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Remote sensing for wetland classification: a comprehensive review

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Wetlands are valuable natural resources that provide many benefits to the environment. Therefore, mapping wetlands is crucially important. Several review papers on remote sensing (RS) of wetlands have been published thus far. However, there is no recent review paper that contains an inclusive description of the importance of wetlands, the urgent need for wetland classification, along with a thorough explanation of the existing methods for wetland mapping using RS methods. This paper attempts to provide readers with an exhaustive review regarding different aspects of wetland studies. First, the readers are acquainted with the characteristics, importance, and challenges of wetlands. Then, various RS approaches for wetland classification are discussed, along with their advantages and disadvantages. These approaches include wetland classification using aerial, multispectral, synthetic aperture radar (SAR), and several other data sets. Different pixel-based and object-based algorithms for wetland classification are also explored in this study. The most important conclusions drawn from the literature are that the red edge and near-infrared bands are the best optical bands for wetland delineation. In terms of SAR imagery, large incidence angles, short wavelengths, and horizontal transmission and vertical reception polarization are best for detecting of herbaceous wetlands, while small incidence angles, long wavelengths, and horizontal transmission and reception polarization are appropriate for mapping forested wetlands.

Keywords: wetland; wetland characteristics; wetland classification; wetland inventory; remote sensing

Introduction

"Wetland is a land transitional between terrestrial and aquatic systems, where the water table is usually at or near the surface or the land is covered by shallow water" (Mitsch and Gosselink 1993). Wetlands are highly beneficial to the environment and provide vital habitats for several unique species of flora and fauna. Water purification, protection from natural hazards, conservation of soil and water, as well as recreational values are some of the benefits associated with wetlands (Grenier et al. 2007; Powers, Hay, and Chen 2012; Ji, Xu, and Murambadoro 2015). According to Melton et al. (2013), wetlands cover at least 7 million km^2 of the earth. Unfortunately, however, wetlands are prone to an accelerated degradation (Millennium Ecosystem Assessment 2005) due to extensive irrigation practices, extraction of groundwater, and drainage (Koch et al. 2012). Furthermore, many wetlands have been

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changed to urban or agricultural lands. In fact, thus far up to 57% of the world's wetlands have been converted or lost (Davidson 2014). Therefore, mapping and monitoring wetlands is of crucial importance.

Many stakeholders have realized the value of wetlands as well as the high potential of remote sensing (RS) for mapping these valuable natural resources, and consequently have developed different wetland inventories for this purpose. Wetland inventories can be defined as maps illustrating the area and the distribution of wetlands over geographical regions, and are useful tools for evaluating the effectiveness of wetland polices. Producing wetland inventories, however, demands developing classification schemes to describe the type of wetland classes to be mapped. Consequently, for implementation of classification schemes numerous classification methods were generated, which can be widely divided to field-based and RS methods. Unlike field-based methods, RS is a cost-effective tool that is capable of acquiring frequent measurements from inaccessible places and providing timely information. Given the current need for up-to-date information, as well as the widespread coverage of wetland maps, satellite RS has been demonstrated to be the most efficient and cost-effective method for this purpose (Ozesmi and Bauer 2002).

Despite many advances in RS technology, wetland classification is still a challenging task from the RS perspective (Landmann et al. 2010; Corcoran et al. 2012). A major reason for this difficulty is that although each of the wetland classes has several distinctive characteristics, they share some ecological similarities with each other (Boon et al. 1997), and with other non-wetland classes (Henderson and Lewis 2008). Therefore, different wetlands exhibit similar spectral and/or backscattering information in RS imagery (Amani et al. 2017a). In addition, wetlands vary significantly in space and time (Gallant 2015; Moser et al. 2016). Despite these difficulties, RS approaches are preferential, especially since fieldwork is the potential alternative, which is a laborious, comparatively costly, and time-consuming task. Therefore, many studies have attempted to develop innovative and effective RS methods for the purpose of wetland mapping with minimal need of *in situ* measurements.

There are several review papers published on wetland classification and various challenges associated with this task. For instance, Ozesmi and Bauer (2002) conducted an inclusive review on various sensors used for wetland mapping and monitoring, in which SAR sensors were covered in a small section. Different methods for the classification of wetlands, including aerial photo interpretation, and unsupervised and supervised classification methods, were also investigated in this review paper. Henderson and Lewis (2008) also presented a comprehensive review on wetland detection using synthetic aperture radar (SAR) sensors. This review provides the readers with considerable insights on the benefits and limitations of SAR sensors for wetland detection. Besides, it advises the users on choosing the appropriate sensor configuration. In another paper, Adam, Mutanga, and Rugege (2010) reviewed wetland classification using multispectral and hyperspectral RS sensors, and explored spectral characteristics of various vegetation within wetlands. Similarly, Dronova (2015) did a thorough and useful literature review on object-based wetland classification and explored object-oriented mapping of wetlands in terms of its pros and cons, and the elements that affect its accuracy. Additionally, Gallant (2015) explained RS methods briefly for wetland classification and investigated the challenges of mapping wetlands. Finally, Brisco (2015) investigated the SAR RS methods for mapping and monitoring surface water and wetlands.

Each of the mentioned reviews has explored wetland classification from a specific point of view. Therefore, there is a need for a more inclusive literature review, which contains an introduction to wetland importance and the reason for the need on wetland mapping and monitoring, as well as a diverse description of the various methods for classifying and monitoring wetlands using RS. In this review, the aim is not to simply report the method and results of each study, but rather, to recapitulate the research on a variety of subjects and present the benefits and limitations associated with each. This review is especially useful for the users who intend to become familiar with characteristics and importance of wetlands, and also need a general knowledge on the classification of wetlands to decide what approach conforms to their requirements in the best way.

This paper is organized as follows. First, various definitions of wetlands are provided. Then, the benefits and extent of wetlands, and the threatening rate of wetland loss are reviewed. Wetland inventories and classification schemes are discussed in the next section.

Wetland classification methods and their features are then presented on an individual basis. Readers are also referred to several studies, which have utilized each method of wetland classification. In addition, the benefits of object-based compared to pixel-based classification are presented in this section. Further, various classifiers for wetland mapping are explored and reviewed. Finally, the summary and conclusions, along with some recommendations for the future, are provided.

Wetland definition

Although wetlands share many similar characteristics, they are highly variable in terms of size, location, and hydrology (Boon et al. 1997). At the same time, they often constitute transitional zones on the edge of explicit terrestrial and aquatic regions (Boon et al. 1997). This fact creates difficulty in defining these natural resources and is the reason for the existence of various definitions of "wetland" in the literature (Boon et al. 1997; Bourgeau-Chavez et al. 2009).

One of the most commonly used definitions of wetland is provided by the Ramsar Convention (Davis 1997): "Areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed 6m."

Although this definition suffices for the majority of international purposes, most nations have their own definition of wetland developed for various scientific, managerial, and governmental purposes. The United States Fish and Wildlife Service (USFWS), for example, defines wetland as follows (Mitsch and Gosselink 1993):

> "Wetland is a land transitional between terrestrial and aquatic systems, where the water table is usually at or near the surface or the land is covered by shallow water. For the purposes of this classification, wetlands must have one or more of the following three attributes: (i) at least periodically, the land supports predominantly hydrophytes; (ii) the substrate is predominantly undrained hydric soil; and (iii) the substrate is non-soil and is saturated with water or covered by shallow water at some times during the growing season of each year."

Another well-known definition applied in Canada is defined by the National Wetland Working Group (National Wetlands Working Group 1997). The group describes a wetland as "an area that is saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation and various kinds of biological activities that are adapted to a wet environment."

To summarize, wetlands can be described as occupying zones where terrestrial and aquatic regions meet (Sura 2012), and share some characteristics of both ecosystems.

Notably, wetlands contain water for some parts of a year (Sura 2012). Bourgeau-Chavez et al. (2009) provided a simple definition of wetlands by introducing three main features by which wetlands can be described: the presence of (i) water, (ii) hydric soil, and (iii) specific vegetation adapted to a wet environment. It is worth noting that artificial water bodies are not usually considered as wetlands by many classification systems (Barson and Williams 1991).

Wetland importance

Since the realization of the potential of RS for various applications, many researchers have exploited RS for wetland classification/monitoring. Wetland classification has attracted much attention amongst RS experts for several reasons, including the numerous advantages associated with wetlands, the considerable global coverage of wetlands that can be estimated using RS tools, and vulnerability of wetlands to loss and degradation that can be similarly estimated by application of RS methods. Therefore, in this section, each of those reasons is described so that the readers are acquainted with the significance of wetland classification at the current time.

