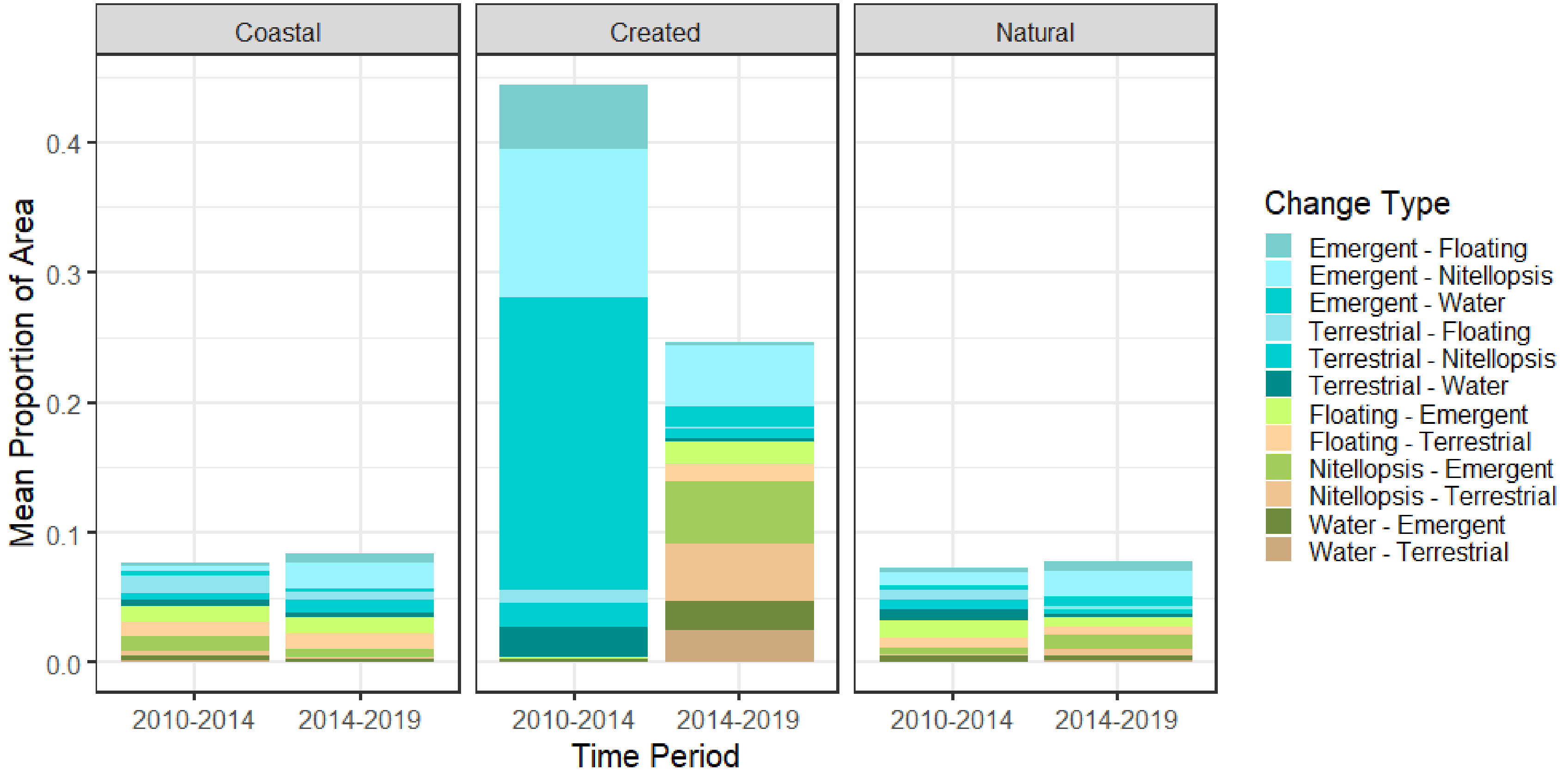

Figure 6: Mean proportional change in aquatic habitat at the class level per pond type between summer images. Areas that did not change, changes within non-aquatic ecotypes (e.g., emergent and terrestrial), and aquatic classes that did not change to a different ecotype (e.g., conversion from floating to *Nitellopsis*) are not shown in this figure.

