A Review of Canadian Wetlands

Current practices, methods, candidate methodologies, and data sources for wetland mapping

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# Table of contents

[Table of contents 1](#_Toc493074520)

[Executive summary 3](#_Toc493074521)

[Introduction to wetlands 3](#_Toc493074522)

[The Importance of Wetlands 4](#_Toc493074523)

[Wetlands in Alberta 4](#_Toc493074524)

[Wetland Classification 6](#_Toc493074525)

[Existing wetland Classifications and Inventories in Alberta 6](#_Toc493074526)

[The Canadian Wetland Classification System 6](#_Toc493074527)

[The Alberta Wetland Classification System 7](#_Toc493074528)

[Key Wetland Characteristics 9](#_Toc493074529)

[Peat Accumulation 9](#_Toc493074530)

[Water Regime 10](#_Toc493074531)

[Wetland Chemistry 10](#_Toc493074532)

[Soil Characteristics 11](#_Toc493074533)

[Wetland Vegetation 12](#_Toc493074534)

[Classifying Wetlands by AWCS 14](#_Toc493074535)

[Wetland Class Summary 15](#_Toc493074536)

[Alberta Wetland Mapping Specification 16](#_Toc493074537)

[Prairie/Parkland biomes 16](#_Toc493074538)

[Boreal/Foothills biomes 17](#_Toc493074539)

[Wetland Classification: A Data Review 18](#_Toc493074540)

[Field Acquisitions 19](#_Toc493074541)

[Optical Imagery 19](#_Toc493074542)

[Aerial 19](#_Toc493074543)

[Satellite 20](#_Toc493074544)

[Hyperspectral sensors 20](#_Toc493074545)

[LiDAR 21](#_Toc493074546)

[SAR 22](#_Toc493074547)

[Polarimetry 23](#_Toc493074548)

[Decompositions 25](#_Toc493074549)

[Interferometry 25](#_Toc493074550)

[Hydroperiod 26](#_Toc493074551)

[Future Wetland Remote Sensing 27](#_Toc493074552)

[General advantages & limitations of remote sensing 27](#_Toc493074553)

[Wetland Classification: A Methodological Review 27](#_Toc493074554)

[Techniques 28](#_Toc493074555)

[Problem Statement 28](#_Toc493074556)

[Framework 28](#_Toc493074557)

[Candidate data 28](#_Toc493074558)

[Candidate methodologies 29](#_Toc493074559)

[Concluding Remarks 29](#_Toc493074560)

[References 30](#_Toc493074561)

# Executive summary

As global climate changes, water resources have become stressed, key amongst which are wetlands, which comprise approximately 14% of the land area of Canada. Despite their broad areal coverage, these sensitive ecosystems are in rapid decline and a contemporary inventory is now required. Since the conception of wetland inventory, mapping technology has advanced dramatically, thus a review of contemporary methods and candidate data for wetland classification is required, particularly with respect to maximizing accuracy and minimizing cost. In reference to these needs, the current document will review literature surrounding the current practices, methodologies, and candidate methodologies and data sources for wetland classification across the globe. The desired outcome is to develop a streamlined workflow capable of classifying wetlands across the prairie and boreal biomes of the province of Alberta (with possible extension to Saskatchewan) in Canada. The workflow will be built on the foundation of remote sensing data to yield products that meet the requirements of official stakeholders and policymakers. The technical and functional specification of the wetland products intended for production are expected to be determined at a stakeholder workshop which took place on 23rd March 2017 in Leduc, Alberta, Canada.

# Introduction to wetlands

The Canadian [National Wetlands Working Group (1997)](#_ENREF_180) (NWWG) defines a wetland as: land that is saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic (adapted to life in water or water-tolerant) vegetation and various kinds of biological activity which are adapted to a wet environment.

In some wetlands, little vegetation is present and soils are poorly developed as a result of frequent and drastic fluctuations of water level, wave action, water flow, turbidity, or a high concentration of salts or other toxins in the water or soil. Mineral wetlands also include mineral soil areas that are modified by water control structures (e.g. dams) or that are tilled and planted, but would become saturated for prolonged periods if anthropogenic drivers ceased to act on the area.

Wetland development is a function of climate (precipitation, temperature, wind, and insolation), hydrology (internal and external drainage), chemistry (water and soils), geomorphology (landform and soil parent material), and biology (fauna and flora). Wetland development is dynamic as often various types of wetlands represent transitions from one type to another, meaning wetlands often share characteristics of more than one wetland class, form, or type (subform).

Given the highly dynamic nature of wetlands, they are often difficult to characterize by traditional methods such as aerial/satellite imagery, and or field techniques, as such methods are either time consuming, expensive, or both. The field of remote sensing has the capacity to characterize wetlands over large-scales and even through time. However, existing remote sensing methodologies do not address the problem of large-scale wetland classification in its entirety. In order to fully address this issue an in-depth understanding of wetland function and evolution with respect to water level, vegetation, and other wetland attributes is required. Furthermore, an assessment of current remote sensing technologies and methodologies is required to identify potential data and analysis techniques in order to obtain accurate wetland classifications over a diversity of wetland ecosystems.

## The Importance of Wetlands

Wetlands are a known provider of substantial economic, environmental and social value through a host of vital services. For example, wetlands play a crucial role in the replenishment and storage of groundwater, not only serving as natural water retention ponds that prevent flooding and erosion, but also by filtering and purifying water. Wetlands can also play a significant role in climate change mitigation ([Erwin 2008](#_ENREF_65), [Crooks et al. 2011](#_ENREF_55), [Ramsar 2015](#_ENREF_196), [Howard et al. 2017](#_ENREF_106)). Furthermore, wetlands directly influence wet area extent, riparian vegetation zone extent, hydrological regimes, and biodiversity ([Russi et al. 2013](#_ENREF_209)); it is estimated that wetlands provide a habitat to an estimated one third of all Canada’s species at risk ([Stewart et al. 1971](#_ENREF_224), [National Wetlands Working Group 1997](#_ENREF_180), [Government of Alberta 2013](#_ENREF_83)). In addition, wetlands often provide locations for human recreation and incubate socio-cultural values through fishing and hunting activities within native communities.

Despite the role of wetland ecosystems in local ecology, wetlands have become one of the world’s foremost threatened ecosystems, and continue to decline in abundance and health due to numerous climatic and anthropogenic processes ([Daily 1997](#_ENREF_57), [Mitsch et al. 2007](#_ENREF_170)). The global extent of wetlands have reportedly declined by up to 74 % in the 20th century, this is of fundamental importance within Canada as the country exhibits approximately 24% of global wetlands (over 150 million hectares across all biogeoclimatic ecozones) ([Government of Canada 1991](#_ENREF_85)). The monetary loss associated with the degradation of global wetland ecosystem services and surrounding areas between 1997 and 2011 was estimated at almost US$ 10 trillion per year. That is, over this period losses due to changes in swamps and floodplains were approximately US$ 2.7 trillion per year, whereas changes associated with marshes and mangroves were estimated at US$ 7.2 trillion per year ([Costanza et al. 2014](#_ENREF_51)).

In recent times, even water rich countries such as Canada have targeted wetland decline and degradation as great cause for concern as the country exhibits one of the greatest rates of boreal forest disturbance globally (approximately 78%) due to natural resources extraction, land cover change, agriculture, and natural disturbances ([Mora et al. 2013](#_ENREF_175)). In Alberta alone, approximately 66% of wetlands found in settled parts of the province no longer exist, primarily as a result of agricultural drainage and urban development ([Government of Alberta 2013](#_ENREF_83)). Within less populated boreal biomes, warmer temperatures and reduced precipitation trends have caused wetland surface water’s and groundwater’s to dry considerably, resulting in changes to hydrology, vegetation succession, and increased respiration and methane production which, over large-scales, could exacerbate positive feedbacks to the climate system ([Roulet 2000](#_ENREF_207), [Stow et al. 2004](#_ENREF_225), [Klein et al. 2005](#_ENREF_122), [Riordan et al. 2006](#_ENREF_202), [Tarnocai 2009](#_ENREF_228), [Chasmer et al. 2016a](#_ENREF_40)); as a result, rates of boreal wetland change have not been accurately quantiﬁed. This has been identified as a knowledge gap by policy makers, who share the responsibility to ensure a healthy, secure and sustainable water supply.

Given the recognized importance and wealth of wetlands throughout Canada, wetland ecosystems policy makers oversaw the creation of a system to classify and monitor wetlands and characterize their far reaching influence. The Canadian wetland classification system (CWCS) has been well positioned to subject the great array of wetlands to a common ruleset that can be recognized by all.

## Wetlands in Alberta

The province of Alberta in western Canada is approximately 660,000 km2, home to approximately 4 million people. Almost 20% of the provinces surface area is covered by wetlands, most of which (> 90%) are peatlands ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)). The natural regions of the province include: grassland, parkland, boreal forest, and montane ecosystem. Each region can be characterized by one of the following five distinct wetland classes: bogs, fens, marshes, swamps, and open-shallow water, where each exhibit unique biological characteristics and dynamic season water extents ([Stewart et al. 1971](#_ENREF_224), [National Wetlands Working Group 1997](#_ENREF_180)).

Alberta wetlands occur across its diverse landscapes, including floodplains, springs, river islands, and glacial channels. They may occur in basins or depressions in the landscape that are hydrologically isolated or connected to other waterbodies and/or wetlands (sometimes though complex subsurface hydrological pathways). Climatic and landscape factors, such as precipitation, temperature, topography, geology, landscape position, and water inputs and interactions determine the conditions that enable wetlands to form and be sustained ([Vitt et al. 1996](#_ENREF_250)).

In the context of the current project, Alberta wetlands are discussed within the two major regions of the province: the prairie (or parkland) biome, and the boreal (or foothills) biome. The prairie biome of Alberta is part of the west-central North America parent region that extends from Central Alberta south to the state of Iowa, USA. Prairie wetland basins are typically depressions in the landscape that resulted from glacial retreat during the last ice age, approximately 12,000 years ago ([Winter 1989](#_ENREF_263)). Wetlands that exist within these depressions are highly variable in size and permanency, but typically exhibit a water depth of < 1 m at peak volume ([Sethre et al. 2005](#_ENREF_217), [Zhang et al. 2009](#_ENREF_272)). The majority of wetlands in this region are mineral wetlands (such as shallow open water and marshs) that form due to frequently fluctuating water levels common in the region throughout the year ([Vitt et al. 1996](#_ENREF_250)). Most wetlands exist as isolated (or closed) basins that only connect within a hydrological system during wet conditions where depressions reach ‘bank-full’ conditions and begin to spill in to adjacent depressions; known as the ‘spill and fill’ mechanism ([Winter et al. 2003](#_ENREF_264)). The temporal longevity of wetlands on the prairie landscape varies dramatically. Some are present during peak saturation only (temporary), others exist for the duration of the wet season and sometimes beyond (seasonal to semi-permanent), whereas others exist year round (permanent). Typically temporary or seasonal wetlands are most abundant across the southern prairies thus making them sensitive to multi-year climate cycles, such as El Niño-southern oscillation (ENSO) events ([Cowardin et al. 1979](#_ENREF_52)). The highly dynamic nature of wetland permanancy on the prairies often makes their classification challenging. This often impacts agricultural practices, land development, and other anthropogenic activities as basins can flood with relatively little water input.

Alberta’s boreal biome extends north from central Alberta’s Parkland region to the border of the Northwest Territories, spanning the width of the entire province, intersecting both the Boreal Plains and Taiga Plains ecozones. Peatlands (such as bogs, fens, and some swamps) dominate the landscape in northern Alberta, and cover large geographies of the boreal region ([Tarnocai 2009](#_ENREF_228)); mineral wetlands do exist, but with lower prevalence. Boreal wetlands exist in regions where the water table is near or at the surface, and as such tend to settle within landscape depressions or on regions of flat land that is poorly drained. Due to the water rich environment most boreal wetlands are semi-permanent or permanent, however, temporary wetlands can exist near man-made structures such as roads. More northern peatlands are typically made up of three major land classes: peat plateaus, flat bogs, and rich and poor fen channels ([Quinton et al. 2009](#_ENREF_195)); in some peatland complexes permafrost, defined as ground based earth materials that remain at < 0 °C for more than 2 consecutive years ([Chasmer et al. 2016b](#_ENREF_41)), underlies flat ground and often cause ground deformation to form plateaus ([Zoltai et al. 1975](#_ENREF_276)). These peat plateaus offer refuge for varying densities of treed and non-treed vegetation and generate runoff to adjacent bogs and fen channels, promoting the movement of water within the region ([Quinton et al. 2009](#_ENREF_195)). Boreal wetland hydrology is often more complex than their prairie counterparts as wetlands are often connected allowing the movement of water both above and below the surface.

The hydrology of wetlands within both the prairie and boreal biomes are affected by the anthropomorphic pressures of the oil and gas industries, and urban development. Agricultural practices exhibit far greater pressures within the prairies than in the boreal, whereas oil, gas, and mining activities are more influential in the boreal biome. These factors have potential to dramatically influence wetland function, evolution, and even alter landscape hydrology beyond the effects of global anthropogenic warming trends.

# Wetland Classification

## Existing wetland Classifications and Inventories in Alberta

A total of four different wetland classification systems have been used historically within the province of Alberta. The [Stewart et al. (1971)](#_ENREF_224) system has been widely used in southern Alberta to classify the prairie biome. The [Cowardin et al. (1979)](#_ENREF_52) and ecosite guides for Alberta ([Beckingham et al. 1996a](#_ENREF_18), [Beckingham et al. 1996b](#_ENREF_19)) have also been utilized to classify wetlands for varying purposes in Alberta. The Canadian Wetland Classification System (CWCS; [National Wetlands Working Group (1997)](#_ENREF_180)) was developed to support wetland classification at a national scale within Canada, and has been widely applied in central and northern regions of Alberta where peat lands are more prevalent. The CWCS provided a baseline criteria for synthesizing different wetland classifications, and defined the minimum requirements for Federal expectations with respect to wetland classification.

A number of wetland classification inventories exist in Alberta. For example, the Ducks Unlimited Boreal Plains Ecozone Classification ([Smith et al. 2007](#_ENREF_221)) and the Alberta Wetland Inventory (AWI; [Halsey et al. (2003)](#_ENREF_93)) have been applied in the boreal biome, while the Grassland Vegetation Inventory identifies lentic ecosystems in southern Alberta. These datasets in conjunction with others (from an array of partners) constitute the Alberta Merged Wetland Inventory (AMWI), reclassified to meet CWCS requirements where necessary, and represents the first provincial wetland inventory of its kind in Alberta ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)). In addition, Ducks Unlimited Canada have spearheaded the Canadian Wetland Inventory (CWI) and have applied their classification model to much of Canada, and extensively in Alberta’s prairie and boreal biomes.

## The Canadian Wetland Classification System

Given current provincial wetland inventories are built on the CWCS, this section was included to provide a broad overview of the national wetland classification regime. The first phase of development of a Canadian wetland classification was completed in 1973 as an organic terrain classification system by the National Committee of Forest Lands. Subsequently, [Russi et al. (2013)](#_ENREF_209) proposed a four-level hierarchical, ecologically-based wetland classification system which formed the basis of the current, more comprehensive CWCS ([National Wetlands Working Group 1997](#_ENREF_180)). The publication of the first edition of the CWCS in 1987 represented a national synthesis of existing information at the time, the second edition (circa 1997) reflected interests to consolidate differences in wetland classification philosophies across the country.

As wetlands are products of the interaction of various environmental factors, they usually develop different characteristics that can be used to group them into classes. The CWCS is built upon this rationale and has been refined by NWWG on the basis of experts from across the country which focused the system on three hierarchical levels of classification:

1. Class: recognized on the basis of properties of the wetland that reflect the overall genetic origin of the wetland ecosystem and the nature of the wetland environment.
2. Form: subdivisions of each wetland class based on surface morphology, surface pattern, water type and morphology characteristics of underlying mineral soil. Many of the wetland forms apply to more than one wetland class. Some forms can be further subdivided into subforms.
3. Type: subdivisions of the wetland forms and subforms based on physiognomic characteristics of the vegetation communities. Similar wetland types can occur in several wetland classes whereas others are unique to specific classes and forms.

As of the publication of the second edition of the CWCS, 49 wetland forms and 72 subforms were recognized, however, wetland form and type will continue to be revised as additional knowledge about Canada’s wetlands is gained over time. It is important to recognize that in some cases, wetlands are created by anthropogenic means, however, over time, these sites evolve into naturally functioning wetlands and are classified accordingly. Constructed wetlands, such as those for habitat enhancement and wastewater treatment, are often included in the mapping of Canadian wetlands. However, they essentially lie outside the focus of the CWCS.

Despite the wealth of existing classification systems and inventories, no system consistently characterized Alberta’s wetlands based on a unified ruleset. To address this identified gap, the Alberta Wetland Classification System (AWCS) has been developed for use and application across the province with the goal of characterizing Alberta’s wetlands based on flora and ranges of environmental, geological and climatic characteristics.

## The Alberta Wetland Classification System

Historically, wetland classification and function within Alberta has been largely based on the work of [Stewart et al. (1971)](#_ENREF_224), which describes different types of prairie wetlands in detail, with a particular focus on vegetation as indictors of wetland type and permanency. This system was widely used in Alberta’s crown (green) and private (white) lands in order to implement strategies to preserve wetlands during industrial and urban development.