Wetland advantages

Wetlands are one of the most important natural resources that provide many advantages to the environment and humans. Purification of water, reduction of flood risk, protection of shorelines, conservation of soil and water, filtration of sediment, removal of pollution, as well as esthetic and recreational values are only some of the benefits associated with wetlands (Grenier et al. 2007; Powers, Hay, and Chen 2012; Ji, Xu, and Murambadoro 2015). Wetlands are also a great habitat for hundreds of plants and animals, including one-third of all species at risk (Ozesmi and Bauer 2002; Reimer 2009; Kingsford, Basset, and Jackson 2016). Due to their vital biological services, wetlands have been called the kidneys of nature (Mitsch and Gosselink 2000) and are important indicators of environmental health (Touzi, Deschamps, and Rother 2007). Other than the countless natural benefits of wetlands, the local economy is dependent on wetlands for fisheries and grazing (Amanuel 2015). Therefore, monitoring wetlands is of vital significance, and the first step in monitoring is mapping.

Wetland geographical extent

Currently, there are only a few studies that have estimated the global coverage of wetlands. Referenced global estimates are often compiled from numerous localized wetland inventories or are predicted using models that apply various types of data inputs. Table 1 introduces these studies and illustrates a summary of their obtained results. There are, however, disagreements in total estimates of global wetland extent among various studies. These disagreements are due, at least in part, to the difficulties in obtaining accurate and cohesive wetland distribution estimations from around the world (Finlayson et al. 1999). Most of the predicted global wetland extents may be considered as minimum estimates as several countries have not yet completed or even initiated the collection of wetland inventories (Maltby and Barker 2009). More accurate and improved global wetland estimates could be theoretically obtained through the creation and implementation of a global standardization for conducting wetland inventories (Finlayson et al. 1999). This is an ideal case, however, and the creation of such standardization is a substantial

Table 1. Various estimates of the global wetland extent.

Study	Summary of results
Mitsch and Gosselink (1993)	Between 4% and 6% of Earth's land surface is wetland, equivalent to roughly 7–9 million km^2.
Matthews and Fung (1987)	Estimated the global wetland extent to be 6.8 million km^2. The study stated that the majority of wetlands are located in the polar and boreal zones. Asia contained the most wetlands with North America a close second.
Lehner and Döll (2004)	Estimated that global wetlands make up 8–10 million km^2 of land surface (excluding that of Antarctica and glaciated Greenland), and the majority of wetlands were found in Asia, followed by North America.
Melton et al. (2013)	Their applied models showed disagreement in their estimations of annual global wetland extent, which ranged from ~7.1 million km^2 to ~26.9 million km^2.

challenge that requires the availability of data sets, methods, and funding in all countries on the earth.

Wetland loss

Despite the numerous services provided by wetlands, they were widely regarded as undesirable in the past and were frequently drained to be replaced with other types of human land use, such as urban space and agriculture (Mitsch and Gosselink 2000; Dechka et al. 2002; Fraser and Keddy 2005; Millennium Ecosystem Assessment 2005; Baldassarre, Bolen, and Saunders 2006; Gallant et al. 2007; Ji, Xu, and Murambadoro 2015). Other than land use, climate change also affects the integrity of wetlands (Boon et al. 1997; Karl 2009; Ji, Xu, and Murambadoro 2015). Furthermore, wetlands have been and continue to be seriously affected by exhaustive land irrigation, groundwater extraction, and draining (Koch et al. 2012). Drought, salinization, eutrophication, and pollution also negatively affect wetlands (Klemas et al. 1974; Sánchez-Carrillo and Álvarez-Cobelas 2001; Alvarez-Cobelas et al. 2008).

While the statistics regarding destruction of wetlands worldwide are concerning, they are challenging to estimate. This is, in part, due to the lack of historical documentation, in addition to the multitude of wetland definitions and the temporal variability of these ecosystems (Fraser and Keddy 2005). However, there are some old documents used by the USFWS to report on wetland loss between the 1780s and the 1980s, stating that approximately 53% of wetlands were lost in the lower 48 states within 200 years (Dahl 1990). Documentation of wetland destruction in Canada dates back as early as the 1600s, during which time at least 85% of salt marsh habitats in the Bay of Fundy (between Nova Scotia and New Brunswick) were drained and dyked by settler Acadians (McAlpine and Smith 2010).

Other than the few described studies, most research estimated wetland loss during the last century, when aerial photographs, satellite imagery, and detailed documentation were extensively available (Papastergiadou et al. 2008; Stein et al. 2010; Fickas 2014; Cellone, Carol, and Tosi 2016). In an assessment of 189 published scientific studies and reports covering various time periods and geographies, Davidson (2014) reported that as much as 54–57% of the world's wetlands have been converted or lost and was most accelerated during the twentieth and early twenty-first centuries. Other studies have occasionally reported various amounts of wetland loss. For example, more than half of the total mangrove area in the world was destroyed in recent decades (Millennium Ecosystem Assessment 2005). By the same token, more than 60% of the wetlands in Europe and North America have been drained and transformed for agricultural use (Millennium Ecosystem Assessment 2005).

Wetland inventories

Since the value of wetlands, along with the great potential of RS for wetland mapping/ monitoring, has been well realized, the concept of wetland inventory was developed. Assessing the effectiveness of wetland policies requires an understanding of the extent of current wetland resources as well as a basis for trend analysis of wetland distribution and extent change. A way that this can be done is through the creation and maintenance of wetland inventories (Finlayson and Van der Valk 1995; Ramsar Convention Secretariat 2010). A wetland inventory is a map that displays the extent and distribution of wetlands over a geographical area. Inventories around the world have been carried out, all with varied purposes, methods, and geographical coverages ranging from local to nationwide (Milton and Hélie 2003; Ramsar Convention Secretariat 2010; Kloiber et al. 2015).

One example of a nationwide inventory is the National Wetland Inventory (NWI). The NWI was established in 1975 by the USFWS and was mainly conducted via the manual interpretation of aerial images (Tiner 1990) along with the inclusion of other data types, such as soil data and topographic maps (Dugan 1993; Lyon 1993). Since its implementation, the NWI has mapped wetlands throughout the United States. Another example is the Canadian Wetland Inventory (CWI). Although Canada had several prior attempts for provincial-based inventories, the lack of a national inventory was not addressed by Canada until 2002 upon the establishment of the CWI partnership between Ducks Unlimited Canada, the Canadian Space Agency, the North American Wetlands Conservation Council, as well as various other institutions (Milton and Hélie 2003).

The initiation of wetland inventories was followed by the development of wetland classification systems. Examples of classification systems range from the early peatland classifications of Europe and North America (Davis 1997; Mitsch and Gosselink 2000) to the globally applied and conservation-based Ramsar Wetland Classification System (Ramsar Convention Secretariat 2013). Several classification systems address only a specific wetland type and are designed for application in specific situations, and localized geographic contexts, while others are developed for countrywide use (Cowardin et al. 1979; National Wetlands Working Group 1997; Gong et al. 2010). A major purpose behind the development of these countrywide classification systems is the creation of national inventories of wetlands. For example, countrywide classification systems applied in the context of North American wetland inventories include the Cowardin Classification System (CCS, Figure 1) and Canadian Wetland Classification System (CWCS, Figure 2), which are applicable to the US NWI and the CWI, respectively.

The classification of wetlands and deep water habitats of the United States (CCS) was developed in 1979 for use in a nationwide inventory and was designed for resource managers. Like many other national classification systems, the CCS is structured hierarchically, beginning with a broadly defined system level, and moving toward more specificity at the subsystem and class levels. The classes can be further divided into subclasses and dominance types. Brief descriptions of each system level in the CCS are provided in Table 2.