APPENDIX

IMAGE DATA PREPARATION AND CLASSIFICATION

Methods

Image data preparation

All spring/fall data were pan-sharpened by the imagery distributor to 1.5 metre resolution and georectified on delivery. The summer imagery (including the sole SPOT-5 image) were pan-sharpened in ArcGIS Pro (2.6.2, ESRI, Redlands, California) using the Gram-Schmidt method (Laben et al. 2000) with default parameters for their respective satellites (i.e., SPOT-5 and SPOT-6). These data were then manually georectified to basemap imagery as they were delivered ungeoreferenced; this resulted in a slight shift in image pixels and therefore a separate pond outline was derived for these data. As a result of this slight spatial misalignment, differences in the total area within each pond were evident between spring/fall and summer imagery; direct comparisons between seasons were thus not undertaken.

Image classification

All remote sensing analyses were conducted in ArcGIS Pro (2.6.2, ESRI, Redlands, California). For spring/fall imagery, a simple binary thresholding procedure was applied in ArcGIS Pro using the Otsu method (Liu and Yu 2009) on the infrared band to determine the extent of water. This method creates two classes while reducing within- and between-class variance. Thresholding can rapidly generate results with minimal user input (only requiring one value to separate two classes) and Otsu-based thresholding is entirely autonomous. A downside to this method is that it can produce some speckle ("salt and pepper" effect), as small areas of water and naturally darker patches within stands of emergent vegetation (including shadows) can be identified as water. To mitigate this effect, the data are converted to polygons wherein ponds and their channels become contiguous polygons. The speckle can be easily excluded in this manner by manual deletion of polygons that appear to be incorrectly classified as water or by filtering out polygons that are smaller than some set threshold.

Supervised classification was conducted on summer imagery using an object-based approach. The Random Forest ("Random Trees" in ArcGIS Pro) algorithm uses training data for known land cover types to teach the computer what class to assign to all objects in an image (Pal 2005; Belgiu and Dragu 2016). Image segmentation parameters were set independently in each image to maximize the effectiveness of this step (see , Table 1A for input parameters). Classification data were validated with a distinct set of manually delineated objects (i.e., a different group from the objects used to train the classification) and confusion matrices were generated to outline overall and per-class accuracy (Aronoff 1982a, Aronoff 1982b, Aronoff 1985). Overall accuracy describes the total number of objects in the validation dataset that were classified correctly, producer's accuracy describes the number of true ground features correctly classified on the map (inverse of omission error), and user's accuracy describes the number of map features that truly represent ground features (inverse of omission error). Many studies aim for classifications that would achieve an overall accuracy greater than 80% (comparable to past wetland classification results; Wei and Chow-Fraser 2007), with individual land cover class accuracies for those of interest (in this case, aquatic habitat types) greater than 80% (Aronoff 1985). All steps of the Image Classification Wizard in ArcGIS Pro were followed except for the final manual reclassification. For an accurate classification, multiple rounds of image classification (wherein the input training data were modified or updated based on the success or failure of the previous iteration) were required with an average of three attempts (range one to seven) per image in order to achieve overall classification accuracies over 80%. This type of iterative approach is commonly used in the development of classification workflows since it allows the user to add more (or more distinct) training data points to better separate classes (San Miguel-Ayanz and Biging 1996). It is important to note that the validation dataset was not modified or updated at the same time as the training data, but rather represented a fixed collection of validation objects.

Georeferenced point or map data of a land cover type that has been confirmed in the field are typically required to implement (i.e., train) and confirm the accuracy of (i.e., validate) the classification of an image. However, for the present study field data could not be acquired due travel restrictions. Therefore, all training and validation data were derived through manual delineation by J. Marcaccio and were informed by past experience with remote sensing-based mapping of wetland vegetation in Great Lakes wetland systems. The initial number of land cover classes that were manually delineated was greater than what was ultimately reported. This was done to allow the classification approach to correctly identify similar land cover types that may have unique spectral signatures within the image (e.g., wavy water and calm water appear different in imagery and were separately classified but then concatenated as "water"; San Miguel-Ayanz and Biging 1996). As a result, land cover classes can be organized in a hierarchical structure, with the largest number of classes being manually delineated and then concatenated into higher-level classes at two nested levels of organization: 1) class (e.g., water, floating vegetation), and 2) ecotype (e.g., terrestrial, emergent vegetation, or aquatic; Table 1).