During June 2015, the Government of Alberta recognized the value of updating Alberta’s wetland policy and classification system. Updates were implemented with the goal of creating a more comprehensive system that accounts for a wider variety of wetland forms whilst recognizing the importance of vegetation structure and water permanence with respect to wetland hydrology, biodiversity, and biological process. As a result the new Alberta Wetland Classification System (AWCS) recognizes and incorporates value-added information based on previous inventories and satisfies key wetland stakeholders such as: Ducks Unlimited ([Smith et al. 2007](#_ENREF_221)), AWI ([Halsey et al. 2003](#_ENREF_93)), field ecosites guides to Alberta ([Beckingham et al. 1996a](#_ENREF_18), [Beckingham et al. 1996b](#_ENREF_19)), and the CWCS ([National Wetlands Working Group 1997](#_ENREF_180)). The AWCS is tailored specifically for wetlands in Alberta, providing a ruleset that aids wetland classification. The overall intent of the AWCS is to achieve a standardized provincial wetland classification system that meets the following objectives:

* Provide a consistent the provincial wide classification of wetlands
* Promote a consistent understanding of wetlands
* Apply classification keys that relate to provincial wetland characteristics associated with hydrologic, biogeochemical, and biotic processes
* Remains compatible with existing wetland classification and inventories
* Remains aligned with appropriate legislation and policies, such as the Water Act, Public Lands Act, and Alberta Wetland Policy
* Is applicable within Canadian Geographic Information System (GIS) databases and inventories

Similar to the CWCS the AWCS recognizes three means of wetland classification: class, form, and type (or sub form; Table 1); the AWCS also shares the same five broad wetland classes as the CWCS: bog and fen (peatlands), marsh, swamp, and shallow open water. These five classes are divided in to form based on vegetation, and subsequently to type based on salinity, water permanence (based on [Stewart et al. (1971)](#_ENREF_224), not applicable to peatlands), and alkalinity (peatlands only).

The AWCS is tailored around key wetland characteristics that are distinguishable on the landscape; such characteristics define the nature of each wetland within the AWCS hierarchical classification system from class to form to type. Following the AWCS ruleset will lead to repeatable and consistent results despite the challenges associated with intermediary wetland characteristics, such as intermediate states between marshes and fens.

Table 1 Wetland classes, forms, and types in the Alberta Wetland classification System. Wetland classification codes (for mapping purposes) are noted in square brackets.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Class** | **Form** | **Type** | | |
| **Salinity** | **Water permanence1** | **Acidity-alkalinity** |
| Bog [B] | Wooded, coniferous [Wc]  Shrubby [S]  Graminoid [G] | Freshwater [f] | - | Acidic [a] |
| Fen [F] | Wooded, coniferous [Wc]  Shrubby [S]  Graminoid [G] | Freshwater [f] | - | Poor [p] |
| Freshwater [f] | - | Moderate-rich [mr] |
| Freshwater [f] to slightly brackish [sb] | - | Extreme-rich [er] |
| Marsh [M] | Graminoid [G] | Freshwater [f] to slightly brackish [sb] | Temporary [II] | - |
| Freshwater [f] to moderately brackish [mb] | Seasonal [III] | - |
| Freshwater [f] to brackish [b] | Semi-permanent [IV] | - |
| Shallow open water [W] | Submersed and/or floating aquatic vegetation [A]  Bare [B] | Freshwater [f] to moderately brackish [mb] | Seasonal [III] | - |
| Freshwater [f] to sub-saline [ss] | Semi-permanent [IV] | - |
| Slightly brackish [sb] to sub-saline [ss] | Permanent [V] | - |
| Submersed and/or floating aquatic vegetation [A] | Saline [s] | Intermittent [VI] | - |
| Swamp [S] | Wooded, coniferous [Wc]  Wooded, mixedwood [Wm]  Wooded, deciduous [Wd]  Shrubby [S] | Freshwater [f] to slightly brackish [sb]2 | Temporary [II] 2 | - |
| Freshwater [f] to slightly brackish [sb] 2 | Seasonal [III] 2 | - |
| Moderately brackish [mb] to sub-saline [ss] 2 | Seasonal [III] 2 | - |
| 1Roman numerals are equivalent to wetland classes by [Stewart et al. (1971)](#_ENREF_224)  2Swamp types are not applicable to wooded swamps due to lack of available information | | | | |

# Key Wetland Characteristics

Factors that affect wetland characteristics at the regional scale include climate, landscape, and surface and subsurface hydrology ([Vitt et al. 1996](#_ENREF_250), [National Wetlands Working Group 1997](#_ENREF_180)). Such factors influences hydrologic, biogeochemical, and biotic processes such as:

* The capacity of a wetland to receive, store, moderate, and release surface water and groundwater in a watershed
* Acid-base reactions, ion exchange and oxidation-reduction reactions, decomposition, nutrient cycling, and carbon sequestration
* Biological productivity and competition

In the context of the AWCS, wetland characteristics that reflect such processes are used to identify wetland class, form and type; these are (described in respective sections):

* Peatland accumulation
* Water regime
* Chemical gradients
* Soil characteristics
* Vegetation structure

It is important to note natural (e.g. wildfire) and anthropogenic (e.g. land development) disturbance and how each may influence wetland classification, as noted by [Naiman et al. (1994)](#_ENREF_178). Permanent wetland classification changing disturbances include tilling, partial infilling or drainage, storm water input, groundwater inflow loss, or peatland drainage; poor plant health, abnormal species or a combination of both typically indicate recent disturbance ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)). In addition, it is important to note long-term climatic trends when classifying wetlands, as some wetlands exhibit natural fluctuations of water levels that can influence vegetation communities and structure ([Miller et al. 2003](#_ENREF_169), [Johnson et al. 2004](#_ENREF_114)).

## Peat Accumulation

The presence and depth of peat are characteristics that distinguish peatlands from mineral wetlands.

Peatlands typically contain ≥ 40 cm (consistent with soil classification standards established by [Stewart et al. (1971)](#_ENREF_224)) of accumulated peat on which organic soils (excluding fossils) develop. Peat can be comprised of a wide variety of organic materials in an unconsolidated or partially decomposed state, and may include materials such as: bryophytes, herbaceous vascular plants and woody debris ([Mitsch et al. 2007](#_ENREF_170)). For a wetland to be considered a peatland its soils must primarily constitute organic matter in an undecomposed to moderately decomposed state. Mineral wetlands have < 40 cm of peat build-up and are found in areas where an excess of water collects on the surface but produce little to no organic matter for geomorphic, hydrologic, biotic, edaphic (soil related), or climatic reasons. Whilst mineral wetlands can support organic soils (in excess of 40 cm) they must exhibit a Von Post ranking > 5 within the upper 40 cm of soil. The Von Post decomposition scale is based on field estimates of organic matter decomposition, where values < 5 are peatlands, whereas those ≥ 5 are typically mineral wetlands.

Under the CWCs and AWCS bog and fens are classified as peatlands, whereas swamps, marshes, and shallow open waters are typically classified as mineral wetlands, however, peatland swamps have been observed in Canada ([Locky et al. 2005](#_ENREF_141)).

## Water Regime

Peatlands, divided in to bogs and fens (and some swamps), are differentiated by their water source: bogs are fed exclusively by water sources from precipitation (ombrogenous), whereas fens accumulate water from a variety of sources. As a result fens are minerogenous as they accumulate minerals through water that has been in contact with surface and subsurface soils, and bedrock ([National Wetlands Working Group 1997](#_ENREF_180)). All peatlands in Alberta tend to have relatively stable water tables whilst simultaneously exhibiting permanently saturated soil which promotes anaerobic conditions and reduces decomposition rates ([Vitt et al. 1993](#_ENREF_252)). However, peatlands in permafrost zones can be exceptions to this rule as they exhibit perennial ice that can often be above the water table ([Vitt et al. 1994](#_ENREF_251)). In general the water table associated with bogs is well below the surface, whereas for fens the water table tends to be at or near the surface ([National Wetlands Working Group 1997](#_ENREF_180)).

Conversely to peatlands, water tables associated with mineral wetlands tend to fluctuate from near, at, or above the ground surface as they receive water from a variety of different sources throughout the year ([Stewart et al. 1971](#_ENREF_224), [National Wetlands Working Group 1997](#_ENREF_180)). Swamps, marshes, and shallow open water basins can be closed (or isolated) and therefore receive water through precipitation and/or surface runoff exclusively. Less isolated wetlands can exhibit complex groundwater-surface interactions and underground connectivity to other wetlands, lakes, streams, or ponds ([National Wetlands Working Group 1997](#_ENREF_180)). Variable water levels increase anaerobic decompositions which influences water chemistry, nutrient availability, and vegetation characteristics such as community and structure ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)).

## Wetland Chemistry

The AWCS recognizes acidity-alkalinity and salinity as chemical properties from which to determine wetland type, where the former analysis is applicable to peatlands, only. Peatland acidity is an index of hydrogen production through cation exchange (not applicable to mineral wetlands as cation exchange is dominated by metals); the more hydrogen produced the more acidic a wetland becomes. For fens, particularly those that receive carbon-rich groundwater, hydrogen production is buffered resulting in a relatively basic regime. Conversely, the low mineral content precipitation fed to bogs provides no buffer thus producing a more acidic environment.

Salinity is another influential property of wetland vegetation community structure and composition ([Stewart et al. 1971](#_ENREF_224)). Typically little vegetation is noted in peatlands with elevated salinity due to vegetation intolerances, therefore, healthy peatlands exhibit low salinity. Conversely, some mineral wetlands provide a habitat for vegetation communities that are adapted to survive in a highly saline environment ([Stewart et al. 1971](#_ENREF_224)). In either case, the electrical conductivity of surface water (where accessible) provides an index for estimating wetland salinity type based on specified ranges (Table 2).

Table 2 Salinity types and corresponding conductivity ranges adapted from [Stewart et al. (1971)](#_ENREF_224).

|  |  |
| --- | --- |
| **Wetland type** | **Conductivity (µS cm-1)1** |
| Freshwater | < 500 |
| Slightly brackish | 500 – 2,000 |
| Moderately brackish | 2,000 – 5,000 |
| Brackish | 5,000 – 15,000 |
| Sub-saline | 15,000 – 45,000 |
| Saline | > 45,000 |
| 1µS cm-1 represents electric conductivity as micro Siemens per centimeter | |

## Soil Characteristics

Soil characteristics are important for distinguishing wetland areas from non-wetlands (or uplands) and delineating their ecological boundaries; such characteristics are development long term, and are generally stable. Furthermore, as the rooting zone for most wetland vegetation falls within the uppermost 40 cm of the soil profile, soils are key in determining wetland type ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)). As noted previously, the development of organic matter is key in characterizing wetland attributes; the accumulation of organic matter may occur on peatlands or mineral wetlands, where the majority of organic matter must be peat for the former.

In peatlands, permafrost development is possible when mean annual temperatures and the insulating properties of peat combine to maintain a temperature less than 0 °C throughout the year within the soil profile ([Vitt et al. 1994](#_ENREF_251)). Wet soil processes are more typical of mineral wetlands. When mineral soils are saturated for extended periods, metals such as iron and manganese are reduced (i.e. gains electrons). This leads to colour changes in the soil profile, often to a blue-grey colour, commonly referred to as gleying ([Soil Classification Working Group 1998](#_ENREF_222)); reduced iron can often concentrate itself in specific regions of the soil profile, indicated by localized discolouration. During a period of water table recess these metals are exposed to oxygen and are oxidized (or re-oxidized) resulting in red or brown mottles ([Soil Classification Working Group 1998](#_ENREF_222)).

The presence of gleying and mottling in the rooting zone is diagnostic of mineral wetlands and its location within the soil profile can aid the characterization of wetland type. The former suggests soil exposure to prolonged periods of saturation, whereas the latter indicates water level changes are common which results in alternating periods of reduced and oxidized states. Such processes are most common in gleysolic soils, however, under certain conditions, other mineral wetland soils fail to exhibit any evidence of gleying and/or mottling for the following reasons:

* Sufficient alkalinity inhibiting metal reduction
* Active deposition of sediments
* Limited saturation depth through restrictive soil layers
* Parent material colour (e.g. dark soils)
* Recent establishment (e.g. creation or restoration)
* Agricultural disturbance (e.g. tilling)

It is important to note that whilst the presence of gleying and mottling indicates the presence of saturated soils, the absence of these indicators does not confirm the area is not a wetland.

## Wetland Vegetation

Wetlands are often diverse vegetation habitats housing a plethora of vegetation structure and composition characteristics, both of which can be used to index wetland class, form, and type. Vegetation growth is promoted in a zone-like fashion at varying radial bands from wetland centres, the vegetation communities within which are distinct and depend on ground water level ([Stewart et al. 1971](#_ENREF_224)). A typical mineral wetland can be divided in to up to five vegetation structure zones based on its topographic relief and hydrology: upland, shrub-land, wet meadow, emergent, and sub-mergent/floating (Figure 1). It is important to note that not all wetlands follow this schematic layout; boreal peatlands may not exhibit any clear vegetation structure zones, such a layout is more common of mineral wetlands.

Vegetation structural characteristics define wetland forms which are based on the tallest vegetation within the wetland, or by the form occupying the central (and often deepest) zone of the basin (for marshes and shallow open waters, only). Species composition or diversity varies with vegetation structure due to structure’s high correlation with hydrological processes, e.g. taller vegetation inhabiting areas with lower mean ground water levels. As a result vegetation diversity is generally greater in zones that exhibit more complex structure than those with a simple structure ([Kenkel 1987](#_ENREF_118)). Furthermore, wildlife ecological behaviors also relate to wetland vegetation structure as different vegetation species provide different food and shelter resources for different species.

Many wetlands, particularly those in boreal biomes where evapotranspiration often exceeds precipitation, are sensitive to changes in ambient temperatures. The resulting warming and drying trends affect wetland hydrology which in turn influences vegetation successive cycles and diversity ([Devito et al. 2005](#_ENREF_60), [Petrone et al. 2007](#_ENREF_192)). The implication of such sensitivities dictate that vegetation zones and often species composition within many wetland environments vary seasonally and/or annually; this can change the way in which individual wetlands are classified as a function of time.

Important environmental characteristics such as water levels, hydroperiod, acidity-alkalinity, salinity, and nutrient availability can be inferred from vegetation species indicators. However, the presence of a particular vegetation species or group of species does not offer definitive assistance to wetland classification, rather overall wetland vegetation species and structure should be considered ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)).

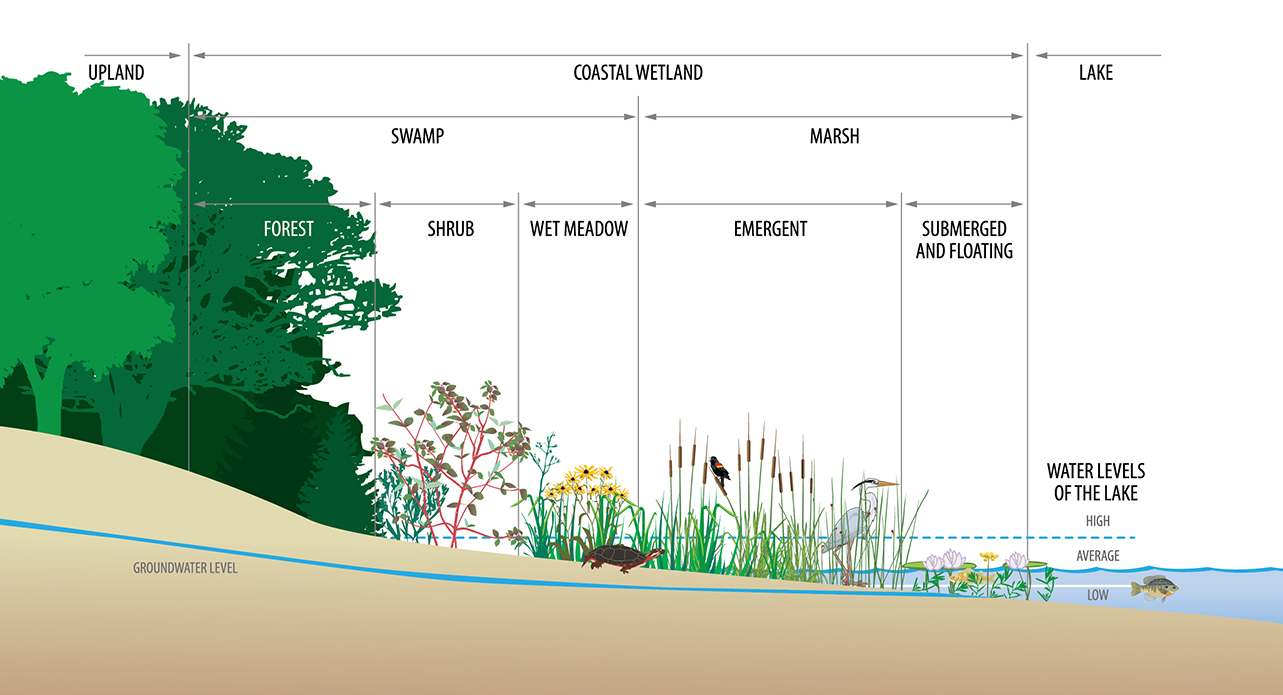


Figure 1 Schematic of vegetation zones of a typical mineral wetland indicating the transition from woody upland vegetation to hydrophytic sub-mergent/flaoting vegetation, based on descriptions from Stewart and Kantrud (1971, 1989).