In a similar vein, though developed some time later, the CWCS was published in 1987 by Environment Canada and was last updated in 1997. This system was specifically

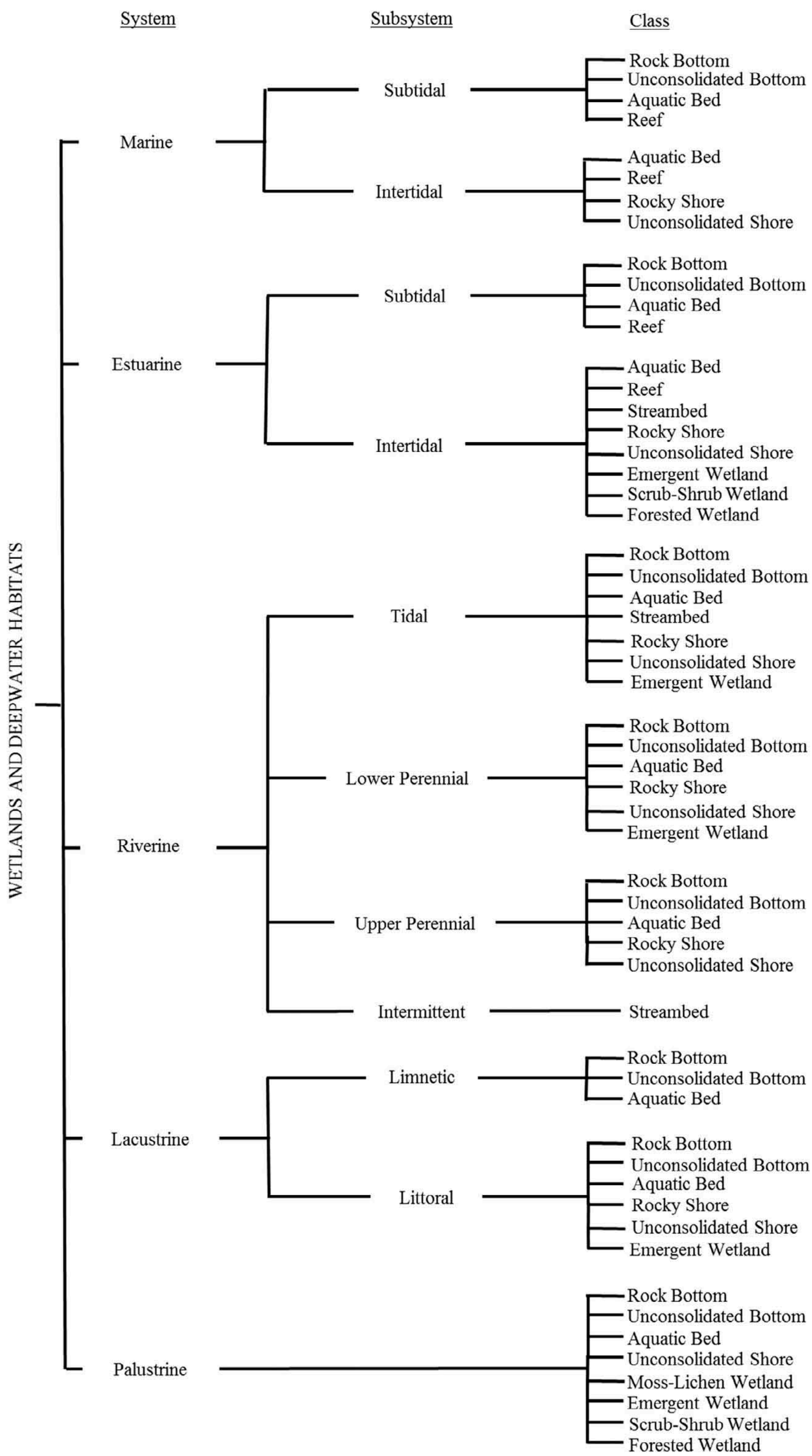

Figure 1. Cowardin Classification System (CCS, Cowardin et al. (1979)).

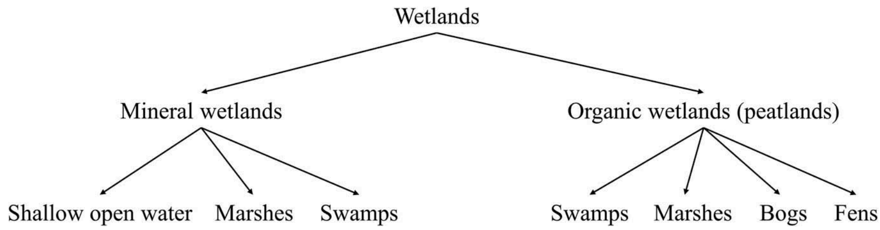

Figure 2. Canadian Wetland Classification System (CWCS, Alberta Wetland Policy 2017).

Table 2. Classification system of wetlands and deep water habitats of the United States (see Cowardin et al. 1979 for more details).

System	Description
Marine	Open ocean and associated coastline that are exposed to waves and currents, influenced by tides and winds, and have high salinities.
Estuarine	Tidal deep water and wetland habitats open partially to the ocean and influenced by some freshwater runoff. Salinity levels can vary depending on the circumstances.
Riverine	Wetlands and deep water habitats contained within a channel, a channel being an open conduit that contains periodically or continually moving water.
Lacustrine	Wetlands and deep water habitats found in topographic depressions or dammed river channels that occur in sizes greater than 8 ha.
Palustrine	Non-tidal wetlands dominated by trees, shrubs, and persistent emergent vegetation.

designed for practical use by both specialists and non-specialists, as well as for use in both local and regional contexts (National Wetlands Working Group 1997). Due to its overarching geographical application, CWCS was selected as the official classification system of the CWI (Fournier et al. 2007). The CWCS defines a three-level hierarchy of class, form, and type. Categories within the class level are defined on the basis of broad descriptions of soil, vegetation, hydrology, and chemistry. Variations in these characteristics designate a wetland as being bog, fen, swamp, marsh, and shallow water wetland classes (Figure 3), the specifics of which are summarized in Table 3.

Wetland classification methods

Wetland classification grew out of a managerial need (Mitsch and Gosselink 2000) to describe these highly diverse ecosystems in a systematic manner, as well as to create baseline references for the exchange of wetland information across space, time, and disciplines (Zoltai and Vitt 1995). The process of wetland classification is carried out by grouping wetland ecosystems into categories on the basis of sharing several common ecological characteristics (Zoltai and Pollett 1983) that are usually described by a classification system, as explained in the previous section. During the past few decades, diverse approaches have been applied for mapping and monitoring wetlands, in which they can be generally divided into traditional (i.e. *in situ*) and RS methods.

Traditional wetland classification

Wetland identification and classification in the field may variably involve the application of previously established wetland classification systems (Cowardin et al. 1979; National

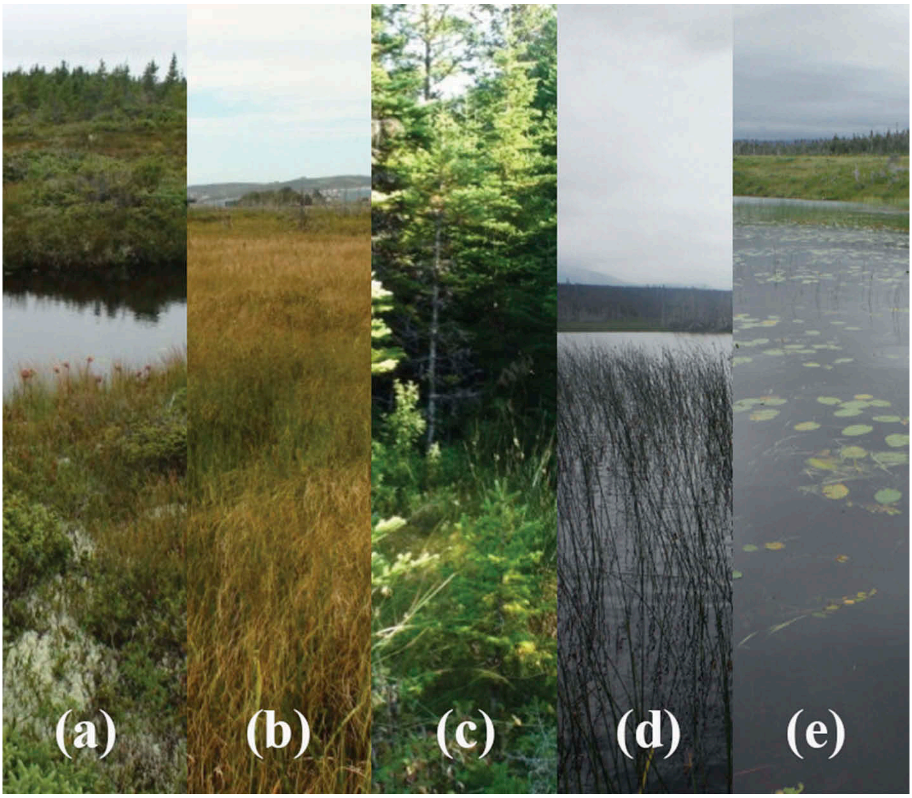

Figure 3. Wetlands located in Newfoundland, Canada, classified following the Canadian Wetlands Classification System: (a) bog, (b) fen, (c) swamp, (d) marsh, and (e) shallow water.