Results

Image classification assessment

For the spring/fall imagery, the binary thresholding polygons were manually selected which negated the potential for incorrect image classifications while adding minimal processing time. This also precluded conducting a traditional accuracy assessment like that done for the summer imagery classification. Some areas required an additional step to split classified areas where correct water bodies were connected by a single pixel to incorrectly classified areas. This only occurred in seven distinct pond subsets through all four image dates and were easily removed; the excess data had a median of +13% area and a range from +3-202% area. There was no omission within these data.

For the summer imagery (all years), three distinct ecotypes were classified, with eight final classes identified across all ecotypes (Table 1). For ecotype, our classifications well exceeded the target of 80% overall accuracy with a range of 91–93%: (Table 2A). There was greater variation within ecotype classes with high producer's and user's accuracy for both aquatic and emergent vegetation (>88%), comparable producer's accuracy for terrestrial (>81%), but lower user's accuracy (<78%) for this ecotype. The terrestrial class had lower sample sizes (due to lower total land cover), which partially contributed to this lower accuracy, but was also sometimes confused with emergent vegetation and, to a lesser extent, the aquatic class (Table 2A). The overall accuracy declined for the class level classification, but still remained above our 80% target (range 87–90%) with Kappa scores in the preferred range (i.e., >0.8;, Tables 3A–5A). There was, however, considerable variation in producer's and user's accuracy among individual classes. Water, *Typha*, and roads all had both high (>90%) producer's and user's accuracy, while grass was consistently low (i.e., <66%). The remaining four classes were more mixed, with generally higher producer's accuracy relative to user's accuracy, suggesting that other classes were more likely to be assigned to these four classes than they were to be assigned to another class. For example, for *Nitellopsis*, aquatic classes (e.g., water or floating vegetation) as well as *Typha* were more likely to be classified as *Nitellopsis* than *Nitellopsis* was to be classified as any other class (Tables 3A–5A). *Phragmites* was not observed in the 2010 imagery and was only infrequently observed in the 2014 and 2019 imagery. As a result, accuracy for this class was variable with high producer's and low user's accuracy in 2014 but the inverse in 2019.

Tables 6A and 6B summarize the area of each individual class and ecotype within each pond for each year that imagery were classified.

Discussion

Spring/fall data were much easier to classify into aquatic and non-aquatic area with the use of binary thresholding and manual editing with polygons than summer image classification. On a site of this size, binary thresholding and further polygonization in ArcGIS Pro could be executed in under one minute per image. Selecting relevant polygons (and thereby excluding most commission errors) would take under five minutes, and any editing required (to remove extraneous pieces/attachments of false data) would take under ten minutes (for a total of approximately fifteen minutes per image). Supervised classification following the "Image Classification Wizard" in ArcGIS Pro automates the tools required to analyze the data but takes significantly longer; selection of suitable training polygons alone would take at least fifteen minutes. Combined with an iterative approach to maximize classification accuracy, this workflow routinely took more than one hour to create an acceptable dataset. While the time required is much greater, supervised classification gives significantly more data to work with. Depending on the end goals and needs of the project, supervised classification may give a more complete dataset for monitoring.

Table 1A: Image segmentation parameters for each summer image. Minimum segment size for 2009 is smaller than that of 2014 and 2019 in part because the underlying data were of coarser spatial resolution (4m vs 1.5m, for pan-sharpened imagery).

	2009	**2014**	**2019**
Spectral Detail	18	19	19
Spatial Detail	44	17	19
Minimum Segment Size in Pixels	15	60	40

Table 2A: Confusion matrices outlining per-ecotype and overall accuracy for each of the summer image periods. The values reflect the number of objects in the validation dataset that were assigned into each ecotype by the supervised classification.