Vegetation strata recognized by the AWCS are: wooded (tree species > 3 m tall), shrubby (woody specie ≤ 3 m tall), gramminoid, acquatic, and bare earth; within wooded forms the AWCS also recognizes species i.e. wooded-coniferous, -deciduous, or –mixedwood. These characteristics assist in characterizing wetland form and can vary across peatlands and mineral wetlands. Peatlands offer a fresh, slow-moving, relatively stable water table environment that suppport a well-established ground cover of bryophytes ([Vitt et al. 1993](#_ENREF_252), [National Wetlands Working Group 1997](#_ENREF_180)). Such characteristics promote anaerobic conditions that lower decomposition rates and thus maintain peat. As a result, during peat accumulation, nutrient deficiences become common as they are stored in a non-available form which enables specifically adapted vegetation to establish themselves within the wetland ([Mitsch et al. 2007](#_ENREF_170)).

In contrast to peatlands, vegetation distributed within mineral wetlands such as marshes and shallow open waters are more closely linked with water availability. In fact, vegetation communities organize themseleves as a function of decreasing water availability radially from the basin centre. Submersed and/or floating species occupy the deepest part of a shallow open water wetland basin (up to 2 m deep). A deep wetland vegetation zone surrounds the shallow open waters within the basin and exclusively supports graminoids such as rushes and cattails, which are tolerrant of prolonged flooding. Deep wetland zones are surrounded by a shallow wetland vegetation zone, often representing the transition from marsh to swamp, and supports vegetation adapted to seasonal flooding, primarily narrow-leaved graminoids ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)). Beyond Wetland medows exist beyond the shallow wetland zone which supports water tolerant graminoids and forbs that are adapted to periodic flooding or saturated conditions. Beyond these zones, shrubs and tall wooded vegetation mark the transition from swamp to upland.

These vegetation zones are highly dependent on water availability which may vary rapidly over time; the AWCS recognizes such temporal variability (as indexed from vegetation community) under wetland type. The enables the hydroperiod of a wetland to characterized, however, due to the nature of the hydrology associated with different wetland classes, only marshes and shallow open water wetlands are subject to this temporal classification (Table 3). Moreover, the AWCS does not recognize ephemeral wetlands, noted as class I under the [Stewart et al. (1971)](#_ENREF_224) regime.

Vegetation community should not be used exclusively as a means of determining wetland class in mineral wetlands as climatic cycles influence water level beahviours, which in turn influence vegetation communities ([Stewart et al. 1971](#_ENREF_224), [Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)). Such water level fluctuations facilitate decomposition and productivity, elemental cycling and biogeochemical reactions which in turn growing conditions and habitat for a mucg greater diversity and variability of vegetation species than would be found under stable conditions. As a result marsh and shallow open water wetlands may not exhibit the same wetland type between cycles or even year on year. Therefore wetland classification based on a temporal snapshot does not reflect its dynamic nature, multi-temporal information (multiple months or years) is often required to classify wetlands adequately ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)).

Table 3 Vegetation community zones and associated wetland hydroperiod definitions for marshes and shallow open water wetlands.

|  |  |  |
| --- | --- | --- |
| **Wetland type** | **Hydroperiod** | **Vegetation community zone1** |
| Temporary (II) | Surface water is present for a short period following a flooding event such as snowmelt or precipitation | Wet meadow |
| Seasonal (III) | Surface water is present throughout the majority of the growing season, but is often dry by summer’s end | Shallow wetland |
| Semi-permanent (IV) | Surface water is present almost year-round, excluding periods of drought | Deep wetland |
| Permanent (V) | Surface water is persists year-round | Open water |
| Intermittent (VI) | Alternates between saline open water and exposed bottom | Alkaline |
| 1Vegetation zone reflects that found in the deepest part of a wetland covering > 25% of the total area in the majority of years and can be used as an idicator of wetland type. Roman numerals are equivalent to wetland class as noted by [Stewart et al. (1971)](#_ENREF_224). | | |

## Classifying Wetlands by AWCS

The AWCS key presents a set of constraining features to identify wetland class, only one selection from which should be applied at a unique location. Once class has been identified, a second set of features is utilized to determine form, which may lead to a follow-up feature set to identify wetland type. Bogs and wooded swamps are not identifiable to type but only to form due limited information available for each within the province of Alberta. Furthermore, truly aquatic ecosystems are not included within the classification system, as has been the case historically ([National Wetlands Working Group 1997](#_ENREF_180), [Smith et al. 2007](#_ENREF_221)).

Often a site may conform to more than one broad wetland class, for example, marshes surrounded by shrubby swamp, or fens that support bog islands ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)). In such cases, all unique wetland classes should be identified and mapped where they meet suitable mapping specifications. However, in cases of unavoidable aggregation, multiple characteristics and attributes should be considered in order to determine the dominant wetland class; in some cases professional judgement may be required to overrule the key, particularly where hydrological disturbance is evident. For example, a drained fen that no longer has 40 cm of accumulated peat but exhibits many other fen characteristics should still be considered as a fen.

The full detail of the AWCS key is beyond the scope of the current document, for a detailed overview of how to identify wetlands under the AWCS rubric see [Alberta Environment and Sustainable Resource Development (2015)](#_ENREF_4) (pp. 11-32).

## Wetland Class Summary

The wealth of information for wetland classification within Canada and Alberta is extensive. As a result a synthesis of the five major wetland class definitions is outlined below within the context of the proposed study. Therefore, details regarding wetland form and type will be excluded.

**Bogs** are wetlands that have accumulated > 40 cm of peat overtime and are found almost solely in the boreal biome. They are often elevated above the surrounding local terrain and receive most water and nutrients from precipitation. Due to limited water and nutrient sources, bogs are the most nutrient-poor wetlands in Alberta and exhibit low vegetation diversity as a result. The water table is maintained at or just below the surface and remains stagnant.

**Fens**, like bogs also exhibit a minimum of 40 cm of peat and are almost only found in the boreal biome. However, they are influenced by the slow lateral movement of water overtime and are often called fen channels or green rivers. Fens obtain water from precipitation and runoff, where water acquired by the latter is nutrient-rich by virtue of contact with the mineral-rich land surface. This process typically makes (rich) fens more productive and biologically diverse than bogs, however, poor fens can exhibit vegetation characteristics that are analogous to bogs. The hydrology of a typical fen, like bogs, can be complex, where surface and sub-surface water interactions are common. Fens are the most extensive wetlands within the western boreal forest of Canada.

**Swamps** are predominantly a mineral based wetland group that occur across a variety of landscapes in Alberta, although peat accumulation (< 40 cm) can occur in some settings. Typical swamps have hummocky ground that promotes the localised pooling of water and tend to occur in the transition zones between uplands and other wetlands such as marshes and shallow open water. Swamps occur in treed and shrub forms near the shoreline areas of streams, lakes, and floodplains and exhibit seasonally fluctuating water levels sourced from precipitation, runoff, and flooding from adjacent wetlands. As a result of variable water sources, soil nutrients can vary from poor to rich dependent on vegetation species.

**Marshes** are exclusively mineral wetlands located in the transition zones between open water and shorelines. They occur with low frequency throughout the boreal biome, but are extremely prevalent throughout the prairies. Water levels fluctuate seasonally, sourced from precipitation, runoff, groundwater, and stream inflow. With such a wealth of water supply, marshes typically exhibit nutrient rich soils that support numerous emergent vegetation types; marshes are the most biologically diverse wetlands in Alberta.

**Shallow Open Water** wetlands exist between marshes and deep water bodies and are classified by exhibiting water depths no greater than 2 m. Floating and submerged vegetation can occur in more nutrient rich wetlands, but water depths are too great for emergent (marsh) vegetation to establish. Water levels are near stationary but may vary slightly throughout the season depending on source availability from precipitation, runoff, groundwater, and streams; in some cases a sufficient reduction in water level can expose mudflats.

# Alberta Wetland Mapping Specification

On the 23rd March, 2017, stakeholders within the Alberta wetland community convened to identify a wetland mapping specification to which any within province inventory should be standardised against. The meeting represented numerous perspectives from across the province including those of federal, provincial, and municipal governments, academics, and industry leaders. Key among attendees were those from the provincial government, who will lead the initiative to standardise the identification, classification, and delineation of wetlands across the province.

The need to standardise wetland inventories was originally identified by the Alberta wetland community within the AMWI as classifications are of varying vintage, quality, and resolution ([Government of Alberta 2017](#_ENREF_84)). In addition, concerns expressed by data contributors (such as municipalities), along with changes in policy and the need to continually assess policy effectiveness also drive the need for the establishment of provincially recognised standards ([Alberta NAWMP Partnership 2017](#_ENREF_5)). The establishment of such standards will not only allow policy assessments to evolve over time, but establish a standardised baseline of information important for user and contributor understanding, as well as providing baseline data for future monitoring investigations. Furthermore, the standardisation of, and improvement to current inventories, will allow for improved wetland management to meet Alberta Wetland Policy (AWP) goals, AWCS requirements, whilst also aligning with national standards outlined by the CWI.

It was noted that the standardisation of wetland inventory could not be static and needed to differ by biome (e.g. prairie/parkland or boreal/foothills), and possibly with the transition between biomes. As a result attendees separated in to biome specific breakout sessions where minimum wetland classification, minimum mapping unit (spatial resolution), boundary delineation, and completeness accuracy were discussion points. Discussions were guided by policy with respect to classification, as any classification needed to conform to the standards established by the AWCS and CWCS. Furthermore, discussions were also guided by data availability and cost effectiveness; expensive data were identified as a non-practical option where large geographical mapping is concerned. Therefore, discussions were predominantly focussed on the use of open source\very low cost data for determining key wetland characteristics.

## Prairie/Parkland biomes

Within prairie/parkland biomes mandatory classification objectives were to i) discriminate between wetland and upland with a minimum of 90 % accuracy, and ii) determine any wetland (if present) as treed or non-treed to one of the 5 major AWCS classes with a minimum accuracy of 80 %. The identification of AWCS forms and types may also be noted optionally (Figure 2). Classification accuracies are expected to be achieved at a minimum mapping unit (MMU) of 40 m (0.04 Ha), a MMU guided by the foreseeable use of open source Sentinal-2 imagery (10 m pixel). Consensus on a 40 m MMU was favoured over a 10 m single pixel as singular pixels may be a source of noise if analysed in isolation, whereas an aggregate 2 x 2 pixel grouping reduces this possibility. It was noted that a 0.04 Ha MMU should be sufficient to capture a minimum of 70 % of wetland features across the landscape. The boundary between upland and wetland within the prairie landscape is known to vary through time, as a result any boundary delineation would fast become outdated. Therefore, the identification of wetland boundaries will be determined at a high level by confirming the presence or absence of a wetland within a pixel via the classification process. Field acquired data should be utilised for a more detailed, high resolution boundary delineation.

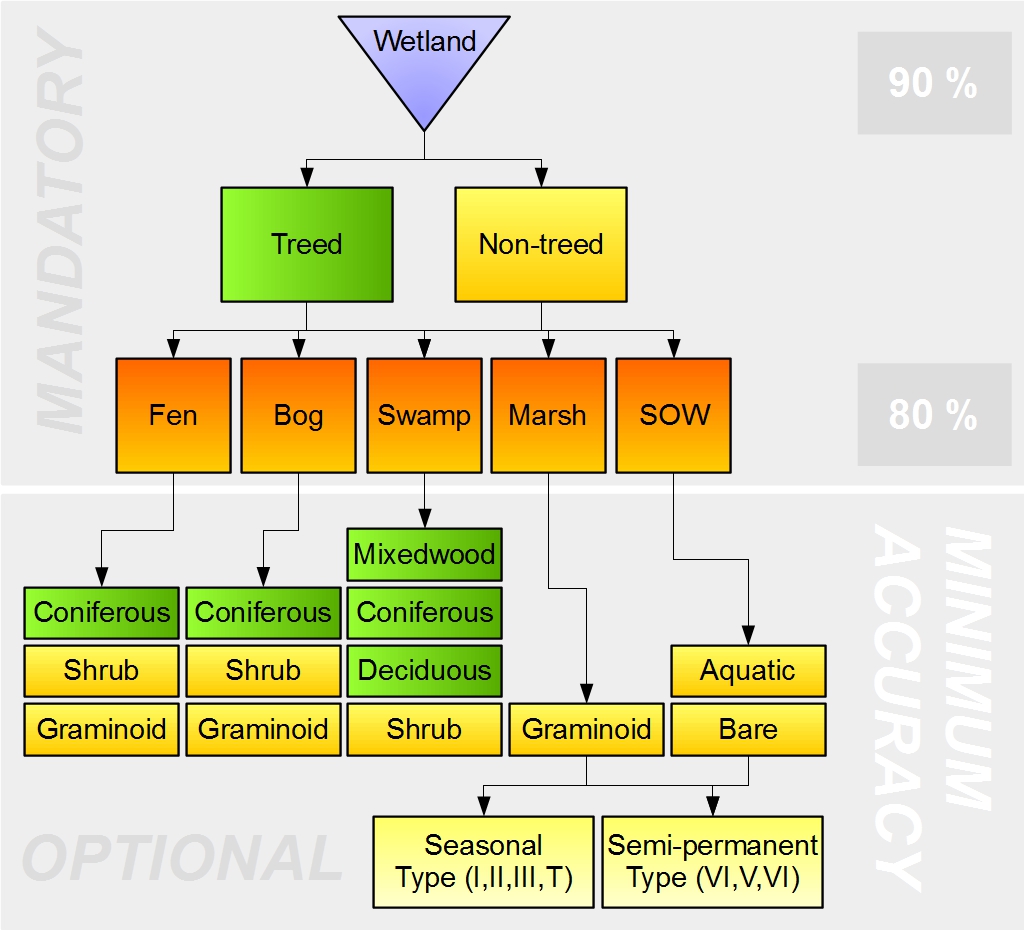


Figure 2 Hierarchal conceptual classification diagram for prairie/parkland biome wetlands. Note, SOW is shallow open water, and wetland types conform to those outlined by ([Stewart et al. 1971](#_ENREF_224)).

## Boreal/Foothills biomes

Across boreal biomes the distinction between upland and wetland was identified as the most important criteria, with a desired accuracy of 95 %. A second priority was identified as the ability to distinguish between peatlands and mineral wetlands down to the 5 major AWCS classes with 90 % accuracy. Beyond class boreal wetlands should be identified to one of a possible 13 AWCS forms with a 75 % accuracy for vegetated/treed classes, but at a 90 % accuracy for non-treed (open water) classes. The MMU at which classifications should be made also varies as a function of wetland class: 0.9 Ha for vegetated/treed classes, and 0.09 Ha (30 m pixel size) for open water classes. The former was driven by the already established use of Landsat open source imagery in boreal wetland classification within the Ducks Unlimited Canada (DUC) - Boreal Enhanced Wetland Classification (EWC) ([Ducks Unlimited Canada 2011](#_ENREF_64)). A similar consensus on boundary delineation was reached for the boreal biomes as was for the prairies i.e. wetland boundaries are challenging to map, therefore the confirmation of the presence or absence of a wetland will define its spatial boundary at the pixel level.

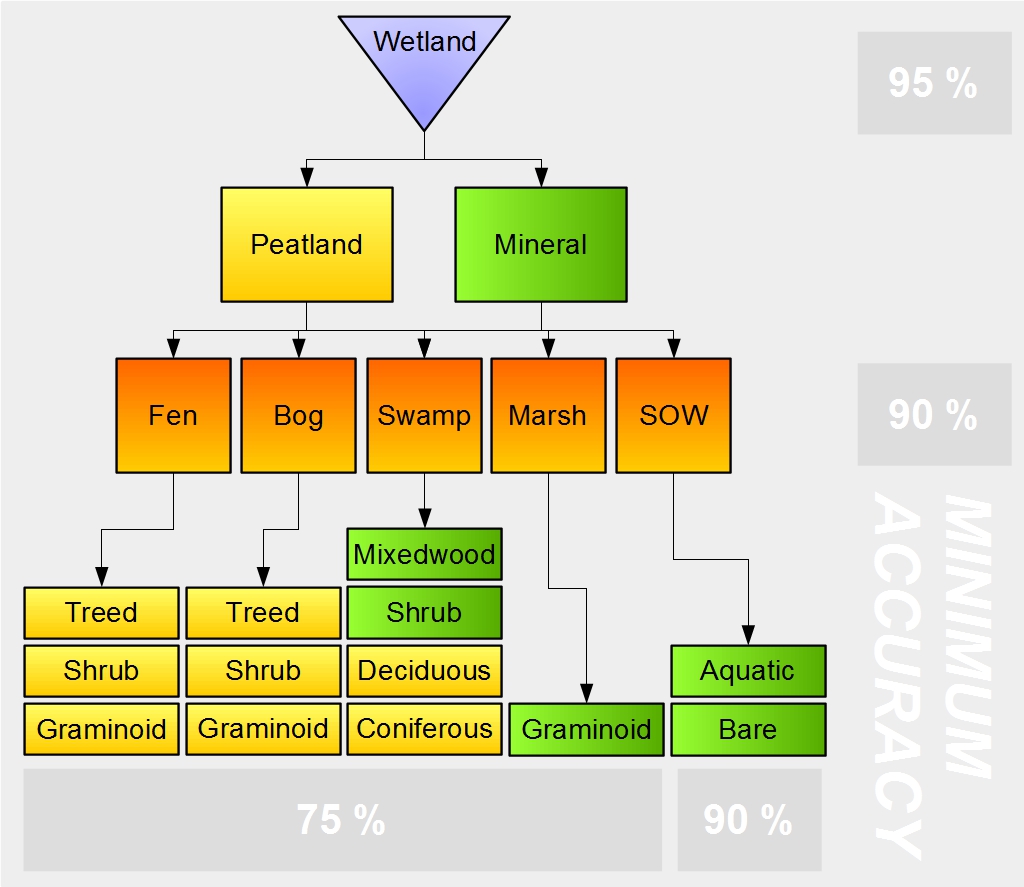


Figure 3 Hierarchal conceptual classification diagram for boreal/foothill biome wetlands. Note SOW is shallow open water.