Table 3. Wetland classes defined by the Canadian Wetland Classification System (see National Wetlands Working Group 1997 for more details).

Class	Description
Bog	Ombrotrophic peatland dominated by sphagnum moss species.
Fen	Minerotrophic peatland dominated by graminoid species and brown mosses.
Swamp	Peatland or mineral wetland dominated by woody vegetation.
Marsh	Minerotrophic wetland with periodic standing water or slow-moving water, dominated by graminoids, shrubs, forbs, and emergent plants.
Shallow water	Minerotrophic wetland where water is up to 2 m deep for most of the year and where there is less than 25% of emergent plants or woody plants.

Wetlands Working Group 1997), wetland field guides (Racey et al. 1996; MacKenzie and Moran 2004), delineation manuals, and the use of tools and sampling methodologies (Tiner 1999). *In situ* methodologies have long been used to delineate and monitor ecosystem structure, function, and condition (National Research Council 1995; Lawley et al. 2016). Many wetlands can be identified by their characteristic vegetation. This serves as a major basis for in-field wetland identification and classification (Tiner 1999). Both the CWCS and CCS apply vegetation-based descriptions of wetlands. However, vegetation alone cannot always identify and classify a wetland, and assessments of hydrology and hydric soils are also necessary for this purpose (Tiner 1999).

Although *in situ* methodologies are important and necessary for effective wetland management, at large managerial scales (Fournier et al. 2007), the techniques have many disadvantages for wetland mapping. *In situ* methods are infeasible given the cost and time requirements, as well as the difficulties of accessing many wetlands. A large number of wetlands are located in remote areas, where topography, vegetation cover, and hydrology make field visitation challenging and costly (Belluco et al. 2006; Rampi, Knight, and Pelletier 2014; Yoshino et al. 2014; Dronova 2015; Klemas 2015). Therefore, reliance on field methodologies alone would mean disregarding many large and diverse wetland areas (Dronova 2015). Moreover, given the temporal variability of wetlands over time, repeated in-field visitation is necessary (Henderson and Lewis 2008; Gallant 2015). Additionally, classification using *in situ* information often requires cover percentage to be estimated visually, or needs other sources of data (Adam, Mutanga, and Rugege 2010; Gallant 2015). Consequently, *in situ* method can be feasibly practiced only in a small geographical context (Adam, Mutanga, and Rugege 2010; Gallant 2015; Moser et al. 2016), despite the current needs of wetland information at wider ranges, such as at watershed, continental, or global scales (Gallant 2015). On the other hand, RS methods resolve these issues of cost, time, accessibility, and repeatability effectively.

RS-based wetland classification

In the context of this paper, RS includes using any Earth Observation (EO) data such as aerial photos, satellite imagery, and so on. RS provides numerous advantages over the previously described traditional approach. RS is a comparatively cost-effective and timely method for the collection of data over a wide area at the same time. It also allows for repeated measurements in short time intervals (Rundquist, Narumalani, and Narayanan 2001; Ozesmi and Bauer 2002; Dronova 2015). Likewise, RS is capable of acquiring images from inaccessible places, where many wetlands are located. Additionally, RS can provide information on the landscapes surrounding wetlands and their variation over time and, therefore, can give the users information about wetland loss (Ozesmi and Bauer 2002). Another benefit of RS for monitoring wetlands is that RS products can be conveniently imported into Geographical Information System (GIS) to be combined with other types of information (Ozesmi and Bauer 2002). Additionally, many researchers have mentioned that since wetlands appear in various sizes their mapping should also be performed at several spatial scales, which can be easily carried out using RS tools (Powers, Hay, and Chen 2012; Dronova 2015; Ji, Xu, and Murambadoro 2015). As a result of these advantages, many researchers have reported that RS is effective in terms of the operational classification and monitoring of wetlands (Li and Chen 2005; Schmitt and Brisco 2013; Kumar and Sinha 2014; Dabboor et al. 2015).

However, although RS methods reduce the need for detailed on-site-based methods considerably compared to the ground-based methods, they do not completely eliminate this requirement. In terms of wetland classification and inventory, *in situ* data are needed to train and validate the RS methods. For instance, there is a need for a sufficient number of field-validated measurements to conduct accuracy assessments on classified RS images (Grenier et al. 2008a). Thus, most wetlands classification schemes require the application of both RS and *in situ* data (Faber-Langendoen et al. 2016).

Limitations in RS-based wetland classification methods

Though RS provides efficient tools for wetland mapping and monitoring, there are various technical limitations in wetland classification using RS data. These limitations are briefly outlined and discussed below.

- Wetland morphology is a considerable difficulty of wetland classification using RS data (Bourgeau-Chavez et al. 2009; Gallant 2015). Wetlands of one type, which lay in one class according to most classification systems, can be forested, shrubby, or herbaceous (Rundquist, Narumalani, and Narayanan 2001; Bourgeau-Chavez et al. 2009). This fact causes a single wetland class to demonstrate different spectral and/or backscattering signature in RS data (Gallant 2015; Amani et al. 2017a). On the other hand, some specific wetland types, which should be classified separately according to the classification systems, share some ecological characteristics. This fact causes these classes to have similar spectral and/or backscattering behavior in optical and SAR data. Consequently, high confusions are observed when classifying these wetland types (Henderson and Lewis 2008). In summary, wetlands have high intra-class and low interclass variability, which makes their classification challenging.
- Although the presence of water is a common feature of all wetland types and is expected to alleviate distinguishing them, it does not make the detection of wetlands easier. The reason is that the water in wetlands can often be under the earth's surface, where the plant roots are located (Gallant 2015). To further complicate matters, the water level in wetlands can change seasonally, sometimes rapidly resulting from snowmelt or precipitation, or gradually as a result of anthropogenic activities (Cowardin et al. 1979; Mitsch and Gosselink 1993; Cowardin and Golet 1995; Gallant 2015; Moser et al. 2016).
- Wetlands normally lack a defined boundary and their border is almost always fuzzy since they gradually transit from wetland to other land cover classes, such as upland or open water, or even other types of wetlands (Dronova 2015). In addition, the ecotones in and around wetland areas are sometimes very narrow, which makes their detection difficult (Gallant 2015). Therefore, the quality of image interpretation and feature extraction methodologies in wetland classification, and generally in all types of land cover classification, should also be considered (Dronova 2015).
- Wetlands, especially in boreal regions, are located in areas that are less accessible for collecting field samples. Furthermore, even with having Global Positioning System points determining a few points on wetland areas, delineating exact wetland boundaries surrounding the point using fine spatial resolution imagery is challenging, and there are always chances of overlapping with other wetland types. This fact sometimes results in having insufficient training samples for a specific wetland type.
- RS images are also restricted to a specific spatial resolution, which might limit detection of small wetlands (Ozesmi and Bauer 2002; Ji, Xu, and Murambadoro 2015). For example, if we consider a cluster of three-by-three pixels as the minimum detectable size of wetlands in an image, Landsat TM would only be able to delineate wetlands that are larger than approximately 0.01 km^2.

To recapitulate, it is quite challenging to reach a high overall accuracy for wetland classification using only RS techniques (Dronova 2015), and the ecological characteristics of wetlands cause many difficulties in wetland classification using RS methods (Cordeiro and Rossetti 2015; Gallant 2015).

Wetland classification using aerial imagery

One common method for the delineation of wetlands is the interpretation of aerial images, which was the first RS method for mapping wetlands (Seher and Tueller 1973; Shima, Anderson, and Carter 1976; Howland 1980; Tiner 1990). Aerial images usually have a higher spatial resolution compared to that of satellite imagery and, consequently, allow for the recognition of small or narrow wetlands (Ozesmi and Bauer 2002). Furthermore, aerial images can be useful when detailed mapping of wetlands is required (Ozesmi and Bauer 2002; Gallant 2015).

However, applying aerial images for wetland monitoring can be expensive and more time-consuming when compared to the application of spaceborne imagery. Satellite RS is more appropriate when the budget is limited and the area is rather unknown in terms of wetland and non-wetland areas (Ozesmi and Bauer 2002). In addition, most aerial images have limitations in spectral and temporal resolutions (Arzandeh and Wang 2002; Adam, Mutanga, and Rugege 2010), which hinders differentiation between the spectrally similar wetland classes, as well as the ability to frequently update the maps.