2010	Aquatic	Emergent	Terrestrial	**Total**	**User's Accuracy**
Aquatic	115	1	2	118	97%
Emergent	2	122	1	125	98%
Terrestrial	3	11	49	63	78%
Total	120	134	52	306	
Producer's Accuracy	96%	91%	94%		
				Overall Accuracy	0.93
2014	Aquatic	Emergent	Terrestrial	**Total**	**User's Accuracy**
Aquatic	120	5	3	128	94%
Emergent h	1	151	5	157	96%
Terrestrial	7	8	35	50	70%
Total	128	164	43	335	
Producer's Accuracy	94%	92%	81%		
				Overall Accuracy	91%
2019	Aquatic	Emergent	Terrestrial	**Total**	**User's Accuracy**
Aquatic	121	8	2	131	92%
Emergent	0	138	0	138	100%
Terrestrial	8	11	33	52	63%
Total	129	157	35	321	
Producer's Accuracy	94%	88%	94%		
				Overall Accuracy	91%

Table 3A: Confusion matrices outlining per-class and overall accuracy for the 2010 summer image. The values reflect the number of objects in the validation dataset that were assigned into each ecotype by the supervised classification.

Class	Road	Grass	Forest	Water	Floating	*Nitellopsis*	*Typha*	*Phragmites*	**Total**	**User's Accuracy**
Road	8	0	1	0	0	1	0		10	80%
Grass	0	7	5	0	0	0	0		12	58%
Forest	0	3	34	0	2	1	11		51	67%
Water	0	0	0	62	2	2	0		66	94%
Floating	1	0	1	1	36	0	0		39	92%
Nitellopsis	0	0	1	1	5	6	1		14	43%
Typha	0	0	1	0	0	2	122		125	98%
Phragmites										
Total	9	10	43	64	45	12	134		317	
Producer's Accuracy	89%	70%	79%	97%	80%	50%	91%		**Overall Accuracy**	87%
									Kappa	0.82

Table 4A: Confusion matrices outlining per-class and overall accuracy for the 2014 summer image. The values reflect the number of objects in the validation dataset that were assigned into each ecotype by the supervised classification.

Class	Road	Grass	Forest	Water	Floating	*Nitellopsis*	*Typha*	*Phragmites*	**Total**	**User's Accuracy**
Road	10	0	0	0	0	0	0	0	10	100%
Grass	0	6	0	0	2	0	2	0	10	60%
Forest	0	1	28	2	3	0	6	0	40	70%
Water	0	0	1	69	1	0	0	0	71	97%
Floating	0	0	0	3	32	1	0	0	36	89%
Nitellopsis	0	2	0	0	5	9	5	0	21	43%
Typha	0	0	1	0	1	0	145	0	147	99%
Phragmites	0	3	1	0	0	0	4	2	10	20%
Total	10	12	31	74	44	10	162	2	345	
Producer's Accuracy	100%	50%	90%	93%	73%	90%	90%	100%	**Overall Accuracy**	87%
									Kappa	0.82

Table 5A: Confusion matrices outlining per-class and overall accuracy for the 2019 summer image. The values reflect the number of objects in the validation dataset that were assigned into each ecotype by the supervised classification.

Class	Road	Grass	Forest	Water	Floating	*Nitellopsis*	*Typha*	*Phragmites*	**Total**	**User's Accuracy**
Road	9	0	0	1	0	0	0	0	10	90%
Grass	0	7	0	0	1	0	1	1	10	70%
Forest	0	1	25	1	4	2	5	4	42	60%
Water	0	0	0	73	0	0	0	0	73	100%
Floating	0	0	0	0	16	1	0	0	17	94%
Nitellopsis	0	1	1	0	1	30	8	0	41	73%
Typha	0	0	0	0	0	0	137	1	138	99%
Phragmites	0	0	0	0	0	0	1	9	10	90%
Total	9	9	26	75	22	33	152	15	341	
Producer's Accuracy	100%	78%	96%	97%	73%	91%	90%	60%	**Overall Accuracy**	90%
									Kappa	0.86

Table 6A: Total area (ha) of each class and ecotypes based on the classification year, pond type, and pond number.