# Wetland Classification: A Data Review

Numerous means exist for the purpose of classifying wetlands. Historically, wetland information and maps were compiled from in-situ field acquisitions ([Wilen et al. 1993](#_ENREF_261)). Aerial photography later pioneered larger-scale wetland delineation and mapping, which was then complimented by satellite multispectral optical photography ([Sethre et al. 2005](#_ENREF_217)). Both represented an important advance in the field of natural resource inventory and monitoring, including wetlands. More recently the use of other remote sensing technologies has become more prominent in large-scale wetland detection and mapping, primarily, light detection and ranging (LiDAR) and synthetic aperture radar (SAR). Both have demonstrable success in water detection and/or wetland classification when applied in isolation or as part of a data fusion workflow.

The current section will explore the use of each data source for the purpose of wetland classification within a remote sensing context and discuss the advantages and disadvantages associated with each.

## Field Acquisitions

Field acquired data is rightly deemed the most reliable source of wetland classification as it is capable of providing very high levels of detail, however, it is not without shortcomings. Field acquired data is often very costly, time consuming, provides logistical challenges in areas with limited access, and occasionally reflects the subjectivity of the technician that acquired the data ([Roller 1977](#_ENREF_203)).

Within Alberta, field technicians characterise wetlands by use of a rubric specific to the level of detail required for any particular project, starting in either a top-down or down-up approach to characterise wetland information. By being on site technicians can directly measure or infer information pertaining to soils, pH, vegetation parameters (species, density, height, etc.), hydrology, nutrient availability, depth to water table, and more; in appropriate boreal biomes the presence and depth of permafrost can also be determined ([Smith et al. 2007](#_ENREF_221)). In reference to the AWCS rubric for example, the determination between peat and mineral soil type is key for class discrimination. Whereas wetland hydrology and the identification of key vegetation species and general vegetation diversity are good indicators of wetland class and form. Measurements of water salinity (or conductivity) and pH provide key information for peatland types, whereas salinity measurements and the inference of water permanence are key in identifying mineral wetland types.

A key advantage of in-situ data collection is the ability to accurately delineate wetland boundaries. This is typically done by use of a hand held or differential global navigation satellite system (GNSS), which allows the measurement of wetland boundaries with sub-metre and sometimes sub-centimetre accuracy. However, GNSS are not always reliable in remote regions, especially in close proximity to tall vegetation where accuracies can decrease considerably due to signal attenuation. Due to the typically high accuracy at which information can be inferred from within the field, such data are typically utilised in numerous AWP evaluation criteria to determine wetland values and conservation practices.

## Optical Imagery

### Aerial

The classification of wetlands through remote sensing dates back to the 1970’s by use of aerial and satellite photography ([Work et al. 1974](#_ENREF_266), [Work et al. 1976](#_ENREF_265), [Roller 1977](#_ENREF_203)). Aerial photography was the predominant means of determining wetland inventory (and monitoring) as images provided a medium of hypothetically mapping wetlands from local to regional and national scales across a number of different wetland environments at relatively high spatial resolution ([Cowardin et al. 1979](#_ENREF_52), [Hood et al. 2008](#_ENREF_103), [Szantoi et al. 2013](#_ENREF_227)). Common analytical practice involved the manual delineation of the acquired photography, however, such a technique typically required specific knowledge and experience with respect to analyzing image tones and other subtleties ([Anderson et al. 1973](#_ENREF_10)). Moreover, even with high delineation accuracies (between 85 % and 90 %), field validation was still required to ensure adequate representation of the wetlands vegetation communities and other biological data ([Cowardin et al. 1981](#_ENREF_53)).

Whilst aerial photographs provide the fine spatial resolution desirable for mapping large and small wetland features they also exhibit numerous inherent limitations. Aerial photography of wetlands are time consuming and expensive to acquire and process, lack the ability to penetrate canopy structures (if present) , exhibit limited application for quantitative estimates of biophysical properties and their change over time, and are not cost-effective at very large scales (national inventories) ([Anderson et al. 1973](#_ENREF_10), [Taylor et al. 1995](#_ENREF_229), [Alberta NAWMP Partnership 2017](#_ENREF_5), [Mahoney et al. 2017](#_ENREF_154)). As a result, the use of aerial photography for wetland inventory has become less common ([Gallant 2015](#_ENREF_76)) despite the development of multispectral and hyperspectral capabilities of present day sensors, the utility of which are key in discriminating wetland (vegetation) features and biogeochemical features – ideal for determining wetland class. However, a number of aerial photography acquisition program within the context of wetland mapping are still conducted at present. Beyond the listed limitations, this decline in use is attributed to the advances of other technologies that are well suited to wetland identification and classification but exhibit much smaller time and monetary constraints.

### Satellite

With technological evolution came the emergence of satellite imagery ([Anderson et al. 1973](#_ENREF_10), [Wilen et al. 1995](#_ENREF_260)) which has become favored for wetland inventory applications over very large scales (>1000 km2) due to wide geographic coverage. Landsat has been the favored system for such applications due to its relatively high resolution (30 m), spectral diversity (up to 8 bands), it’s temporal archive depth (back to 1972), and freely available data (since 2008) ([Klemas 2013b](#_ENREF_124)). For small scale inventories the use of aerial photographs remain dominant as Landsat’s 30 m resolution is deemed too coarse for certain applications, whilst the cost associated with higher resolution imagery (i.e. Worldview at 0.5 m) is considerable.

Landsat has demonstrated success in mapping wetlands within coastal, prairie, and boreal ecozones with variable success ([Work et al. 1976](#_ENREF_265), [Sethre et al. 2005](#_ENREF_217), [Baker et al. 2006](#_ENREF_17), [Riordan et al. 2006](#_ENREF_202), [Sass et al. 2007](#_ENREF_212), [Frohn et al. 2009](#_ENREF_73)). Although in general, satellite sensors have been applied for mapping coastal wetlands more frequently than their inland counterparts ([Klemas 2013b](#_ENREF_124)). It is important to note that Landsat is one of many satellite imaging sensors that have been utilized in wetland mapping; SPOT (Satellite Pour l’Observation de la Terre) Worldview, Quickbird, and MODIS (Moderate Resolution Imaging Spectroradiometer) have also been successfully utilized ([Grenier et al. 2008](#_ENREF_87), [Laba et al. 2008](#_ENREF_131), [Carle et al. 2014](#_ENREF_38), [Hu et al. 2015](#_ENREF_107)). The utility of a particular satellite sensor is application dependent, for example, MODIS may be preferable for coastal purposes due to its larger spatial resolution, whereas SPOT will be better suited for the mapping of smaller basins.

Whilst some of the disadvantages of aerial photography apply to satellite imagery, technological advancements associated with the latter have enabled global data acquisitions across multiple wavebands at spatial resolutions approaching those of aerial photographs. This makes satellite imagery an attractive option for large-scale applications, especially those with spectral diversity. However, key disadvantages associated with satellite images surround the inability to control when acquisitions take place. As a result images can be cloud contaminated (variable with geographic location) which can render them unusable. Some locations (i.e. mountainous and/or tropical regions) can exhibit very few cloud free images throughout the year. Due to the inherent challenges associated with working with satellite imagery in isolation, the use of such data in conjunction with other sources in so called data fusion approaches ([Li et al. 2005](#_ENREF_139), [Bourgeau-Chavez et al. 2009](#_ENREF_24), [Maxa et al. 2009](#_ENREF_163), [Millard et al. 2013](#_ENREF_168)) has been adopted to improve classification accuracy ([Klemas 2013b](#_ENREF_124), [Government of Alberta 2017](#_ENREF_84)).

## Hyperspectral sensors

Hyperspectral imaging spectrometers are available in airborne and satellite forms and operate in much the same way as optical sensors (discussed above), but acquire data reflected and emitted in at least 20 narrow wavebands, typically between 400 nm to 2,500 nm. The large number of spectral signatures allows for detailed analysis to be performed on each pixel within an acquired image enabling the determination of atmospheric column constituents, surface compositions, and biogeochemical elements (ideal for wetland vegetation discrimination) ([Govender et al. 2007](#_ENREF_82), [Adam et al. 2010](#_ENREF_2)). The handling of hyperspectral data differs slightly to that of multispectral information, where the former typically occupies much larger volumes and is often conceptualized as a ‘data cube’ to accommodate the large number of available bands. This very fine spectral resolution enables distinct variations associated with different land cover types to be identified, including different vegetation characteristics ([Erwin 2008](#_ENREF_65)) that are important in aiding the identification of wetland class ([Adam et al. 2010](#_ENREF_2)). Such great data dimensionality has led to the development of different image processing techniques that focussed on spectral-unmixing, useful for better delineating wetland boundaries ([Hirano et al. 2003](#_ENREF_98)).

Airborne hyperspectral sensors such as NASA’s Airborne Visible and Infra-red Imaging Spectrometer (AVIRIS) sensor, and the Itres Inc. Compact Airborne Spectrographic Imager (CASI) have been utilized most commonly in wetland applications ([Government of Canada 1991](#_ENREF_85), [Hirano et al. 2003](#_ENREF_98), [Howard et al. 2017](#_ENREF_106)). However, the acquisition of such data remains expensive and can be expensive and time consuming to process due to the large data volumes typically acquired. With regards to the availability of satellite hyperspectral data, NASA’s Hyperion sensor onboard the Earth Observing (EO)-1 satellite offers limited spatial coverage (especially in norther regions), the European Space Agency’s PROBA sensor has somewhat restricted access, whereas Indian Microsatellite hyperspectral data is cost restricted. As a result, the use of hyperspectral imagery for wetland mapping remains somewhat uncommon relative to other forms of remote sensing, hence, the depth of literature to draw from regarding hyperspectral-based wetland mapping is limited.

## LiDAR

Light Detection And Ranging (LiDAR) is an active (emits its own energy source for later re-measurement) remote sensing technology, and has been acquired from onboard airborne and satellite platforms. LiDAR emits a laser pulse and records the reflected pulse from an intersected target on or near the Earth’s surface; thus, LiDAR data represents the location of the intersected targets in three dimensional space. Furthermore, the active nature of the technology allows for sub-surface penetration of some land surface features such as waterbodies and vegetation canopies ([Hopkinson et al. 2005](#_ENREF_104)).

Airborne LiDAR, commonly referred to as airborne laser scanning (ALS), is the most common form of the technology and has been applied across a multitude of disciplines within: forestry ([Means et al. 2000](#_ENREF_165), [Lefsky et al. 2002](#_ENREF_137)), bathymetry ([Ramsar 2015](#_ENREF_196)), and the cryosphere ([Crooks et al. 2011](#_ENREF_55)). In general, ALS data will be recorded in one of two formats: a discrete multiple return point cloud, or a continuous waveform profile. The former is a synthesized representation of the latter and has historically been more commonly utilized due to ease of processing, but typically does not impart as much knowledge about the intersected target as waveforms ([Sun et al. 2008](#_ENREF_226)). Waveform LiDAR data were historically recorded (from 2003 to 2009) by the Geoscience Laser Altimeter System (GLAS) previously onboard NASA’s Ice, Cloud, and land Elevation Satellite (ICESat) ([Zwally et al. 2002](#_ENREF_277), [Abshire et al. 2005](#_ENREF_1)). Data proved useful in biosphere and cryosphere applications ([Molijn et al. 2011](#_ENREF_173), [Los et al. 2012](#_ENREF_143), [Mahoney et al. 2016](#_ENREF_155)), but the spatially coarse nature (along orbital track separation of approximately 170 m, and between track separation of up to 10’s km) of the data were unsuitable for applications that required high data density’s ([Harding et al. 2005](#_ENREF_94)), including wetland mapping. Therefore any application of LiDAR for wetland mapping should be done so by the use of ALS, only.

Historically ALS pulses were (and still are) emitted and re-detected at the 1064 nm waveband in the near infra-red portion of the electromagnetic radiation (EMR) spectrum. This single channel has demonstrated ability for mapping terrain elevation and determining canopy structure attributes across a diversity of ecosystems, including a boreal wetland ecosystem in Alberta ([Hopkinson et al. 2005](#_ENREF_104)). In fact a number of studies have demonstrated the utility of ALS data for automatically delineating wetland edges, classes, and morphological and vegetation characteristics ([Zoltai et al. 1975](#_ENREF_276), [Nico et al. 2004](#_ENREF_181), [Quinton et al. 2009](#_ENREF_195), [Richardson et al. 2009](#_ENREF_199), [Richardson et al. 2010](#_ENREF_200), [Ducks Unlimited Canada 2011](#_ENREF_64), [Chasmer et al. 2016b](#_ENREF_41), [Langlois et al. 2017](#_ENREF_136)). In addition, the benefit of utilizing multiple LiDAR acquisitions to monitor wetland dynamics and extent over time have been noted ([Lang et al. 2009](#_ENREF_135)), however, such an approach is often cost-prohibitive ([Lang et al. 2013](#_ENREF_132), [Riley et al. 2017](#_ENREF_201)).

LiDAR provides a clear advantage over optical technologies as it characterizes the landscape in three dimensions, however, it lacks spectral diversity relative to most optical sensors. As a result, single channel (1064 nm) systems often get absorbed by water and are never re-detected by the sensor, unless emitted at or near nadir ([Brisco et al. 2011](#_ENREF_29)). However, even with such an inherent limitation, ALS is capable of discriminating numerous wetland vegetation types including those at the water surface.

Similarly to aerial photography, ALS data can be costly, are often spatially limited, and are not always practical to acquire at very large-scales. However, the unique capabilities of ALS (and LiDAR in general) have prompted multiple governments across the globe to invest in the acquisition of national ALS datasets ([Henderson et al. 2008](#_ENREF_95), [White et al. 2015](#_ENREF_256)). This also applies within Alberta, where a provincial ALS dataset was acquired between 2006 and 2015, although some access restrictions apply to the public. Given the Alberta-centric nature of the proposed project, the use of the provincial ALS data is encouraged.

## SAR

Synthetic Aperture Radar (SAR) is another form of active remote sensing technology, similar to LiDAR, but emits pulses in the microwave portion of the electromagnetic spectrum ([Henderson et al. 2008](#_ENREF_95)). SAR has greater lineage within the scientific community (first established in 1951 for terrain imaging) and has since been utilized to map environmental features such as, but not limited to, topographic relief and water bodies ([Nico et al. 2004](#_ENREF_181), [Brisco et al. 2011](#_ENREF_29), [White et al. 2015](#_ENREF_256)). SAR has been utilised in both airborne and spaceborne settings, where the latter is far more commonly used for broad-scale wetland mapping ([Touzi et al. 2007](#_ENREF_233), [Brisco et al. 2011](#_ENREF_29), [Martinis et al. 2015](#_ENREF_160)). Airborne acquisitions suffer the same impracticalities with respect to large-scale acquisitions as those associated with aerial imagery and ALS. Spaceborne data are favoured due to their broad coverage and capability to acquire ‘repeat pass’ data i.e. acquire data at the same location at different points in time. Data acquisitions are separated by discrete time intervals that vary by platform; for example, Radarsat-1 had a 24 day repeat cycle which is mimicked by Radarsat-2, but the upcoming Radarsat constellation mission (RCM) is anticipated to exhibit a 4 day repeat cycle ([Thompson 2015](#_ENREF_231)). From here on in, SAR is referred to in its spaceborne form only.

SAR backscatter are sensitive to dielectric properties (soil and moisture contents), and geometric (surface roughness) attributes of the illuminated surface ([Henderson et al. 2008](#_ENREF_95)), thus making the technology ideal for water detection. In particular, reflected backscatter amplitude sensitivity is function of sensor geometry, wavelength (or band), polarization, and illuminated target electric properties. Platforms are often configured with distinct geometry, wavelength, and polarization characteristics; where unique combinations of each are best suited to specific wetland identification and monitoring applications. A key advantage of SAR over optical sensors in particular (similar to LiDAR) is its ability to penetrate vegetation canopies ([Martinez et al. 2007](#_ENREF_159)). However, penetration can be limited depending on vegetation density parameters ([Miliaresis et al. 2009](#_ENREF_167)). The unique electromagnetic properties of SAR also means that it is capable of acquiring data in regions where cloud-cover and/or low light conditions may be otherwise be problematic for optical and thermal sensors.