Despite the abovementioned difficulties, several researchers still prefer to interpret aerial images rather than applying optical or SAR satellite images (Neumann, Reigber, and Ferro-Famil 2005; Farrell et al. 2010; Cserhalmi et al. 2011; Berkowitz, Pietroski, and Krenz 2016). Moreover, there are a number of aerial sensors that are rich in terms of spectral bands, including Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), and Compact Airborne Spectrographic Imager. Several programs, such as the United States Natural Agriculture Imagery Program, also support more frequent flights over some areas in the recent years (Gallant 2015). Nevertheless, using satellite images along with aerial photos will probably provide more useful information than either image type alone (Ozesmi and Bauer 2002), for example, in a sampling strategy such as regression estimators.

Wetland classification using multispectral optical imagery

Generally, multispectral sensors are especially useful in analyzing the spectral characteristics of wetlands since they acquire information in various spectral bands, including the visible and near infrared, shortwave infrared, and thermal infrared parts of the electromagnetic spectrum (Figure 4) (Klemas et al. 1974; Wang et al. 1998; Arzandeh and Wang 2002; Gosselin, Touzi, and Cavayas 2014; Gallant 2015). It should also be mentioned that most optical data have already been geometrically and radiometrically corrected, and is ready to be used in the classification. Therefore, preprocessing optical satellite data is easier than most other RS data, including SAR, Light Detection and Ranging (LiDAR), and Unmanned Aerial Vehicle (UAV). Several prepared products of optical data are also freely downloadable for users (e.g. various products of MODIS and Landsat 8).

However, optical sensors provide poor information regarding the vegetation's physical characteristics, such as morphology and height (Gallant 2015), and are hindered by the inability to penetrate through clouds (Zhu and Woodcock 2012; Amin et al. 2013; Amani and Mobasheri 2015). As a result, some of the information that would otherwise be obtainable using satellite optical imagery is lost when the weather is cloudy. This is a common problem when monitoring wetlands and is a drawback in the applicability of optical imagery given the operational need for continuous monitoring (McNairn et al.

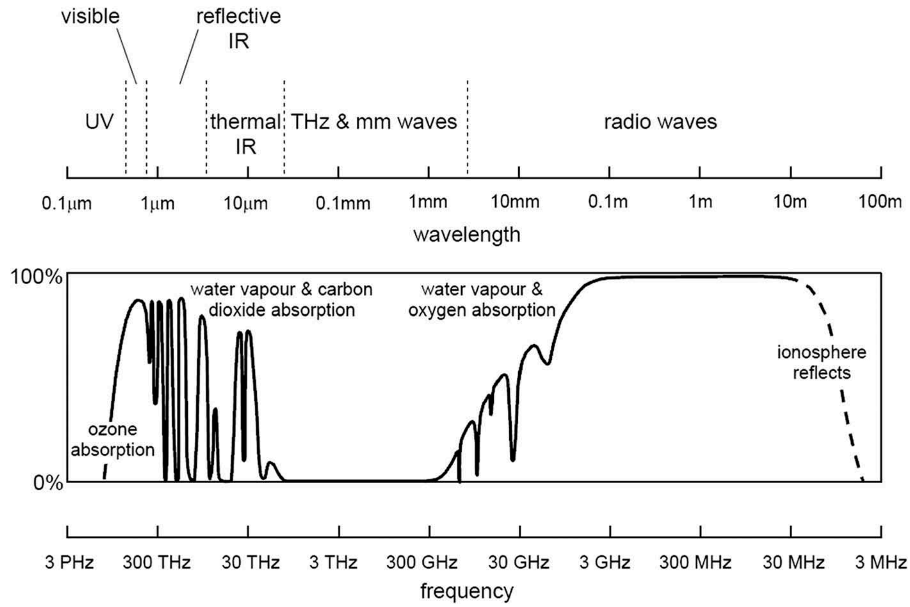

Figure 4. The electromagnetic spectrum (Richards 2009).

2009). This problem can be partially addressed through the use of optical imagery with higher temporal resolution providing the users with the ability to select cloud-free images (Gallant 2015). It should also be noted that the penetration depth of optical sensors is so low that detection of the water beneath trees/dense vegetation is not possible (Li and Chen 2005; Gallant 2015). As a result of the mentioned disadvantages of optical data, several studies have reported that the sole use of optical sensors is not sufficient for accurate classification of wetlands (Ozesmi and Bauer 2002; Bourgeau-Chavez et al. 2009).

Nevertheless, there are many studies that have attempted to map wetlands with the sole use of optical images. Dechka et al. (2002) evaluated both supervised and unsupervised classification methods (i.e. Linear Discriminant Analysis and ISODATA, respectively) for wetland classification using multitemporal IKONOS-2 imagery. The Normalized Difference Vegetation Index and several texture features were used to identify 22 different vegetation classes, as well as shallow water, deep water, and road in the study. Comparing the obtained accuracies in different seasons, the highest accuracy (overall accuracy = 96%) was obtained using the fused IKONOS imagery captured in May and July, plus the texture information. Moreover, Leahy et al. (2005) used multitemporal satellite images obtained by different Landsat satellites (Landsat 2, 3, 4, 5, and 7) for long-term change detection of wetlands in Ontario, Canada. Two different methods, including postclassification comparison and multitemporal data clustering, were evaluated to detect the changes in the Long Point wetlands over a 23-year period. Grenier et al. (2008b) also used SPOT-4 images for wetland classification in the context of greenhouse gases emissions. In their study, the multiscale object-based method based on the CWCS was used to estimate a regional carbon budget. They also reported that SPOT-4 images with finer spatial resolution compared to those of Landsat and RADARSAT-1 data were more suitable for identifying various wetland classes. As another example, Powers, Hay, and Chen (2012) used SPOT images in a decision tree algorithm to classify wetlands based on two different classification schemes (i.e. CWI and DU) in five different scales. Incorporating texture information into the classification also improved the results. Finally, Ji, Xu, and Murambadoro (2015) investigated wetlands in different scales using SPOT imagery. First a general maximum likelihood classification was applied on the images to detect large wetland areas, and then, a knowledge-based classification was used to fine-tune the identified regions. The authors reported that the knowledge-based classification method improved the results.

Currently, there are many operating optical sensors that could be applied for wetland classification. The most important difference between these sensors is the spectral resolution (the range and number of spectral bands) that the sensors employ.

As mentioned before, the optical bands include red, green, blue, red edge, near infrared, shortwave infrared, and thermal infrared. The role of visible bands in classification is not central, which is not surprising, because wetlands are difficult to distinguish visually. The red edge band is located between the red and near-infrared bands, where the reflectance value of green vegetation significantly rises from the red band to the near-infrared band. The red edge band, although not available in all sensors, provides additional information for the studies that investigate vegetation and quality of inland water bodies with relatively high phytoplankton content (Weichelt et al. 2011; Wen et al. 2014). The reflectance value in this band is related to vegetation biochemical parameters (e.g. chlorophyll content), biophysical parameters (e.g. Leaf Area Index), and water deficit in vegetation biomass (Filella and Penuelas 1994; Clevers et al. 2002; Mutanga, Adam, and Cho 2012). Consequently, the red edge band is a useful spectral band for wetland classification (Schmidt and Skidmore 2003; Adam, Mutanga, and Rugege 2010; Mutanga, Adam, and Cho 2012; Hong et al. 2015). Many studies have reported that vegetation in different wetland classes show the greatest variation in the red edge and near-infrared bands. Therefore, these two bands are the most useful optical bands for the detection of wetlands (Asner 1998; Cochrane 2000; Schmidt and Skidmore 2003; Thenkabail et al. 2004; Kamaruzaman and Kasawani 2007; Adam, Mutanga, and Rugege 2010; Amani et al. 2017a).

The shortwave infrared bands are sensitive to soil moisture and vegetation moisture. Thus, they are important bands for obtaining moisture characteristics of both soil and vegetation in wetlands (Crist and Cicone 1984; Amani et al. 2016; Mobasheri and Amani 2016; Amani et al. 2017d).

Thermal infrared bands collect the energy emitted by land surfaces and, therefore, are useful for obtaining Land Surface Temperature information. Several studies have illustrated that there is a correlation between the water temperature acquired by thermal sensors and different types of vegetation within water (Jensen et al. 1985; Rundquist, Narumalani, and Narayanan 2001). Thermal bands are useful in discriminating water areas from dense vegetation, as well as inundated regions of wetlands (Leblanc et al. 2011). A problem associated with thermal bands, however, is the coarse spatial resolution of these bands. Both visible and infrared (near, shortwave) bands usually have finer spatial resolution than thermal bands and, therefore, provide more detailed information about wetlands.