Year	Pond Type	Pond Number	Aquatic Water	Floating	*Nitellopsis*	Aquatic Total	Emergent *Typha*	*Phragmites*	Emergent Total
2010	Coastal	5	10.42	37.77	11.99	60.18	40.49	0.00	40.49
		8	8.63	12.07	9.53	30.23	55.86	0.00	55.86
	Created	1	0.17	0.05	0.07	0.29	19.76	0.00	19.76
		2	0.00	0.00	0.00	0.00	16.30	0.00	16.30
		3	0.10	0.01	0.00	0.10	14.92	0.00	14.92
	Natural	4	0.98	1.41	1.34	3.73	67.27	0.00	67.27
		6	23.97	18.73	7.75	50.45	74.66	0.00	74.66
		7	5.79	34.18	4.81	44.77	53.01	0.00	53.01
2014	Coastal	5	12.63	32.52	14.31	59.47	52.10	0.45	52.55
		8	18.12	15.01	4.48	37.62	63.34	0.73	64.07
	Created	1	5.06	1.61	3.80	10.47	12.16	0.55	12.71
		2	3.60	1.35	3.01	7.95	8.77	0.64	9.41
		3	5.97	0.65	1.38	8.00	8.12	0.19	8.32
	Natural	4	1.53	2.28	2.71	6.53	68.06	0.30	68.36
		6	41.24	20.01	9.88	71.13	84.08	0.35	84.43
		7	15.95	21.77	14.04	51.76	57.05	0.97	58.02
2019	Coastal	5	11.28	14.23	34.01	59.53	47.52	3.39	50.90
		8	9.91	5.53	15.86	31.31	58.43	1.23	59.67
	Created	1	3.80	0.33	4.29	8.42	11.32	0.94	12.26
		2	3.83	0.05	1.69	5.57	6.39	1.17	7.56
		3	5.23	0.11	1.54	6.88	6.83	0.51	7.34
	Natural	4	1.46	1.91	3.66	7.03	66.12	1.58	67.70
		6	18.01	5.01	28.66	51.68	80.56	1.67	82.23
		7	16.68	13.01	15.03	44.71	56.10	0.73	56.82

Table 6B: Total area (ha) of each class and ecotypes based on the classification year, pond type, and pond number.

Year	**Pond Type**	**Pond Number**	**Terrestrial** Forest	Grass	Shrubs	Road	**Terrestrial Total**
2010	Coastal	5	14.45	3.56	0.00	0.00	18.00
		8	8.31	1.29	0.00	0.41	10.02
	Created	1	4.41	0.34	0.00	0.00	4.75
		2	1.25	0.27	0.00	0.00	1.52
		3	1.90	0.45	0.00	0.00	2.35
	Natural	4	6.69	0.75	0.00	0.00	7.44
		6	13.52	1.15	0.00	0.00	14.68
		7	6.64	0.36	0.00	0.00	6.99
2014	Coastal	5	4.85	0.08	1.73	0.00	6.65
		8	1.46	0.00	2.03	0.00	3.49
	Created	1	0.49	0.02	1.11	0.00	1.62
		2	0.25	0.06	0.15	0.00	0.46
		3	0.60	0.00	0.46	0.00	1.06
	Natural	4	1.44	0.01	2.11	0.00	3.55
		6	2.98	0.02	1.85	0.00	4.84
		7	0.28	0.25	2.44	0.00	2.97
2019	Coastal	5	7.50	0.73	0.00	0.00	8.24
		8	5.01	0.11	0.00	0.02	5.14
	Created	1	3.91	0.21	0.00	0.00	4.12
		2	4.67	0.02	0.00	0.00	4.69
		3	3.04	0.11	0.00	0.00	3.15
	Natural	4	3.55	0.16	0.00	0.00	3.71
		6	5.65	0.23	0.00	0.00	5.88
		7	2.97	0.27	0.00	0.00	3.24