Due to the relatively broad range of the microwave portion of the electromagnetic spectrum, SAR data have been acquired across a range of different wavelengths (or bands), including: X-, C-, and L-bands. Although more SAR bands exist, these bands have demonstrated most success in wetland applications to date ([Lucas et al. 2007](#_ENREF_146), [Wdowinski et al. 2008b](#_ENREF_254), [Hong et al. 2010b](#_ENREF_102), [Brisco et al. 2011](#_ENREF_29), [Merchant et al. 2017](#_ENREF_166)). Certain bands are favoured for use in certain environments, for example, longer wavelengths are often utilized in regions dominated by forest land cover types as they can more readily penetrate the canopy than their shorter wavelength counterparts ([Hall 1996](#_ENREF_92), [Ouchi 2013](#_ENREF_186), [Brisco et al. 2015](#_ENREF_30), [Manavalan et al. 2017](#_ENREF_156)). It is for this reason that L-band SAR is often favoured for work in boreal biomes where various vegetation types and densities are present, however, it must be noted that C-band data have also demonstrated success in this region ([White et al. 2015](#_ENREF_256), [Merchant et al. 2017](#_ENREF_166)).

For any incident SAR signal there are three major scattering mechanisms, these are:

* Surface – specular or diffuse scattering of incident radiation from the water surface where scattering type is dependent on wavelength and surface roughness.
* Double-bounce – the subsequent imaging of 2 surfaces, that is, the incident radiation is reflected twice before reception at the detector
* Volumetric – a diffuse scattering mechanism that occurs as the incident radiation interacts with multiple targets (> 2)

The first mechanism(s) are common from open water surfaces, where specular scattering occurs over near still water (i.e. incident radiation wavelength >> water roughness features), whereas the latter becomes more common as the water surface is increasingly disturbed (i.e. surface roughness is promoted) typically by wind ([Marechal et al. 2012](#_ENREF_157), [Kuenzer et al. 2013](#_ENREF_130), [Bolanos et al. 2016](#_ENREF_22)). The first backscatter mechanism results in a weak to non-existent return signal from water surfaces, that is, water surfaces appear darker than other terrestrial surfaces ([Klemas 2013a](#_ENREF_123)). However, it should be noted that specular scattering often exhibits high intensities, but radiation is reflected away from the detector. Diffuse scattering often produces a bright signal which can lead to water surfaces being misidentified ([White et al. 2015](#_ENREF_256)). Double-bounce scattering is common over wetlands with emergent vegetation as incident radiation is first specularly reflected from the water surface and is subsequently brightly reflected from nearby vegetation ([Dobson et al. 1992](#_ENREF_62), [Brisco et al. 2011](#_ENREF_29), [Klemas 2013a](#_ENREF_123), [Mahdianpari et al. 2017](#_ENREF_153)). In caution to this mechanism the use of small incidence angles has been noted to enhance the ability to map sub-canopy hydrological features through greater canopy penetration, thus probabilistically reducing the prominence of double-bounce scattering ([Hess et al. 1990](#_ENREF_97), [Crevier et al. 1996](#_ENREF_54), [Adam et al. 1998](#_ENREF_3), [Lang et al. 2008b](#_ENREF_134)). Volumetric scattering typically occurs within forest canopies as the within canopy structure presents a highly heterogeneous surface to scatter incident radiation multiple times ([Brisco et al. 2011](#_ENREF_29), [Schmitt et al. 2013](#_ENREF_214)).

### Polarimetry

The high utility of SAR data for water detection is in part due to its ability to polarimetrically discriminate signal information, where the definition of polarization follows the strict physics definition (i.e. restricting the transverse vibration of an electromagnetic wave to one direction). The most common SAR polarizations are ‘horizontal’ (i.e. 0° from the horizontal plane perpendicular to the direction of travel of the emitted radiation) and ‘vertical’ (i.e. 90° from the horizontal plane perpendicular to radiation travel; orthogonal to horizontal plane) ([Boerner et al. 1998](#_ENREF_21)). The horizontal (H) and vertical (V) signal components are recorded by unique antenna components and stored in isolation by the systems electronics. A SAR system with H and V polarizations can provide the following data channels:

* HH – horizontal transmission and detection
* VV – vertical transmission and detection
* HV – horizontal transmission and vertical detection
* VH – vertical transmission and horizontal detection

Both HH and VV are known as like-polarized as the transmitted and detected polarizations are identical, whereas HV and VH are referred to as cross-polarized as the transmitted and detected polarizations are orthogonal to each other.

The polarization complexity of recorded SAR data varies as a function of how many data channels are stored. Depending on the SAR system electronics complexity either single, dual, or four polarizations can be stored. For example, for a SAR system with H and V capabilities the different levels of polarization complexity available are ([White et al. 2015](#_ENREF_256)):

* Single polarized – HH or VV or HV or VH
* Dual polarized – HH and HV, VV and VH, or HH and VV
* Four polarizations – HH, VV, HV, and VH

Some SAR systems are capable of recording these polarizations and the associated phase difference between channels and magnitudes, however, such capabilities are limited to quadrature (four) polarized (i.e. polarimetric) systems and dual-polarized systems.

Single polarization (single-pol) SAR data have demonstrated success in the mapping of water body extents ([Oberstadler et al. 1997](#_ENREF_184), [Horritt et al. 2001](#_ENREF_105), [Townsend 2001](#_ENREF_235), [Töyrä et al. 2001](#_ENREF_237), [Karvonen et al. 2005](#_ENREF_116), [Li et al. 2005](#_ENREF_139), [Kuang et al. 2011](#_ENREF_128), [White et al. 2015](#_ENREF_256), [Wilusz et al. 2017](#_ENREF_262)). However, such data exhibit relatively poor potential for the mapping of wetland vegetation characteristics when utilized in isolation ([Touzi et al. 2007](#_ENREF_233)). Past approaches often employed satellite optical imagery to supplement single-pol SAR data for such purposes ([Töyrä et al. 2001](#_ENREF_237), [Li et al. 2005](#_ENREF_139)), illustrating early fusion analyses. However, such data have been noted to achieve increased success in detecting beneath canopy water bodies during leaf-off conditions ([Ustin et al. 1991](#_ENREF_243)).

Of available single polarizations HH and/or HV are best suited to open water mapping ([White et al. 2014](#_ENREF_257)). HH polarization is often the best choice for this application as it is not so sensitive to small vertical displacements caused by waves. By this capability, HH provides greater differences in backscatter between land and water surfaces ([Hess et al. 1995](#_ENREF_96), [Bourgeau-Chavez et al. 2001](#_ENREF_23)). HV provides better water detection when high wind conditions or surface roughness is present as there is less response in the backscatter compared to HH ([Scheuchl et al. 2004](#_ENREF_213), [Vachon et al. 2011](#_ENREF_244), [White et al. 2014](#_ENREF_257)).

The use of dual or quad polarized data provide far superior results for mapping flooded vegetation with respect to single-pol data ([White et al. 2015](#_ENREF_256)). In fact, both dual- and quad-pol SAR have been employed for mapping open water and flooded vegetation ([Pope et al. 1997](#_ENREF_194), [Townsend 2002](#_ENREF_236), [Touzi et al. 2004](#_ENREF_232), [Brisco et al. 2011](#_ENREF_29), [Lopez-Sanchez et al. 2011](#_ENREF_142), [Hong et al. 2015](#_ENREF_100), [Amani et al. 2017a](#_ENREF_8), [Buono et al. 2017](#_ENREF_35), [Mahdavi et al. 2017](#_ENREF_152), [Manavalan et al. 2017](#_ENREF_156), [Merchant et al. 2017](#_ENREF_166), [Pham-Duc et al. 2017](#_ENREF_193)), both of which are important for wetland classification ([Gallant 2015](#_ENREF_76), [White et al. 2015](#_ENREF_256), [Guo et al. 2017](#_ENREF_90)). Multi-pol data are common of the latest satellite SAR missions ([Ouchi 2013](#_ENREF_186)), whereas single-pol were utilized more commonly in early SAR systems but have since been recognized as somewhat limited with respect to wetland classification.

### Decompositions

Multi-pol SAR data have become increasingly popular as, unlike single-pol data, it provides backscatter intensity information from multiple channels and maintains phase information, thus capturing target polarization diversity ([Touzi et al. 2004](#_ENREF_232), [Brisco et al. 2008](#_ENREF_32)). This polarization diversity can be decomposed to reveal information that was not otherwise apparent ([Touzi et al. 2004](#_ENREF_232), [Brisco et al. 2011](#_ENREF_29), [White et al. 2015](#_ENREF_256)). Such decompositions effectively give rise to scattering mechanism information by counting the number of times the phase difference changes (once per intersected target) when in transit between emission and detection. This decomposition of the scattering matrix from a given target allows the determination of the physical medium (i.e. vegetation, open water, etc.) that induced the determined scattering mechanism. Target scattering decomposition has become common practice when attempting to determine natural target geophysical parameters from polarimetric SAR ([Cloude et al. 1996](#_ENREF_46), [Hajnsek et al. 2003](#_ENREF_91), [Touzi et al. 2004](#_ENREF_232), [Merchant et al. 2017](#_ENREF_166)).

Some common decomposition methods are the Cloude-Pottier ([Cloude et al. 1997](#_ENREF_47)), the Freeman-Durden ([Freeman et al. 1998](#_ENREF_71)), the Pauli ([Cloude et al. 1996](#_ENREF_46)), the Van Zyl ([van Zyl 1989](#_ENREF_247)), the Yamaguchi ([Yamaguchi et al. 2005](#_ENREF_269), [Yamaguchi et al. 2011](#_ENREF_270)), the Touzi ([Touzi et al. 2007](#_ENREF_233)), and the Hong and Wdowinski ([Hong et al. 2015](#_ENREF_100)) decomposition methods, as well as determining texture attributes ([Franklin et al. 2017](#_ENREF_70)). Such methods have become widely researched and most are now commonly implemented in commercial software which are readily available to the scientific community ([Brisco et al. 2013](#_ENREF_31), [Merchant et al. 2017](#_ENREF_166)). A number of these methods have demonstrated success in the identification and characterization of wetland characteristics. For example, the Freeman-Durden approach has success in delineating wetland boundaries through the utility of double-bounce scattering to identify flooded vegetation ([Brisco et al. 2011](#_ENREF_29), [Gallant et al. 2014](#_ENREF_77)). The Cloude-Pottier, Yamaguchi, and Hong and Wdowinski decompositions have demonstrated capability in distinguishing wetland vegetation types and water ([Brisco et al. 2011](#_ENREF_29), [Hong et al. 2015](#_ENREF_100)). Textural products have been noted to be key in distinguishing forest and emergent vegetation ([Clewley et al. 2015](#_ENREF_44)). The use of such SAR-derived products have become common place in wetland characterisation, where the effectiveness of each varies as a function of the SAR sensor (wavelength, look-angle, etc.), wetland location, and the desired classification detail (i.e. wetland class, or specific vegetation functional type, etc.) ([Brisco et al. 2011](#_ENREF_29), [Gallant et al. 2014](#_ENREF_77), [Merchant et al. 2017](#_ENREF_166)).

### Interferometry

SAR interferometry (InSAR) is a technique for the extraction and mapping of physical terrestrial properties. Briefly, InSAR combines information from complex SAR images recorded at different locations or times with slightly different look-angles ([Cloude et al. 1998](#_ENREF_45)), where the resulting interferogram allows the identification of small differences in range, at sub-wavelength scales, for corresponding image pairs ([Madsen et al. 1998](#_ENREF_151)).

InSAR can be configured in one of two ways: single-pass, or repeat-pass. A single-pass approach utilizes two antenna from the same platform and are best for terrain mapping, whereas repeat-pass configurations image the same target by use of the same antenna at two or more points in time. Of key importance is the concept of the complex correlation coefficient between the multiple SAR images. This allows the derivation of interferometric phase, defined as the phase of the complex correlation coefficient, which in its two dimensional form is known as the interferogram. Coherence is another important parameter which informs on the amplitude of the complex correlation coefficient between the multiple SAR images and is used to inform on the quality of the interferogram. For a more in-depth explanation of InSAR see [Madsen et al. (1998)](#_ENREF_151).

Initially, the primary application of InSAR was topographic information generation and terrain deformation mapping ([Moreira et al. 2004](#_ENREF_176), [Krieger et al. 2007](#_ENREF_127)). However, InSAR has also been utilized for mapping water surface dynamics via X- ([Wdowinski et al. 2008a](#_ENREF_253), [Hong et al. 2010b](#_ENREF_102)), C- ([Alsdorf et al. 2001](#_ENREF_7), [Gondwe et al. 2010](#_ENREF_81), [Hong et al. 2010a](#_ENREF_101), [Brisco et al. 2017](#_ENREF_28)), and L-band ([Wdowinski et al. 2008b](#_ENREF_254), [Chul Jung et al. 2010](#_ENREF_43), [Rebelo 2010](#_ENREF_198)) sensors. Such studies concluded that InSAR is a useful tool for monitoring wetland water levels over long time periods (multiple years) ([Wdowinski et al. 2008b](#_ENREF_254)). The successful utility of X-band (TerraSAR-X) InSAR was somewhat unexpected for woody wetlands, as the shorter wavelength may be expected to volumetrically scatter within the canopy, however, it has demonstrated success in the mangroves of Florida ([Hong et al. 2010b](#_ENREF_102)). It has been suggested that TerrasSAR-X (TSX) data should not be utilized in the same way as C- and L-band data because of limitations associated with its small swath-widths (10-30 km) and potential interferogram fringe saturation over areas with large change gradients; TSX is suggested to be better suited to localized applications that require detailed information retrieval ([Hong et al. 2010b](#_ENREF_102)).

The effectiveness of InSAR for mapping wetland dynamics varies as a function of the target, that is, woody vegetation tends to exhibit greatest coherence between image pairs (due to increased double-bounce scattering) whereas herbaceous marshes tend to offer degraded coherence as they experience major growth and change during the growing season ([Wdowinski et al. 2008b](#_ENREF_254), [Brisco et al. 2017](#_ENREF_28)). Coherence values tend to be greater for longer wavelength (L-band) sensors with respect to other shorter wavelength (X- and C-band) sensors, especially for woody wetlands where the former is capable of deeper canopy penetration ([Kim et al. 2009](#_ENREF_120)). Furthermore, InSAR coherence varies as a function of temporal baseline, that is, with increasing time between repeat-passes a degradation in coherence is expected ([Chul Jung et al. 2010](#_ENREF_43)). However, seasonal variations must also be considered as the condition of a wetland may appear similar when repeat-passes are aligned with the periodicity of seasonal variation. Based on extensive coherence analysis it is suggested that HH-polarized, small incidence angle observations are most suitable for wetland InSAR mapping ([Kim et al. 2013](#_ENREF_121)). It is important to note that whilst the majority of InSAR studies have been conducted over a variety of wetlands, including tropical wetlands in the Amazon, Louisiana swamps, and mangroves and sawgrass marshes of the Everglades ([Alsdorf et al. 2001](#_ENREF_7), [Lu et al. 2008](#_ENREF_145), [Wdowinski et al. 2008b](#_ENREF_254), [Kim et al. 2009](#_ENREF_120), [Hong et al. 2010a](#_ENREF_101)), [Brisco et al. (2017)](#_ENREF_28) provides a Canadian context for monitoring extensive areas of small wetlands. Moreover, they concluded that coherence measures were acceptable in spring and summer months, but proved more challenging during cold winter conditions where snow and ice presences is common.

### Hydroperiod

Hydroperiod effectively records the frequency that spatially explicit regions are identified as wetland classes over a given time period, it is important for classifying mineral wetland type under the AWCS ([Alberta Environment and Sustainable Resource Development 2015](#_ENREF_4)), and remains an active area of research. Although numerous studies have utilized multi-temporal SAR data, few have explicitly investigated hydroperiod regimes. However, some recent studies have demonstrated that hydroperiod mapping is possible by use of SAR over both intra- and inter-annual timelines ([Bourgeau-Chavez et al. 2005](#_ENREF_25), [Lang et al. 2008a](#_ENREF_133), [Marechal et al. 2012](#_ENREF_157), [Gallant et al. 2014](#_ENREF_77), [Díaz-Delgado et al. 2016](#_ENREF_61)). In addition, the use of hydroperiod analysis can identify the areal change in wetlands with differing water permanence ([Montgomery et al. Submitted](#_ENREF_174)), and the change in wetland area as a whole ([Pham-Duc et al. 2017](#_ENREF_193), [Wilusz et al. 2017](#_ENREF_262)). Hydroperiod can be calculated on almost any temporal basis including monthly ([Gallant et al. 2014](#_ENREF_77), [Montgomery et al. Submitted](#_ENREF_174)), conforming to the wetland classification criteria of [Stewart et al. (1971)](#_ENREF_224) whose water permanence criteria inform AWCS standards. Such analyses are simply performed by an equals-frequency analysis (or variant of) and relies on exact geographic locations being understood, with little uncertainty. The introduction of spatial uncertainty between temporally different SAR images may lead to incorrect locations of overlap, which in turn may lead to incorrect frequency analysis.

Of course hydroperiod analysis via remote sensing is not exclusive to SAR data, it has also been realized by exploiting the long archive of satellite optical imagery ([Jin et al. 2017](#_ENREF_112)). Monitoring hydroperiod by use of other technologies (i.e. LiDAR or hyperspectral imagery) is challenging as acquiring repeat-pass data is cost-prohibitive ([Lang et al. 2009](#_ENREF_135), [Lang et al. 2013](#_ENREF_132)), especially as such technologies are only practical for such wetland applications in their airborne configurations. However, a recent study inferred hydroperiod regimes for small depressional wetlands via a single temporal snap-shot LiDAR acquisition ([Riley et al. 2017](#_ENREF_201)), an alternate approach to inference via repeat data acquisitions ([Lang et al. 2009](#_ENREF_135)).