Wetland classification using SAR imagery

SAR images are capable of penetrating through the clouds and can therefore provide imagery in any weather conditions (Hoan and Tateishi 2009; Hong et al. 2015). SAR data with various sensor configurations and all-weather capability are useful in operational monitoring when the information about the extent, location, and conditions of wetlands is necessary (Henderson and Lewis 2008). At the same time, SAR sensors are able to acquire valuable information regarding the ground conditions under vegetation canopies (Li, Chen, and Touzi 2007; Hong et al. 2015). Several studies have reported significant improvements in accuracy of wetland classification, especially for swamps, when utilizing SAR imagery (Henderson and Lewis 2008; Bourgeau-Chavez et al. 2009).

Water bodies, if calm, can also be easily detected by SAR sensors. This is due to the fact that backscattering energy from the calm water is mostly specular as the water surface is flat and, consequently, the backscattered energy is very small (Kumar and Reshmidevi 2013). Many studies have also reported that SAR images are successful in the delineation of flooded areas as a result of the double-bounce scattering between the flooded surface and tree trunks and tall vegetation (Hess et al. 1995; Breiman 2001; Henderson and Lewis 2008; Hong et al. 2015; Moser et al. 2016). Likewise, the coefficient of variation has been reported useful for distinguishing between swamp and upland (Touzi, Deschamps, and Rother 2009). An important feature to be used for discriminating between various wetland types is the dominant scattering type phase $\Phi_{\alpha s}$, which has been introduced by Touzi (2007) and Touzi, Deschamps, and Rother (2007). This parameter is especially useful for distinguishing between bog and fen at C-band. The reason is that this parameter is able to detect water beneath the vegetation at various depths, as explained in Touzi, Deschamps, and Rother (2009). By the same token, the dominant scattering-type phase is able to differentiate conifer-dominated treed bog from deciduous forest in leafy conditions (Touzi, Deschamps, and Rother 2009). As reported by Touzi, Deschamps, and Rother (2009), none of the other polarimetric features, including entropy or phase difference, has such a capability. However, it should be considered that both the dominant scattering-type phase and magnitude are needed for the unambiguous characterization of wetlands (Touzi, Deschamps, and Rother 2007).

Despite the advantages of SAR data for wetland classification, it should be noted that preprocessing of SAR data is more time-consuming than optical images, and sometimes requires knowledge in this field. Equally important, during preprocessing performed by an operator, various uncertainties might be involved in the generation of the final image. For instance, one of the most obvious problems associated with SAR data is the presence of speckle. Speckle degrades the radiometric quality of the image and, therefore, hinders image segmentation and classification (Mahdavi et al. 2016; Mahdavi et al. 2017c). Another issue that results from the presence of speckle on a SAR image is that the training samples must be several times larger than that required for the optical data (Henderson and Lewis 2008).

The first attempt to classify wetlands using SAR images began in the late 1960s and early 1970s (Henderson and Lewis 2008). Subsequently, a host of studies have utilized SAR data for wetland mapping and monitoring. Touzi, Deschamps, and Rother (2007) investigated the potential of full-polarimetric C-band images for wetland mapping using Convair-580 data. Several polarimetric parameters extracted from the Touzi decomposition (Touzi 2007) illustrated a high potential for distinguishing bog and fen. In Whitcomb et al. (2007), JERS L-band SAR imagery was also applied for the generation of a wetlands' thematic map. Similarly, Brisco et al. (2011) evaluated several polarimetric decompositions, including Freeman–Durden (Freeman and Durden 1998) and Cloude–Pottier (Cloude 1985) decompositions, for wetland mapping using Convai-580 data. After separability analyses, the authors concluded that full-polarimetric data are more informative than the other data sources for wetland mapping using a maximum likelihood classifier. Additionally, a study that was conducted by Marechal et al. (2012) applied RADARSAT-2 image time series to investigate the sensitivity of different polarimetric parameters to the change in water level in saturated wetlands. They found that the Shannon entropy is the most useful parameter for the detection of saturated wetland areas. Likewise, a comprehensive study was carried out by Gosselin, Touzi, and Cavayas (2014), who investigated the potential of several polarimetric features, such as the Touzi decomposition, for wetland mapping using a decision tree classifier. Finally, Mahdavi et al. (2017b) investigated the capability of RADARSAT-2 full polarimetric images for wetland classification in the Canadian province of Newfoundland and Labrador.

The SAR system configuration plays a pivotal role in the capability of a SAR system for wetland classification (Wang et al. 1998; Brisco et al. 2011; Brisco et al. 2013; Schmitt and Brisco 2013; Gosselin, Touzi, and Cavayas 2014; White et al. 2015). An appropriate SAR configuration should be adopted such that there is maximum distinction between wetlands and uplands, as well as between different types of wetlands (Bourgeau-Chavez et al. 2009). Therefore, the effects of each sensor specification are summarized in Table 4 and are reviewed in the following subsections.

Wavelength. SAR sensors operate in various bands. These bands, among other SAR bands, include P-, L-, S-, C-, and X-bands with wavelengths of approximately 100, 25, 11, 6, and 3 cm, respectively (Figure 5). L-band was the most used band in early studies for wetland mapping and was frequently cited as the best wavelength for wetland mapping (Henderson and Lewis 2008; Moser et al. 2016; Mahdavi et al. 2017d). Several studies have also reported that longer wavelengths are more appropriate for the separation of forested or densely vegetated wetlands (e.g. swamp) from non-flooded ones (Kasischke et al. 2003; Li and Chen 2005; Whitcomb et al. 2007; Henderson and Lewis 2008; Hong et al. 2015; Mahdavi, Maghsoudi, and Amani 2017a) (Kasischke et al. 2003; Li and Chen 2005; Whitcomb et al. 2007; Henderson and Lewis 2008; Hong et al. 2015; Mahdavi et al. 2017d). The reason is that the penetration depth of P- and L-band signals is high (Li, Chen, and Touzi 2007). Consequently, these signals can pass through the woody vegetation canopy and detect the water beneath the flooded trees and/or dense vegetation. On the other hand, several studies have mentioned the potential of short-wavelength SAR images for characterizing herbaceous wetlands (e.g. bog, fen, and marsh), as well as detecting water beneath the short vegetation (Li and Chen 2005; Henderson and Lewis 2008; Dronova 2015; Hong et al. 2015). Short wavelengths are also able to distinguish between emergent wetlands and agricultural fields/herbaceous uplands (Bourgeau-Chavez et al. 2009). However, it is worth mentioning that there is still a considerable confusion between different short vegetated wetlands, such as bogs and fens in wetland classification using SAR imagery (Sokol, Pultz, and Bulzgis 2001; Li and Chen 2005).

Polarization. SAR sensors can be single-, dual-, or quad (full)- polarized. Each polarization channel is represented in the form of PQ, where P is the transmitting, and Q is the receiving polarization. Both P and Q can either be horizontal (H) or vertical (V) (Figure 6).

Single-polarization SAR data are not very effective for wetland classification because the received energy in a SAR image consists of several different backscattering types, which cannot be distinguished using a single channel (Touzi, Deschamps, and Rother 2007; Brisco et al. 2011; Moser et al. 2016). Single-polarized data, however, have been reported to be effective for the detection of calm open water bodies (Moser et al. 2016).

Table 4. Description of various SAR configurations for wetland mapping.

Wavelength	Short	Best for characterizing herbaceous wetlands
	Long	Most appropriate for detection of frosted or densely vegetated wetlands
Polarization	Co-polarization	HH: useful for detection of flooded forest and inundation – more effective for wetland classification than VV
	Cross-polarization	HV: useful for discrimination between herbaceous and woody vegetation – e.g. discrimination of swamp from marsh
Incidence angle	Small	Useful for detection of water body under vegetation
	Large	Useful for detection of shrubby and herbaceous wetlands
Orbit	Ascending	Recommended for wetland mapping
	Descending	Not recommended for wetland classification because of presence of dew at the time of image acquisition

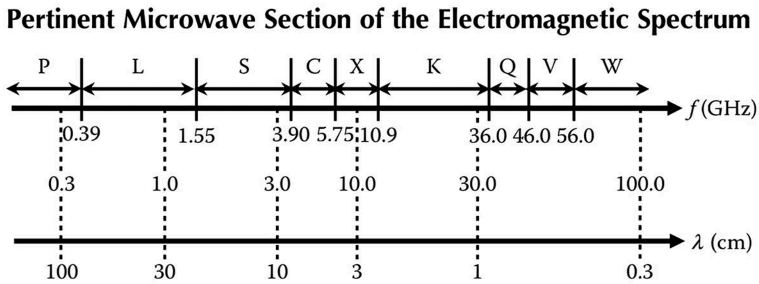

Figure 5. Radar bands (Lee and Pottier 2009).