# Future Wetland Remote Sensing

## Radarsat Constellation Mission

The Radarsat Constellation Mission (RCM) is an initiative lead by the Canadian space Agency (CSA) under the Radarsat project and will serve as the successor to Radarsat-1 and -2 missions. RCM will consist of three Earth observation spacecrafts, each possessing a C-band SAR, providing data continuity to existing Radarsat users ([Thompson 2010](#_ENREF_230)). The first satellite of the RCM was initially expected to launch in 2014 followed by its two companions between 2015 and 2016 ([Flett et al. 2009](#_ENREF_69), [Séguin et al. 2009](#_ENREF_216), [Colinas et al. 2010](#_ENREF_48)), however, a number of set-backs have pushed the expected launch date to 2018 ([White et al. 2017](#_ENREF_258)). The RCM is expected to offer a variety of imaging modes from 100 m low resolutions to very high 3 m resolutions via Spotlight mode; for a full list of RCM imaging modes see [Thompson (2015)](#_ENREF_231). Data will primarily be acquired through dual-polarization compact polarimetry, which will realize many (but not all) of the benefits of quad-polarized data without its restricted swath width ([Thompson 2010](#_ENREF_230)); RCM is expected to offer swath-widths up 350 km in some imaging modes. RCM compact polarimetry is achieved by simultaneous transmissions from the H and V antennas therefore allowing the transmission of electromagnetic radiation with circular polarization, and reception of H and V polarization ([Thompson 2015](#_ENREF_231)). RCM is expected to provide a coherent change detection (CCD) period of 4 days (considering all 3 spacecrafts) opposed to 24 day CCD periods associated with previous missions in the Radarsat programme.

These evolutions within the Radarsat programme have been mandated by the Canadian Government so as to support the following primary mission objectives: maritime surveillance, disaster management, and ecosystem monitoring ([Séguin et al. 2009](#_ENREF_216), [Thompson 2010](#_ENREF_230)). Within these objectives the increased coverage of a constellation mission is key for meeting Canadian government requirements surrounding the following ([Thompson 2015](#_ENREF_231)):

* Daily ship detection within priority zones up to 1,200 nautical miles from the Canadian coastline
* Daily monitoring of ice within Canadian Ice Service areas of interest
* Daily coverage of key maritime areas for the tracking of oil polluters
* Weekly land cover analysis
* Global daily revisits

To date, a number of studies have utilized simulated RCM data from Radasat-2 quad-pol data to assess its potential for meeting these requirements. For example, [Gierull et al. (2012)](#_ENREF_79), [Denbina et al. (2014)](#_ENREF_59), and [Atteia et al. (2015)](#_ENREF_13) indicated that RCM is expected to successfully identify maritime objects such as ships and icebergs, and provide enhanced object tracking. [Samsonov et al. (2015)](#_ENREF_210) successfully demonstrated RCM’s capability to note surface deformations in Alberta’s oil sands region for potential disaster mitigation. Whereas, [Dabboor et al. (2014)](#_ENREF_56) and [Arkett et al. (2015)](#_ENREF_11) presented results on the classification of sea ice, and identifying oil spills in maritime environments. In a comprehensive investigation, Charbonneau (2010) showcased the potential for compact polarimetry within the context of a number of Canadian thematic issues. Simulated data (based on airborne and Radarsat-2 quad-pol SAR) demonstrated high potential for crop classification purposes, ship detection, and sea ice mapping; ship detection results exceeded those achieved by quad-pol data. However, of greatest importance within the context of the current project, [White et al. (2017)](#_ENREF_258) investigated RCM capabilities for separating peatlands, concluding that little difference was notable between the use of RCM data and quad-pol Radarsat-2 data.

Based on the available literature and should future RCM observations match simulated data, RCM is expected to establish itself as a strong candidate for wetland monitoring and its use for such purposes is encouraged, especially as data are anticipated to be open-access.

## NASA-ISRO Synthetic Aperture Radar

The NASA-ISRO Synthetic Aperture Radar (NISAR) mission is a joint venture between NASA and the Indian Space Research Organization (ISRO) that is currently scheduled for launch in 2020 ([NISAR community 2014](#_ENREF_183), [NASA 2017](#_ENREF_179)). NISAR will exist as a single spacecraft that will house both L- and S- band SAR sensors with the purpose of observing the Earth’s surface ([Rosen et al. 2013](#_ENREF_204), [Rosen et al. 2014](#_ENREF_206)). Both sensors are expected to provide wide-swath (> 240 km) data with spatial resolutions between 2 m and 6m for the S-band sensor, and between 2 m and 30 m for the L-band sensor ([Rosen et al. 2015](#_ENREF_205)). The shorter S-band data will offer single- dual- and compact-polarizations as well as quasi quad-pol data (i.e. HH/HV and VH/VV), however, L-band data will be available in single-, dual-, compact-, and quad-polarizations ([Space Application Centre 2015](#_ENREF_223)). Both sensors will be based on the same platform, which is expected to offer a 12-day sampling and repeat orbit ([NISAR community 2014](#_ENREF_183)).

A number of applications have been conceived within the NISAR mission framework to satisfy science requirements of the US and India. Some such applications include: ecosystem monitoring, surface deformation, cryosphere, ocean processes, and other disasters ([Rosen et al. 2013](#_ENREF_204)). For a full list of potential science applications see ([Rosen et al. 2013](#_ENREF_204)). A number of white papers have been published through NASA to showcase the potential of NISAR’s societal benefits, including but not limited to: Fire management, coastal land loss, flood forecasting, forest resources, ice monitoring, and oil spills. A full list of application white papers are available online (https://nisar.jpl.nasa.gov/applications/#). Of key importance is NISAR’s expected capability surrounding wetland mapping applications, including wetland classification and monitoring hydroperiod regimes. Although no recorded or simulated NISAR data are currently available, the current NISAR baseline plan responsible for the characterization of spatial coverage, sensor frequency/polarization modes, resolution, and data latency is already proposed to meet the technical requirements for a variety of wetland mapping applications ([NISAR community 2014](#_ENREF_183)). In fact, it is expected that the use of S-band SAR in conjunction with L-band data will enhance wetland classification accuracies ([NISAR community 2014](#_ENREF_183)).

Although the NISAR mission is at a far less mature stage than that of RCM, the (albeit limited) literature regarding its prospects appear promising regarding wetland applications. Should NISAR meet expectations its utility in future wetland mapping/monitoring applications will likely be of great significance. It is unlikely that NISAR data will feature in the current project due to its 2020 launch date, however, given data will be open-access its use is encouraged in future where possible.

# Advantages & limitations of wetland remote sensing

Although remote sensing provides a highly attractive alternative for wetland mapping, generalized advantages and limitations apply, that is, the specific application of remote sensing for wetland mapping is inherently challenging. This section discusses some globally applicable advantages and limitations to those mentioned above.

In some scenarios, remote sensing offers an alternative approach to wetland mapping over field acquisitions; where field levels of accuracy are required, remote sensing offers complementary data ideal for scaling relevant information. Furthermore, remote sensing can be constrained by a single logical or statistical criteria that mitigates subjectivity and the introduction of human error as well as providing the cost-effective, timely mapping of wetland inventories at large-scales whilst remaining indifferent to areas of limited accessibility. Remote sensing data are often free or inexpensive to buy, however, in some cases data acquisition costs can be significant. In addition, data interpretation can in some instances be more expensive and more time-consuming to process than to acquire and process field data. However, these scenarios are often limited to poorly designed workflows and/or by the choice of ill-suited remote sensing data. Nonetheless, it is important to carefully identify and implement the most suitable data in order to maximize cost effectiveness.

The spatial resolution of remotely sensed data can hinder wetland detection and subsequent analyses depending on the level of detail required. For example, the utility of a sensor is limited for the detection of sufficiently small wetlands (≤ sensor spatial resolution) or subpixel wetlands. This has been noted for Landsat applications within the prairie/foothills biome, where inconsistencies were noted not only for wetlands smaller than a single pixel but also for those as large as 0.9 ha (9 pixels), and very narrow ponds ([Ozesmi et al. 2002](#_ENREF_187), [Sethre et al. 2005](#_ENREF_217)). This makes Landsat problematic for wetland mapping in the PPR as approximately 83% of all wetlands are estimated to be ≤ 0.8 ha ([Johnson et al. 1997](#_ENREF_113)). Should the use of remote sensing be successful within the PPR as well as the across the boreal regions, the use of suitable data and analysis techniques will be paramount.

In addition to spatial limitations, temporal restrictions can also be prohibitive. That is, in popular fusion approaches, data from multiple sensors often exhibit misaligned acquisition dates as each sensor follows a predefined schedule for data acquisition; this is certainly true for most spaceborne sensor. This temporal disparity means that data from each sensor may represent different conditions, the challenge of which increases in magnitude with increasing temporal disparity. This issue often has little impact for data acquisitions separated by only a few days, especially during a stable part of the wetland season. However, temporally disparate data exhibit potential to propagate high uncertainties, particularly if a sudden change is experienced through external mechanisms (e.g. 100 year precipitation event).

It is known that differentiating Canadian and Albertan wetland classes can prove challenging even in the field as some classes share key distinguishing characteristics. The difficulty of this challenge is propagated to the application of remote sensing data, and is often amplified. The difficulty of distinguishing wetland classes varies dependant on biome; the boreal biome is more diverse and wetland rich and typically possess more of a challenge. A well-documented challenge is the differentiation of bogs and fens by remotely sensed data ([Chasmer et al. 2014](#_ENREF_42), [Touzi et al. 2016](#_ENREF_234)) as both classes are characterized by a variety of overlapping characteristics. Regardless of these inherent challenges the differentiation of each of the 5 (AWCS) wetland classes has been demonstrated with remote sensing, however, end users should be aware that the greatest confusion between classifications will occur for bogs and fens.

# Wetland Classification: A Methodological Review

A number of methodologies exist for the classification of wetlands by remote sensing data, these typically vary as a function of the type of data utilized (i.e. SAR, LiDAR, imagery, etc.). Here, data analysis techniques are reviewed with respect to each data type. The details associated with each technique are explored in separate sections so as to identify their advantages and limitations within the context of wetland mapping. Moreover, the potential for integrating each data type to exploit the strengths of each are also analyzed and discussed.

## Optical Imagery

Optical images acquired from space require pre-processing so as to radiometrically and geometrically correct the acquired data. Radiometric corrections remove the effects of atmospheric absorption, whereas geometric corrections account for satellite and sensor look geometries with respect to the sensor target. Performing such corrections result in images representing surface reflectance information. In most cases satellite optical imagery (such as Landsat) can be acquired in an already pre-processed format, alternatively pre-processing algorithms can be applied to any acquired raw data ([Masek et al. 2006](#_ENREF_161), [Vermote et al. 2016](#_ENREF_249)). It is these ore-processed images that are then interrogated for water signatures.

In multiple- and single-band optical imagery water is characterized by its low reflectance values, especially in the near-infrared (NIR) wavelengths. It is because of this reason that some land cover classification studies utilize NIR bands to distinguish water from land, whereas other studies make use of band ratios to identify water bodies ([McFeeters 1996](#_ENREF_164), [Lu et al. 2011](#_ENREF_144), [Jawak et al. 2013](#_ENREF_111)). Some previously investigated ratios are the normalized difference water index (NDWI) ([McFeeters 1996](#_ENREF_164)), the modified NDWI (MNDWI) ([Xu 2006](#_ENREF_267)), and the Automated Water Extraction Index (AWEI) ([Feyisa et al. 2014](#_ENREF_67)). These types of analyses have been utilized in conjunction with unsupervised ([Jones 2015](#_ENREF_115)) and supervised ([Tulbure et al. 2016](#_ENREF_240)) classification techniques, however, more advanced machine learning alternatives such as random forest ([Tulbure et al. 2016](#_ENREF_240))and expert systems ([Pekel et al. 2016](#_ENREF_191)) have also been explored .

These techniques often perform poorly in the presence of shadows (from clouds or other sources), which are often misclassified as water. Moreover, the inability of passive imagery to penetrate vegetation surfaces means it is unsuitable for detecting inundation beneath forest canopies ([Irwin et al. 2017](#_ENREF_110)). Although such limitations make wetland mapping challenging, the use of cloud-free optical imagery scenes have demonstrated success in classifying open water bodies through varying techniques ([Irwin et al. 2017](#_ENREF_110)). In addition, should no cloud free images over the desired region be available, cloud masking algorithms can be applied ([Zhu et al. 2014](#_ENREF_275), [Zhu et al. 2015](#_ENREF_274)).

## LiDAR

Airborne LiDAR workflows are typically well defined and applicable to single- and multi-band systems. However, minor details may vary at certain workflow decision points so as to best exploit the 3 dimensional point cloud for a given application. Post quality control (i.e. low point removal), typical workflows tile flight lines with a given overlap between each tile so as to eliminate edge affects near the tile perimeter. Then ground points are identified from within the point cloud, that is, points that are expected to represent reflections from the ground surface. A number of ground classification methods exist in commercially available software ([Axelsson 1999](#_ENREF_15), [Axelsson 2000](#_ENREF_16)), however, ground classification remains an active area of research in academic settings ([Yang et al. 2016](#_ENREF_271), [Zhao et al. 2016](#_ENREF_273), [Nie et al. 2017](#_ENREF_182)). Once ground points are identified the height of non-ground points above the ground ‘surface’ can be calculated and classified ([Hug et al. 2004](#_ENREF_108)). Typically points are classified according to American Society for Photogrammetry & Remote Sensing (ASPRS) standards ([ASPRS 2011](#_ENREF_12)). Once ground and non-ground points have been classified a host of terrain (DEM, DSM), height, and density metrics can be calculated (height percentiles, point ratios, etc.) directly from the point cloud. LiDAR data are typically analyzed by the utility of proprietary software suites (e.g. Terrascan, Lastools, etc.) which can be expensive in some cases. Few open-source alternatives exist, however, those that do are still under development and offer limited analysis capabilities at present.

Water typically absorbs incident LiDAR pulses, however, this is dependent on the angle of incidence and the wavelength of the laser pulse. LiDAR returns reflected from calm water typically have low intensity at high angles of incidence, and high intensity at low angles of incidence (near nadir) ([Lutz et al. 2003](#_ENREF_148), [Lang et al. 2009](#_ENREF_135)). Moreover, the frequency of dropouts (emitted pulses that are not detected due to either absorption or very weak surface reflection) is very high relative to other terrestrial surfaces, which often results in waterbodies having lower point densities than other terrestrial land cover types ([Höfle et al. 2009](#_ENREF_99)). In addition, water is expected to inhabit depressions in the landscape which can be identified in LiDAR data through the interrogation of areas of low elevation relative to its immediately neighbouring landscape ([Irwin et al. 2017](#_ENREF_110)).

As LiDAR data can penetrate vegetated surfaces and provide multiple returns per pulse they afford the opportunity to identify inundation beneath forest canopies ([Lang et al. 2009](#_ENREF_135)). However, as noted in previous studies, a major strength of LiDAR is its ability to characterize vegetation structure (in more detail than is available from SAR information) ([Hopkinson et al. 2005](#_ENREF_104), [Chasmer et al. 2016b](#_ENREF_41), [Mahoney et al. 2017](#_ENREF_154)). These capabilities showcase potential to identify: wetland vegetation (treed or non-treed) ([Chasmer et al. 2016b](#_ENREF_41)), or delineate a wetland basin from its neighbouring upland ([Riley et al. 2017](#_ENREF_201)). Moreover, as ALS can provide detailed terrain information, the interrogation of elevation models can delineate landscape depressions to identify areas of water occupancy. Potential water misclassification can be rooted in the variability of the return intensities which can lead to water being misidentified as a field or similar land cover. Similarly, flat road ways and fields can be misidentified as water due to their low return intensities ([Irwin et al. 2017](#_ENREF_110)). High wind conditions during a LiDAR acquisition survey can also induce uncertainty in the positional accuracy of terrestrial features, therefore such conditions should be avoided when data are acquired.

## SAR

SAR processing is broadly similar to optical imagery as raw data require pre-processing before in-depth analysis can be performed. Acquired images require geometric and sometimes radiometric calibration which are typically achieved through the process of orthorectification ([Leprince et al. 2007](#_ENREF_138)). Orthorectification effectively corrects distortions in raw images by use of the sensors position and orientation at the time the image was acquired, and a DEM. An orthorectified image has been corrected for the displacement error of terrestrial features, resulting in an image perspective as if viewed from nadir rather than at an oblique angle. A poor understanding of the sensors geometry and/or a poor quality DEM will directly influence the quality of the orthorectified result. An orthorectified image represents radar backscatter information (referred to as sigma-0). Radiometric calibration refers to the process whereby digital numbers stored in raw images are related to physical landscape characteristics, such as reflectivity, phase and location. Radiometric correction removes radiometric value contributions that are not due to target characteristics, hence normalizing backscatter information across the scene. Typically SAR products are delivered after radiometric correction have been applied; where data have not been corrected an accompanying look-up table (LUT) should be supplied by the vendor so as to allow radiometric calibration. The LUT houses information pertaining to a fixed offset and range-dependent gain function to be applied across the image in order to generate sigma-0 values. After sigma-0 backscatter information have been acquired, optional filters can be applied to the image to remove speckle, detect edges analyze texture etc. Such processes are easily applied in proprietary and open-source software suites such as PCI Geomatica ([PCI Geomatics 2017](#_ENREF_190)), the Sentinel Application Platform (SNAP), and the Orfeo toolbox, however, whilst open-source suites are capable they can be inflexible when executing some procedures. However, open-source packages warrant exploration within the scope of the current project so as to minimize software licence expeditures.

Once sigma-0 backscatter information have been retrieved SAR images can be analysed by a variety of methods within the context of wetland characterisation. The most common techniques applied to map water are grey-level thresholding ([Gstaiger et al. 2012](#_ENREF_89), [White et al. 2015](#_ENREF_256)), contour modelling ([Horritt et al. 2001](#_ENREF_105)), and texture-based classification ([Yamagata et al. 1993](#_ENREF_268)). These techniques can be applied to all SAR images regardless of polarization complexity, however, more advanced methodologies can be applied with increasing polarization complexity. That is, backscatter channel decompositions can be executed to retrieve important scattering mechanism information, which in turn can be used to infer the presence of flooded vegetation, or upland forest, or specularly reflecting open water, etc. ([Brisco et al. 2011](#_ENREF_29), [White et al. 2014](#_ENREF_257), [Brisco et al. 2015](#_ENREF_30)).

SAR data can misclassify water due to its oblique look-angle. That is, some areas of the ground surface suffer commission errors through radar shadow or omission errors via layover, caused by terrain, urban environments, or even vegetation ([Mason et al. 2010](#_ENREF_162)). Regardless of these known issues, SAR has proved an invaluable tool for the mapping of open water and flooded vegetation (important aspects of wetland characterization). Moreover, similar to satellite optical data, SAR provides repeat-pass information allowing for the monitoring of wetland characteristics as well as providing contemporary inventories.

## Data Fusion

In remote sensing, data fusion refers to any methodological structure that combines multiple sources of data. Best practices combine different sources of data so as to exploit the strengths of each whilst simultaneously minimizing inherent weaknesses. Data fusion approaches have become increasingly popular within the context of Earth observation remote sensing applications, including wetlands, in the past two decades ([Augusteijn et al. 1998](#_ENREF_14), [Li et al. 2005](#_ENREF_139), [Castañeda et al. 2009](#_ENREF_39), [Irwin et al. 2017](#_ENREF_110)).

A number data fusion approaches have been applied to wetland mapping and monitoring, employing combinations of 2 and 3 of the following data sources: optical imagery, LiDAR, and SAR ([Bwangoy et al. 2010](#_ENREF_36), [Corcoran et al. 2011](#_ENREF_49), [Millard et al. 2013](#_ENREF_168), [van Beijma et al. 2014](#_ENREF_245), [Kloiber et al. 2015](#_ENREF_125), [Franklin et al. 2017](#_ENREF_70), [Fu et al. 2017](#_ENREF_74), [Vanderhoof et al. 2017](#_ENREF_248)). It is predominantly noted (by many) that fusion approaches reduce overall wetland classification uncertainties with respect to models produced by any single data source when analyzed in isolation ([Millard et al. 2013](#_ENREF_168), [van Beijma et al. 2014](#_ENREF_245), [Furtado et al. 2015](#_ENREF_75), [Fu et al. 2017](#_ENREF_74), [Irwin et al. 2017](#_ENREF_110), [Vanderhoof et al. 2017](#_ENREF_248)). This has been noted to withstand the pressures associated with data temporal disparity also ([Irwin et al. 2017](#_ENREF_110)). However, it is unlikely that extreme temporal separations in data acquisitions, particularly where data are sourced from different seasons, will produce such favourable results; the analysis of cross-season data acquisitions should be avoided if possible.

Data fusion approaches favour different analysis structures. Whilst some will classify derivatives from each data source and integrate these through a classification algorithm to obtain a final classification map ([Millard et al. 2013](#_ENREF_168)), others favour logic-based decision trees ([Chasmer et al. 2016b](#_ENREF_41), [Irwin et al. 2017](#_ENREF_110)). The former is often more robust (especially for sophisticated classification algorithms) as such algorithms are statistically governed and are thus capable of making decisions based on the data available. Conversely, logic-based approaches need to be able to anticipate all eventualities within the data prior to analysis, failure to do so will result in either spurious results or model disruption. Both techniques have proved valuable in wetland mapping via data fusion analyses.

## Wetland Classification Techniques

After data have been prepared (i.e. pre-processing and appropriate processing procedures have been applied) they can be interrogated for wetland features and classified. A number of approaches for such purposes exist. Early methods favoured manually delineating and classifying wetlands, but have evolved as computing resource have has evolved, also. Some possible approaches for delineating and classifying wetlands from remote sensing data are discussed here.

### Manual Interpretation

Manual interpretation procedures have been employed since the establishment of remote sensing technology. Typically, such methods have been applied to analyze optical (but are applicable to all forms of) imagery and have therefore been dubbed ‘photointerpretation’. A number of studies have utilized such interpretive approaches for inventory purposes ([Seevers et al. 1975](#_ENREF_215), [U.S. Fish and Wildlife Service 1994](#_ENREF_242), [Bernert et al. 1999](#_ENREF_20), [Kudray et al. 2000](#_ENREF_129), [Wilcox et al. 2008](#_ENREF_259)), whereas others described the dynamics of vegetation invasion between different wetland zones over time ([van der Valk 1994](#_ENREF_246), [Shay et al. 1999](#_ENREF_219), [Grosshans et al. 2004](#_ENREF_88)). Although a number of conventions exist for the interpretation of wetlands from imagery ([U.S. Fish and Wildlife Service 1994](#_ENREF_242), [U. S. Fish and Wildlife Service 1995](#_ENREF_241), [Vitt et al. 1996](#_ENREF_250)), a generalized approach relates to the identification of wetland features through visual means, utilizing image colors and physical features, such as soils, vegetation species and diversity as indicators. Typically wetland edges are distinct from the neighbouring landscape and are easily identified when an unobstructed view is offered, however, edge detection becomes more difficult when objects partially or totally occlude the wetland boundary from view. Moreover, whilst physical indicators are key in identifying wetland zones (not necessarily edges), they can often be problematic to delineate as features change gradually.

Manual interpretation is subject to greater human error than automated techniques, that is, images will often be interpreted differently by different technicians thus introducing uncertainty in the resulting wetland classification, particularly if multiple technicians work towards a common goal ([Work et al. 1976](#_ENREF_265)). Moreover, the manual interpretation of imagery can be very time consuming and therefore does not offer high cost efficiency.

Although manual interpretation poses some challenges it is often regarded as second best to in-situ field acquired data with respect to accuracy. In fact, the high accuracies associated with such interpretations have led to their use in initiatives focussed on masking water from the analysis tropical deforestation rates in the Brazilian Amazon ([Shimabukuro et al. 1998](#_ENREF_220), [INPE 2002](#_ENREF_109)) and in the Democratic Republic of the Congo’s humid tropical forest zone ([Gregorio et al. 2005](#_ENREF_86)). In addition, manually interpreted wetland information is often utilized as a reference dataset to validate/compare results derived from other methods ([Bwangoy et al. 2010](#_ENREF_36), [Chasmer et al. 2016b](#_ENREF_41), [Shadaydeh et al. 2017](#_ENREF_218)).

### Unsupervised Classification

Historically unsupervised classifications were the most common methods of image classification for land cover analyses (including wetlands) via remote sensing ([Ozesmi et al. 2002](#_ENREF_187)). Unsupervised classifications are unguided by any reference information and classification is performed by analysis of data features ‘on-the-fly’ by software ([Ozesmi et al. 2002](#_ENREF_187)). In brief, algorithms utilize techniques to determine which pixels are related and clusters them into groups/classes. The exact algorithm used can be specified by the user, ISODATA being most common. The number of classes to break the image in to can also be specified, however, the user must possess knowledge of the area to be mapped when the intention is to relate classified areas to physical features such as wetlands. Because there is no need to guide unsupervised classifications (other than setting the number of classes) unsupervised classifications are ideal for making inferences where little or no validation data are available as clusters are distinct units; they also remove the time consuming training requirement of supervised classifiers.

Historically a number of studies have utilized unsupervised classifiers for wetland applications ([Palylyk et al. 1984](#_ENREF_188), [Ramsey et al. 1998](#_ENREF_197), [Ghioca-Robrecht et al. 2008](#_ENREF_78), [Martin et al. 2014](#_ENREF_158), [Mohammadimanesh et al. 2016](#_ENREF_171)). Results have generally concluded that the use of a larger number of clusters/classes tend to lead to more successful classification accuracies ([Kempka et al. 1992](#_ENREF_117), [Macleod et al. 1998](#_ENREF_150)). A complimentary principle components analysis (PCA) is sometimes utilized in conjunction with unsupervised (and supervised) classifiers to reduce data dimensionality. One such example performed a PCA to reduce the number of multi-temporal image bands utilized in an ISODATA classifier, where the first principle component (PC1) highlight vegetation, PC2 indicated wetness differences, and PC3 distinguished wetlands from uplands ([Gluck et al. 1996](#_ENREF_80)). PCA has become more commonly utilized for reducing data dimensionality prior to use in unsupervised and supervised classifiers, reducing model complexity and computational time requirements whilst leaving accuracy unaffected ([Millard et al. 2013](#_ENREF_168), [de Almeida et al. 2015](#_ENREF_58), [Dronova et al. 2015](#_ENREF_63)).

Recent advancements have seen the use of unsupervised classifiers embedded within layered algorithms to note change detection in wetland systems. One such example is noted in [Shadaydeh et al. (2017)](#_ENREF_218) who proposed the use of a multi-layer Markov Random Field (ML-MRF) method in order to utilize an unsupervised approach to mapping wetland change detection. Coincident ALS and optical imagery data were initially segmented by use of a k-means clustering approach followed by 2 MRF segmentations which resulted in an unsupervised segmentation and change detection map of any optical image acquired at a different time using the preliminary ALS measurement as a reference.

### Supervised Classification

Supervised classifications are the most common for land cover and wetland applications ([Shadaydeh et al. 2017](#_ENREF_218)). Conversely to unsupervised classifiers, supervised classifiers require a reference dataset that represents certain classes which can be used to direct the algorithm to use these training sites as references for the classification of all other pixels within the image. The reference (or training) data are usually selected by the user, and are related to some physical landscape feature, such as wetlands. The user also dictates how many classes should be applied across the image, and a sensitivity parameter which sets the bounds of how similar pixels need to be so they can be grouped together. Supervised techniques are more suitable for wetland mapping as the user exhibits more control over how images are classified. This level of control is not applicable within unsupervised classifications which has resulted in supervised classifiers being preferred ([Ozesmi et al. 2002](#_ENREF_187)). However, some general issues exist with supervised classifiers, namely the need for training data to represent all possible outcomes over the target landscape. That is, pixels that exhibit properties that are not described by the training dataset are often misclassified. Moreover, supervised classifiers often require more user interaction to maximize classification accuracies. That is, such classifiers should minimize data dimensionality (possible use of PCA) were possible so as to include only the most informative attributes from the training data, this minimizes the introduction of noise within the classifier ([Kotsiantis 2007](#_ENREF_126)). However, if no knowledge of which attribute best inform classification the so called ‘brute force’ approach is implemented, that is, all attributes can be analyzed with the goal of identifying the most suitable class.

The maximum likelihood classifier is most commonly employed in wetland applications, however, others exist; some studies that utilized supervised classifiers for wetland applications are described here. [Wei et al. (2007)](#_ENREF_255) utilized a supervised maximum likelihood classifier to classify open water among 4 other vegetated land covers at two sites in Canada’s Georgian Bay with between 85 % and 90 % overall accuracy with respect to an independent data source. [MacAlister et al. (2009)](#_ENREF_149) similarly used the maximum likelihood classifier to determine wetlands from non-wetlands across 5 sites with overall accuracies ranging from 77 % to 93 %. Some studies have compared unsupervised and supervised classifiers for a variety of land cover and wetland mapping, where the majority conclude that the latter yields superior results ([Mohd Hasmadi et al. 2009](#_ENREF_172), [Camilleri et al. 2017](#_ENREF_37)).

### Decision Trees

Decisions trees are popular supervised classification methods for wetland applications that also have applicability to a wide range of other data problems such as ranking, probability estimation, regression, and clustering. Decision trees are easily interpreted by humans due to their expressivity which is based on a series of logical decisions, however, their high expressivity results in a tendency to overfit models ([Flach 2012](#_ENREF_68)). Decision trees can be partitioned by a known ruleset outlined by the user or can be ‘grown’ (or trained) from top to bottom by successively partitioning (or splitting) the feature space (image to be classified) in to smaller subsets. With each subsequent split over the feature space a ‘node’ is created with the goal of reducing confusion between each class (i.e. make the data more pure), measured by so-called impurity measures ([Sandri et al. 2010](#_ENREF_211)). After each split the decision whether to halt further splitting of the feature space is analysed. This is usually based on some impurity threshold, that is, if class impurity is less than the defined threshold splitting will stop and the node will be labelled as a leaf (terminus), otherwise splitting will continue until the impurity threshold is met. Once a decision tree is formulated external (non-training) data is run through the tree, adhering to its splitting criteria at each node until it reaches a leaf node which yields a class predication.

Some examples of the use of user defined decision trees for wetland classification have utilized single data source and data fusion approaches ([Chasmer et al. 2016b](#_ENREF_41), [Irwin et al. 2017](#_ENREF_110)). For example, [Chasmer et al. (2016b)](#_ENREF_41) produced a boreal wetland classification based on data thresholds from physical observations in LiDAR data. Results demonstrated overall correspondence with a variety of assessment dataset ranging between 53 % and 67 %. More recently [Irwin et al. (2017)](#_ENREF_110) produced independent water masks via unique constructed decision trees applied to SAR, LiDAR, and optical data in isolation. The resulting water masks from each were then combined via a final decision tree to produce a final water mask noting areas likely to be water and areas of uncertainty. Although an independent accuracy was not reported, the uncertainty of water presence decreased when leveraging the strengths of each data source. Whilst no wetland classification information was retrieved, such an approach may prove valuable in identifying waterbodies which can subsequently be interrogated to determine more detailed wetland characteristics such as class. However, this approach has potential to becoming time consuming and inefficient.

The supervised grow of decision trees has been employed broadly, applied to a variety of remote sensing land cover applications, including wetlands ([Friedl et al. 1997](#_ENREF_72), [Roy et al. 2010](#_ENREF_208), [Broich et al. 2011](#_ENREF_33), [Broich et al. 2014](#_ENREF_34), [Khosravi et al. 2017](#_ENREF_119)). A variety of decision tree methods have been employed to map wetland classes, including but not limited to, Classification Tree Analysis (CTA), Stochastic Gradient Boosting (SGB), and CART ([Baker et al. 2006](#_ENREF_17), [Pantaleoni et al. 2009](#_ENREF_189), [Tulbure et al. 2013](#_ENREF_239)). [Baker et al. (2006)](#_ENREF_17) noted SGB to be preferable to CTA for mapping wetland, non-wetland, and riparian land cover classes, however, [Tulbure et al. (2013)](#_ENREF_239) obtained an overall accuracy of 96 % when classifying water bodies from other land cover types. [Pantaleoni et al. (2009)](#_ENREF_189) noted CART to better classify 3 wetland classes from upland land cover types with 73 %. However, it was concluded that even though CART provide promising results, it did not yield high enough accuracies to replace wetland mapping methods based on feature extraction in high resolution image data ([Pantaleoni et al. 2009](#_ENREF_189)).

Decision trees represent an efficient, robust form for represent decision processes for classifying patterns in data, but their potential to overfit warrant alternate methodologies be investigated. A possible alternative utilizes decision trees in an ensemble learning routine, where the utility of multiple decision trees reduces potential overfitting.

### Machine Learning Imputation

The umbrella of machine learning (ML) imputation is broad, covering simple nearest neighbour algorithms to complex decision tree ensemble methods. Such algorithms often rely on a reference dataset and are therefore usually supervised classifiers. This also means that while such algorithms are capable of handling large datasets with high data dimensionality, a reduction in the latter is often beneficial with respect to improved overall classification accuracies ([Millard et al. 2013](#_ENREF_168), [Mahoney et al. 2016](#_ENREF_155)).

One of the simplest ML methods is k-nearest neighbour (k-NN) which takes the modal classification of the k closest samples within the reference dataset. This technique is a non-parametric (no assumption of model form) classified and has been utilized for wetland classification ([Na et al. 2015](#_ENREF_177)). However, the method remains unpopular for wetland mapping as overall accuracies are significantly lower than equivalent results from more sophisticated algorithms such as random forest (RF). The RF algorithm ([Breiman 2001](#_ENREF_27)) is a popular non-parametric ensemble classifier that consists of multiple parallel decisions trees where each tree is trained from a random subset of a parent dataset, utilizing the ‘bagging’ concept ([Breiman 1996](#_ENREF_26)). RF methods have been employed for numerous wetland classification studies with varying degrees of success with typical overall accuracies greater than 70 %, but as high as 99 % depending on the number of unique classes ([Corcoran et al. 2011](#_ENREF_49), [Corcoran et al. 2013](#_ENREF_50), [Millard et al. 2013](#_ENREF_168), [van Beijma et al. 2014](#_ENREF_245), [Kloiber et al. 2015](#_ENREF_125), [Franklin et al. 2017](#_ENREF_70), [Fu et al. 2017](#_ENREF_74)). A common alternative to RF for wetland mapping is the (non-parametric) Support Vector Machine (SVM) algorithm. This method subsets the feature space much like RF, however, it calls upon hyperplanes (linear lines that separate the feature space) to increase data purity. A wetland application of SVM is given by [Li et al. (2011)](#_ENREF_140) who classified rice fields from all other land cover types in rural China by the use of quad-pol SAR data. A number of SAR data product combinations were utilized to drive the SVM, resulting in overall accuracies ranging from 71 % to 93 % ([Li et al. 2011](#_ENREF_140)).