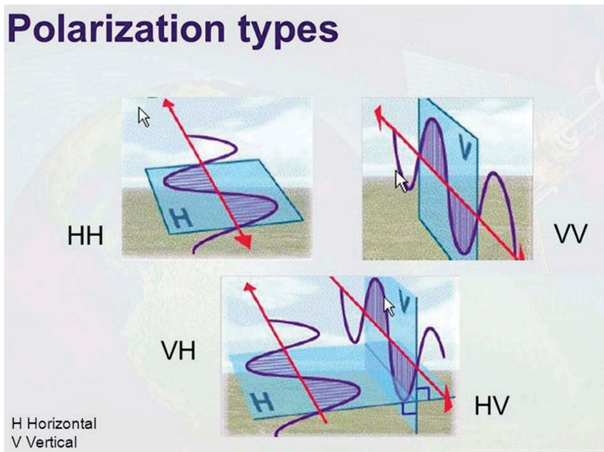

Figure 6. Polarization types (Chuvieco 2009).

Generally, HH polarization is the most useful for wetland delineation (Bourgeau-Chavez et al. 2009). Moreover, L-HH and C-HH are especially effective in the detection of flooded forest, and are more sensitive to inundation than vertical polarization (Henderson and Lewis 2008; Lang and Kasischke 2008; Kasischke et al. 2009; Moser et al. 2016). In addition, the correlation between C-band backscatter and inundation is stronger in leaf-off season (Kasischke et al. 2009). For vertically oriented vegetation, the HH-polarized wave has more penetration into the canopy relative to the VV-polarized wave and, thus, is more sensitive to soil conditions (McNairn et al. 2009). HV polarization is also effective in the discrimination between woody and herbaceous wetlands as a result of its sensitivity to biomass (Bourgeau-Chavez et al. 2009). Although less than the HH-polarized wave, VV polarization is also sensitive to soil moisture and flood conditions (Bourgeau-Chavez et al. 2009; Mahdavi, Maghsoudi, and Dehnavi 2014). When interacting with vertically oriented vegetation, the VV-polarized wave has the most response, and therefore the penetration into the vegetation is reduced (McNairn et al. 2009).

Co-polarized waves (HH and VV) are more effective in the detection flooded from non-flooded wetlands and generate higher contrast between dry forest and flooded swamp compared to cross-polarized waves. The reason for this is that the signal response from like-polarized waves is enhanced in flood conditions (Henderson and Lewis 2008). Cross-polarized waves, however, are more appropriate for distinguishing swamp from marsh (Henderson and Lewis 2008). Dual co-polarized data are also successful in the characterization of flooded vegetation mapping.

Polarization ratios, which include HH backscatter, are also useful for distinguishing flooded versus non-flooded vegetation (Brisco et al. 2011). In addition, the ratio of L-HV and L-HH bands have proved promising for the discrimination of non-forested wetland types (Bourgeau-Chavez et al. 2009).

Phase difference between HH and VV channels also helps in the discrimination of swamp and upland, or flooded from non-flooded vegetation (Hess et al. 1995; Henderson and Lewis 2008; Touzi, Deschamps, and Rother 2009). Furthermore, this phase difference was recognized as the most useful parameter for natural target characterization (Touzi, Deschamps, and Rother 2009).

Incidence angle. To detect water bodies under vegetation, steep incidence angles (smaller than 35°) are the most appropriate (Li, Chen, and Touzi 2007; Bourgeau-Chavez et al. 2009), as low incidence angles have more penetration depth. Several studies have reported that short wavelengths with low incidence angles can be applied for the delineation of forested wetlands in leaf-off conditions (Henderson and Lewis 2008). However, some studies have shown no specific correlation between incidence angle and the vegetation type/structure (Hess, Melack, and Simonett 1990; Durden et al. 1996; Henderson and Lewis 2008). According to Henderson and Lewis (2008), moderate incidence angles do not seem to provide much useful information for wetland detection, especially if the image has fine resolution. Further, fine beam modes of RADARSAT-2, because of having a high incidence angle, are not suggested for the discrimination and classification of wetlands, but are appropriate in terms of spatial details (Li, Chen, and Touzi 2007). Sokol, Pultz, and Bulzgis (2001) also investigated various RADARSAT-2 beam modes (incidence angles) for the discrimination of different wetland types. The main difference was the dynamic range of backscatter for wetland sites, which was the largest in S5 mode and the smallest in F1 mode (refer to Slade 2009 for more information about RADARSAT-2 beam modes). However, it should be considered that the range in incidence angle is small in the Fine mode of RADARSAT-2. Another result of Sokol, Pultz, and Bulzgis (2001) was that a significant difference was not observed between the backscatter of bog and fen in any of the incidence angles. Finally, Li, Chen, and Touzi (2007) reported that low incidence angles can penetrate into both shrubby and herbaceous wetlands, while high incidence angles are only able to pass through low-density vegetation.

Orbit. SAR sensors are capable of acquiring images in both ascending and descending modes. The ascending mode for SAR imagery is recommended for wetland mapping since at the time when the descending image is acquired dew on vegetation can decrease the contrast between wetlands and non-wetlands (Grenier et al. 2007).

Wetland classification using other resources

Digital elevation model (DEM) data. The DEM has proved useful for distinguishing wetland classes. At the same time, many studies have reported that the topographic features extracted from DEM were also effective for finding the distribution and location of wetlands (Li and Chen 2005; Brisco et al. 2011; Smith, Macleod, and Kloiber 2012; Cordeiro and Rossetti 2015; Dronova 2015; Kloiber et al. 2015; Whiteside and Bartolo 2015; Franklin and Ahmed 2017). For example, the Topographic Position Index (Weiss

2001), Compound Topographic Index (Moore, Grayson, and Ladson (1991)), slope, and orientation of the DEM have been used in several studies for wetland classification (Hogg and Todd 2007; Murphy et al. 2007; Smith, Macleod, and Kloiber 2012; Rampi, Knight, and Pelletier 2014; Kloiber et al. 2015). A rather new by-product of TanDEM-x is the WAter indication Mask that can identify water bodies based on the coherency and amplitude of water in a SAR image (Wendleder et al. 2013). DEMs can also be included in the wetland mapping procedure to correct the areas of misclassification as a result of layover and shadowing (Whitcomb et al. 2007; Whiteside and Bartolo 2015). However, it should be noted that the applied DEM should have a resolution high enough for deriving precise topographic information. DEMs obtained from EO images and LiDAR data can yield spatial resolutions up to 1 m and 15–30 cm, respectively.

Lidar data. LiDAR can be effectively used for the extraction of topographic information and structural indices (Dronova 2015). Since topographic information is capable of predicting the location and distribution of wetlands, LiDAR has also been applied in wetland mapping in many studies (Hogg and Holland 2008; Maxa and Bolstad 2009; Lang et al. 2012; Millard and Richardson 2013; Huang et al. 2014; Franklin and Ahmed 2017). In general, information derived from LiDAR is applied as ancillary information in addition to the spectral and textural data (Dronova 2015). For instance, Hogg and Holland (2008) applied DEMs derived from LiDAR instead of the typical DEMs and observed 8% improvement in the accuracy of wetland mapping. Maxa and Bolstad (2009) combined IKONOS imagery with LIDAR data to classify wetlands in Wisconsin and achieved an accuracy of 75%, which was superior to the accuracy of the existing map for that region. Furthermore, Lang et al. (2012) observed a considerable improvement in wetland detection when using LiDAR for mapping streams.

Hyperspectral data. Hyperspectral data have high spectral resolution, which is particularly useful for the detection of detailed variations between various wetland vegetation species (Adam, Mutanga, and Rugege 2010). The data, containing hundreds of bands, have many advantages in assessing the biochemical and biophysical properties of wetlands (e.g. leaf water content, Leaf Area Index, as well as chlorophyll and biomass concentrations). However, it should be noted that the number of bands should be reduced using statistical methods, such as principal components analysis or minimum noise fraction, to omit the redundant information. Furthermore, hyperspectral images are rather expensive, and tedious to process, which hinders their application in wetland studies (Adam, Mutanga, and Rugege 2010). Nevertheless, there are several studies that have used hyperspectral imagery for wetland monitoring and classification (Schmidt and Skidmore 2003; Rosso, Ustin, and Hastings 2005; Vaiphasa et al. 2005; Belluco et al. 2006; Pengra, Johnston, and Loveland 2007). For example, Rosso, Ustin, and Hastings (2005) mapped wetlands in the San Francisco Bay using both Spectral Mixture Analysis and Multiple Endmember Spectral Mixture Analysis and AVIRIS images, and concluded that both methods can be applied for investigating the structure of wetlands. Moreover, Vaiphasa et al. (2005) did a laboratory-based study to see if mangrove species are distinguishable using numerous spectral channels between 350 and 2500 nm. They introduced four bands of 720, 1277, 1415, and 1644 nm as bands that guarantee 80% of overall accuracy.