A number of studies have made direct comparisons of resultant wetland classification accuracies determined from a number of ML algorithms. For example, [Na et al. (2015)](#_ENREF_177) noted considerable improvement of classification results when using RF (kappa k=0.84) over k-NN (k=0.42). Similarly, [Amani et al. (2017a)](#_ENREF_8) identified RF as the best choice for wetland classification amongst SVM, Classification And Regression Tree (CART), k-NN, Maximum likelihood methodological alternatives. This declaration was followed-up by a more in-depth analysis of each classifier for the purpose of classifying each of the 5 AWCS classes in addition to upland, urban areas, and deep water. The study investigated each classifier as a function of each land cover class across 5 different study sites, concluding that RF produced the most accurate results in the majority of cases ([Amani et al. 2017b](#_ENREF_9)).

### Hybrid Approaches

Hybrid approaches utilize both statistical and logic-based analysis techniques. Typically the statistical algorithms will classify data based on internal statistically driven solutions, whereas logic is utilized to refine initial classifications, e.g. removing inappropriately labeled features. Such an approach has been investigated by [Lunetta et al. (1999)](#_ENREF_147) who used a rule-based GIS model to classify wetland and upland vegetation types in SPOT images in the U.S. states of Maryland and Delaware. They showed that a GIS rule-based model could be used post-classification to improve overall accuracy by an average of 17 %. [Li et al. (2005)](#_ENREF_139) utilized a similar approach, applying rule-based decisions to an image post-classification. Their study was focussed over 3 sites in eastern Canada committing to the classification up to 9 classes (site dependent). They concluded that the introduction of the rule-based classification modifier significantly improved results with respect to traditional methods, which included single data source and data fusion analysis ([Li et al. 2005](#_ENREF_139)). More recently [Frohn et al. (2009)](#_ENREF_73) utilized a primarily decision-tree approach optimized by trial and error in order to classify wetlands from Landsat imagery. However, a pair-wise image segmentation clustering analysis was performed before and after the decision-tree analysis has been performed in order to first determine isolated wetlands, and second merge neighbouring objects within the same land cover class. Moreover, after final image segmentation was performed the use of ancillary GIS data layers were employed to quality control the segmented image. That is, buffered hydrology layers were utilized to mask data where potential wetlands intersected stream, river, and lake buffers to prevent them being classified as isolated wetlands. User and producer accuracies (calculated against interpreted aerial images) varied between wetland size classes, ranging from 59 % to 98 %, and from 84 % and 97 %, respectively ([Frohn et al. 2009](#_ENREF_73)).

These studies form a body of literature that suggest such hybrid approaches consistently out perform traditional classification approaches. As a result such an approach warrants considerable investigation, however, decision rules will likely require optimization with respect to accuracy improvements and increases in computation time.

### Segmentation Methods

The segmentation of a dataset is not to be confused with its classification. Segmentation refers to the breaking up of a data image in to defined objects which represent land-based features. Two major methods exist for segmenting images, namely object-based and pixel-based methods. Object-based segmentation will classify an image based on pixel clusters, where each pixel in a cluster has some similarity with those within its overall cluster. In contrast, pixel-based methods classify on a pixel-by-pixel basis and is not concerned with any given pixels similarity with any of its local neighbours.

Object-based analyses require an extra analysis step relative to pixel-based analyses. Although some minor variations exist, in summary an object-based analysis group pixels in to objects based on shape, size, color and pixel topography parameters, set by the user. These parameters vary as a function of the landscape being segmented (i.e. urban area versus forest canopy) and often require some sort of trial and error or optimization based on the landscape characteristics. More advanced methods can consider multiple image layers also, meaning that supplementary information from additional data sources (e.g. LiDAR intensity, DEM, DSM, SAR Sigma-0, etc.) can also be utilized in the segmentation process. Typically the more layers available to the segmentation algorithm, the more refined segmented objects appear. However, with more numerous layers comes increased complexity and computation times resulting in reduced cost-efficiency. Such analyses are typically performed by the use of proprietary software packages such as eCognition ([Trimble 2017](#_ENREF_238)), PCI geomatica ([PCI Geomatics 2017](#_ENREF_190)), and ArcGIS 10.3 onwards ([ESRI 2017](#_ENREF_66)) where eCognition provides the most sophisticated option. However, open-source alternatives are available through SAGA and the Orfeo toolbox ([Orfeo 2017](#_ENREF_185)), but tend to exhibit less flexibility than their proprietary counterparts. The latter utilizes a mean-shift approach similar to that used by ArcGIS and exhibits flexibility to tile data so as not to overwhelm computational resources. Given the cost of proprietary software licences for segmentation analyses an open-source alternative is suggested in the interest of cost-efficiency.

In the context of most wetland mapping scenarios, object-based approaches tend to yield better overall accuracies than pixel-based approaches when validated against independent data ([Frohn et al. 2009](#_ENREF_73), [Kloiber et al. 2015](#_ENREF_125), [Fu et al. 2017](#_ENREF_74)). Although segmentation analyses can be somewhat time consuming and require optimization, they warrant further investigation for wetland mapping as such techniques have demonstrated superiority over historic pixel-based analyses. However, caution is expressed with regards to time commitments dedicated to optimizing segmentation routines.

# Problem Statement

Given the environmental, social, and economic importance of wetlands the Government of Alberta has great interest in updating wetland inventories within the province. Moreover, a newly updated wetland inventory can be leveraged in future as a baseline from which monitoring investigations can be initiated, the results from which may aid in modifying Alberta’s wetland policy so as to maintain its relevance. As Ducks Unlimited Canada (DUC) are a key stakeholder within the wetland conservation community, a contemporary wetland inventory is of great interest. As a result, DUC have engaged the GoA on identifying a mapping specification criteria for the new provincial inventory in order to maintain the relevance of current and future DUC wetland inventories. Within the context of the provincial inventory mapping specification DUC have engaged in the review of candidate remote sensing data and appropriate methodologies so as to effectively contribute to the provincial inventory. The findings from this review will be exploited in order to develop a cost-effective method to inventory wetlands (adhering to provincial specifications) from remote sensing data.

None of the data sources reviewed are capable of characterizing wetland classes with certainty. However, whilst each has demonstrated success for mapping unique wetland characteristics, each possess inherent weakness that confound the characterization of wetland classes and forms (with respect to AWCS definitions). To date, few investigations have characterized wetlands within the confines of the AWCS, and fewer have met the wetland inventory mapping specifications outlined by the GoA. Most studies focus on wetland characterization as a function of the environment in which the study is performed or based on project preferences ([Maxa et al. 2009](#_ENREF_163), [Allen et al. 2013](#_ENREF_6), [Millard et al. 2013](#_ENREF_168), [Kloiber et al. 2015](#_ENREF_125), [Chasmer et al. 2016b](#_ENREF_41)). Moreover, Some studies have utilized licenced data (such as Worldview) with demonstrated success ([Vanderhoof et al. 2017](#_ENREF_248)), however, given restricted resources the use of such data are unfeasible.

Traditional methods that analysis a single source of data in isolation have demonstrated great success relating to certain aspect of wetland mapping. However, recently proposed methods have improved on these techniques by combining multiple methods in complex workflows. These methods, whilst the future direction of the analysis of remote sensing data, have potential to be computationally inefficient and time consuming if executed incorrectly. Within such workflows a number of techniques exist for specific tasks such as orthorectification and image segmentation. These are often proprietary algorithms which have high licence costs. Given project resource limitations, alternate open-source have been identified however, the capabilities of these open source alternatives are often limited with respect to proprietary counterparts and therefore may prove challenging to execute.

In order to meet Government mandated requirements and cost-efficiency priorities in the face of the noted list of potential data and methodological challenges, a semi-automated methodological workflow is proposed as a solution. The workflow will utilize primarily open-source (or low-cost) remote sensing data that are well suited to fusion approaches, that is, SAR, LiDAR, and optical data. The workflow will be as computationally efficient as possible so as to further promote cost effectiveness. This workflow component has been identified as an area of key importance so as to maintain workflow relevance when new Earth observation data (with higher data capture rates, such as RCM) become available and analyses become more frequent.

# Candidate data

Due to the potentially high cost and relative impractically offered by airborne optical imagery, satellite equivalent data is favoured for such an application. Similarly for hyperspectral data, acquisition costs and potentially long processing times make it unattractive for wetland mapping when cost effectiveness is a high priority. The long archive and somewhat frequent repeat acquisitions associated with spaceborne acquired images are attractive for such purposes. However, the inability to operate in all weather and low lighting conditions may become problematic. Therefore, the use of satellite optical imagery in isolation may be challenging. As a result the use of such data is encouraged as part of a data fusion approach, only. Moreover, sensor selection is dictated by Alberta wetland technical mapping spatial resolution and cost-effectiveness, that is only sensor with sufficient resolution that are have open data policies are considered candidates. A list of potential optical imagery data candidates is compiled in Table 4.

ALS data are well suited for the analysis of depressions in the landscape in which water may reside, but also for the identification (and structural analysis) of vegetation within wetland zones. It is through these avenues that ALS data has demonstrable promise for wetland mapping in isolation and in data fusion approaches. However, its spaceborne counterpart, ICESat, is not well suited to the task primarily because it ceased acquiring new data in 2009, but also exhibited a somewhat sporadic, coarse spatial acquisition regime. A further advantage favouring the use of ALS data in Alberta is accessibility to the provincial dataset. Usually such data would be impractical and expensive to acquire over such a large area, however, as the data can be leveraged for multiple purposes, data cost, and in the context of this Alberta-centric study, the use of such high resolution data is encouraged. If access to ALS data is cost prohibitive the utility of high resolution spaceborne elevation data is encouraged.

SAR data is highly relevant for water mapping applications. It is ideally suited to open water and flooded vegetation mapping (given the availability of quad-pol data). Moreover, as SAR data exhibit relatively short repeat pass intervals it has the ability to offer active remote sensing data for monitoring activities. SAR is extremely important within a Canadian wetland context as the Canadian Space Agency plans to launch the RCM by the end of the decade, which has potential to map wetland dynamics over 4 day repeat-pass periods. Airborne data are not favoured in the context of the current study due to large-scale acquisition impracticalities, hence the use of satellite data are encouraged. Moreover, the backscatter sensitivity to dielectric properties associated with SAR data means that it is ideal for water mapping in parts of the province that are often cloud covered. Although SAR may be incapable of identifying small waterbodies (< 10 m2), its demonstrated success in wetland mapping cannot be ignored. A number of SAR systems are currently in operation and can be deemed suitable for wetland classification, however, data access restrictions and costs are crucial in the context of developing of a cost effective framework. Possible SAR sensors capable of meeting project requirements are noted in Table 4. Note that some sensors have been disregarded based on cost of data acquisition and/or inadequate spatial resolution to meet [Alberta NAWMP Partnership (2017)](#_ENREF_5) mapping specifications.

Table 4 Summary of potential remote sensing sensors for use in proposed data fusion framework.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Type** | **Sensor** | **Resolution** | **Availability** | **Notes** |
| Multi-spectral optical imagery | Landsat | 30 m | Free | Existing boreal use |
| SPOT | 6 m | High cost | GoA accessibility |
| Rapideye | 6.5 m | High cost | GoA accessibility |
| Sentinel-2 | 10 m | Free |  |
| LiDAR | SRTM | 30 m | Free | Not widely used for wetland mapping. Large-scale alternate to airborne LiDAR. Limited coverage between ±60° |
| Airborne LiDAR | Variable | High cost | Goa/UoL accessibility |
| SAR | Radarsat-2 | Variable | High cost | GoA/NRCan accessibility |
| Sentinel-1 | Variable | Free |  |
| RCM | Variable | Free | Ready for launch in 2018 |

# Candidate methodologies

A number of methodologies exist for wetland mapping, however, the most successful methodologies utilize the increasingly popular data fusion approach. Such approaches are usually based on either the statistical classification of numerous remote sensing data layers or the application of logic-based decisions to key data layers, or both ([Li et al. 2005](#_ENREF_139), [Millard et al. 2013](#_ENREF_168), [Chasmer et al. 2016b](#_ENREF_41), [Franklin et al. 2017](#_ENREF_70), [Fu et al. 2017](#_ENREF_74), [Irwin et al. 2017](#_ENREF_110)). Both have merit when utilized in isolation, however, literature suggests that the combination of both offers considerable improvements to classification accuracies. However, to date, few studies have utilized this combined approach ([Lunetta et al. 1999](#_ENREF_147), [Li et al. 2005](#_ENREF_139), [Laba et al. 2008](#_ENREF_131), [Frohn et al. 2009](#_ENREF_73)) meaning some exploration is required to optimize such a methodology.

For the statistical classification of a combined (SAR, LiDAR, and optical) dataset non-parametric ML methods are favoured due to their demonstrated success in a variety of wetland applications (water identification, classification, change detection, etc.), but also because of their robust and well documented nature. Such candidate classifiers are: k-NN, SVM, and RF. However, based on literature that compares ML methods for wetland classification RF methods should be considered highest priority for implementation. Moreover, before any classification approach is implemented image segmentation of the available image data should be strongly considered due to its demonstrated superiority over traditional pixel-based classifications. Although image segmentation adds an additional step in the proposed framework (adding extra time expenditure) its documented success cannot be overlooked. An applicable decision criteria cannot be identified with certainty at present as such a criteria will depend on data availability at each study site.

# Proposed Framework

A hybrid framework that utilizes rule-based decisions based on physical observations and statistical analyses through a hierarchal approach is recommended for wetland classification and mapping project activities. Broadly, the proposed framework will adopt the following:

* A data fusion approach as it offers significant improvements over any data source analysed in isolation
* The use of SAR data, essential for water body and flooded vegetation identification (by use of polarimetric decompositions where possible)
* The use of LiDAR data in order to identify topographic features that promote wetland identification (e.g. contour analysis), and discriminate treed and non-treed wetlands
* The use of Multi-spectral imagery so as to discriminate water and vegetation spectral signatures (water indexes)
* An image segmentation approach to inflate classification accuracies compared to pixel-based approaches
* The use of ancillary data (e.g. LiDAR derivatives, soil information, existing hydrology vector layers) because of the potential to significantly improve classification accuracy and offer improved quality control
* Execution of PCA depending on available data and it associated dimensionality
* The use of object-based image classification to combine spatial data from multiple sources where required
* The application of a rule-based decision criteria to allow for logical quality control based on known hydrology information, buffer analysis, and/or other physical indicators
* The use of a frequency analysis to determine wetland hydroperiod information (where possible)

The framework will be built using as many open-source software packages (favour those that be run somewhat autonomously) in order to maximize cost-effectiveness. The proposed foundation package is the R project and/or Python and will be selected based on ease of interfacing capabilities with other supplementary packages. The use of both SAGA and Orfeo toolboxes warrant investigation for orthorectification, image segmentation analyses, and other image manipulation, where the most suitable can be selected after some preliminary investigation. LAStools will be employed for the analysis of airborne LiDAR due to its ease of processing and computational efficiency. Other analyses can be performed within the selected scripting language by purpose built functions. The proposed framework will be primarily implemented in the R-project environment, but may be moved to a more suitable platform (such as python) for possible increased computation efficiency and/or compatibility with open-source software packages.

A high level schematic of the propose framework is illustrated in Figure X, but remains subject to change depending on a cost-benefit analysis of individual methods that links their execution time against classification accuracy.

# Concluding Remarks

This document reviewed the current status of remote sensing data and popular techniques for wetland mapping and monitoring applications. Historic and contemporary literature suggests that remote sensing is ideally suited for such applications and can be utilized to supplement field campaigns when such detailed in-situ acquisitions are necessary.

Based on literature, satellite SAR, optical imagery, and airborne LiDAR datasets are best suited for wetland mapping within the context of the proposed project. SAR due to its ideal applicability for water detection (both open and within vegetated stands), LiDAR for its ability to discriminate vegetation structure and ground surface features, and imagery for water identification through interrogation of spectral indices. These datasets are complimentary to each other and at present represent the state-of-the-art with respect to the characterization of wetland environments by remote sensing data.

Similarly, a methodological workflow will combine the state-of-the-art (open-source) methodologies applicable to each data source in isolation by sophisticated RF methods to form an object-based data fusion classification approach. Methodologies will focus on the identification of landscape depressions for water occupation, combined data use for more robust water identification (following [Irwin et al. (2017)](#_ENREF_110), the decomposition of polarimetric SAR for flooded vegetation identification, and hydroperiod analysis where mutli-temporal data are available. Interim classifications will be subject to a rule-based decision criteria in order to override obvious misclassifications and improve overall accuracies where possible (following [Li et al. (2005)](#_ENREF_139)).

The development of such a framework will take the first steps towards the implementation of a semi-automated operational wetland classification routine that conforms to Alberta wetland policy and technical mapping specifications. The framework is intended to be a commercially viable product and to contribute to the update of Alberta’s provincial wetland inventory. The completed software package will represent an important advancement in the efficient, robust mapping of wetlands by remote sensing data that is applicable over large and small geographies.

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