UAV data. UAV has only recently been applied in natural landscapes, including wetlands (Boon, Greenfield, and Tesfamichael 2016). Images acquired by UAVs contain great advantages over the typical aerial images given that UAV is capable of acquiring images below the cloud cover (Shahbazi, Théau, and Ménard 2014). In addition, UAV images provide a great level of detail as a result of their fine spatial resolution (Shahbazi, Théau, and Ménard 2014; Boon, Greenfield, and Tesfamichael 2016). Consequently, there are several studies that have explored the possibility of using this technology for wetland mapping (Li et al. 2010; Zaman, Jensen, and McKee 2011; Shahbazi, Théau, and Ménard 2014; Boon, Greenfield, and Tesfamichael 2016). For example, Li et al. (2010) processed UAV images using both automatic and manual methods to map wetlands in the Honghe National Nature Reserve and found UAV images useful for this purpose. In a similar study, Zaman, Jensen, and McKee (2011) combined UAV data with a new classification algorithm to map wetlands in Utah with an accuracy of 95%.

However, it is worth noting that many UAVs are limited to acquiring images in the visible and near-infrared domain, and only a few UAVs can provide rich spectral information (Shahbazi, Théau, and Ménard 2014). Moreover, images taken by UAV are prone to many radiometric and geometric errors (Hardin and Jensen 2011; Shahbazi, Théau, and Ménard 2014). Geometric errors, however, can be corrected using ground control points.

Multisource wetland classification

Combining several types of RS data is very common in classification procedures and has also proved useful in wetland classification (Sokol, Pultz, and Bulzgis 2001; Grenier et al. 2007; Henderson and Lewis 2008; Koch et al. 2012; Hong et al. 2015). By combining various types of imagery, it is possible to take advantages of each type of data and improve wetland classification. However, a problem with multisource classification is the large volume of various data sets, many containing different spatial resolutions (Cordeiro and Rossetti 2015). By the same token, there is an inconsistency regarding that combination of data sources yields the best results (Henderson and Lewis 2008).

Reif et al. (2009) combined GIS and RS data to map wetlands in Florida. Kloiber et al. (2015) also used a combination of PALSAR data, aerial imagery, and DEM data in an attempt to update the NWI. The authors also applied other data, such as the soil water regime and the percentage of hydric soil for wetland classification. Similarly, Cordeiro and Rossetti (2015) applied ASTER, ALOS, and DEM data for the object-based mapping of wetlands in North Brazilian Amazonia. Finally, Franklin and Ahmed (2017) conducted a study in northern Canada using RADARSAT-2, Landsat-8, and geomorphometric information extracted from LiDAR data. In general, the accuracy that was obtained using multisource data was superior to using SAR or optical data individually.

Fusion of optical and SAR data is one of the most common, yet most auspicious types of data combination for wetland mapping and monitoring (Wang et al. 1997; Grenier et al. 2007; Henderson and Lewis 2008; Koch et al. 2012; Lin and Yue 2014; Hong et al. 2015; Amani et al. 2017b). For example, Grenier et al. (2007) used a combination of RADARSAT-1 and Landsat data for mapping wetlands at several scales. The classification began at a coarse level using membership functions. Then, the identified areas were masked, and the remaining areas were segmented and classified with a finer scale. This process continued until all the desired areas were detected. Additionally, Durieux et al. (2007) combined Global Boreal Forest Mapping JERS-1 SAR data with MEdium Resolution Imaging Spectrometer optical data for wetland mapping on a continental scale. In their study, an object-based classification was applied to the images. Furthermore, Bourgeau-Chavez et al. (2009) combined SAR and optical data to map wetlands in several regions in Alberta, Canada. Hong et al. (2015) also combined

RapidEye images and various SAR decompositions extracted from TerraSAR-X images for classification of wetlands in Florida. Finally, Amani et al. (2017b) mapped wetlands over five pilot sites across the Canadian province of Newfoundland and Labrador, using a combination of optical and SAR imagery, achieving the accuracy of up to 96%.

Another common type of multisource combination for wetland classification is the use of multiple SAR sensor configurations (e.g. multiple wavelengths or multiple incidence angles). For instance, Henderson and Lewis (2008) reported that using multiple wavelengths is useful for the detection of both forested and herbaceous wetlands. According to their results, multifrequency data are as good as or better than multitemporal data for wetland detection. Multi-incidence angle data, however, are not expected to improve the classification accuracy considerably. Hong et al. (2015) reported that using a combination of polarimetric SAR configurations holds great promise for distinguishing wetland vegetation types. Other studies that have used different configurations of SAR sensors for mapping wetlands are Sokol, Pultz, and Bulzgis (2001), Li, Chen, and Touzi (2007), and Aires, Papa, and Prigent (2013).

Multitemporal versus single date wetland classification

A characteristic feature of wetlands is their dynamicity, which is a result of interactions and feedback between climate, weather, geomorphology, biota, and hydrology and anthropomorphic effects (National Wetlands Working Group 1997; Mitsch and Gosselink 2000). The dynamic nature of these ecosystems causes wetland features, such as water, vegetation, and chemical characteristics to change over time. Consequently, a wetland may look different over years, months, or even days (National Wetlands Working Group 1997; Kluge and Bartels 2001). For example, seasonality influences the availability of water, affecting the growth and lushness of vegetation, resulting in wetland vegetation looking different from summer to winter (Merendino et al. 1990; Kuria et al. 2014). In the short term, rain can cause flooding and briefly fill depressions, which can change the appearance of wetlands within days. On the other hand, in the long term, wetlands can change from one type to another, as demonstrated by the climate-driven fen–bog transitions of the Holocene (Väliranta et al. 2016).

As a result of the ever-changing nature of wetlands, the use of multitemporal images has been found to improve wetland classification accuracy (Dechka et al. 2002; Ozesmi and Bauer 2002; Leahy et al. 2005; Li and Chen 2005; Racine, Bernier, and Ouarda 2005; Bourgeau-Chavez et al. 2009; McNairn et al. 2009; Gosselin, Touzi, and Cavayas 2014; Moser et al. 2016; Amani et al. 2017c; Mahdavi et al. 2017b). It should be noted that the selection of the appropriate acquisition date for images applied for wetland mapping is crucially important, even more so than the number of images. This is because wetland morphology and water level vary considerably throughout a year (Henderson and Lewis 2008; Bourgeau-Chavez et al. 2009). However, an optimum range of image acquisition has not been yet determined (Henderson and Lewis 2008). Henderson and Lewis (2008) reported that adding images from multiple dates can increase the accuracy only to a certain extent. This is because once a certain accuracy is reached the accuracy does not change, or in some cases may even decrease. Typically, summer images (especially images acquired in August in the northern hemisphere) are the best for wetland classification (Munyati 2000; Mahdavi et al. 2017b). The images acquired in spring or fall can be also helpful.

Object-based versus pixel-based wetland classification

Pixel-based classification methods analyze the value of each pixel in an image without considering the spatial or contextual information of the surrounding pixels. Generally, classifying fine spatial resolution imagery using pixel-based methods results in a "salt and pepper" effect and, consequently, the accuracy of classification is reduced (De Jong, Hornstra, and Maas 2001; Campagnolo and Cerdeira 2006; Gao and Mas 2008).

On the other hand, Object-Based Image Analysis (OBIA) is the process of segmenting an image into spectrally and spatially homogeneous objects, and then incorporating the spectral, geometric, and other features of those objects into a classification process (Benz et al. 2004; De Sousa et al. 2012; Powers, Hay, and Chen 2012; Salehi et al. 2012; Whiteside and Bartolo 2015). OBIA has several advantages some of which are reviewed below:

- By applying OBIA, it is possible to include many object-based features, such as textural, geometrical, and morphological features into classification in addition to the spectral features (Shackelford and Davis 2003; Reif et al. 2009; Dronova 2015).
- The result of object-based classification has a more ecologically meaningful interpretation compared to that of pixel-based classification (Reif et al. 2009; Franklin and Ahmed 2017).
- OBIA can facilitate the processing of a large volume of multisource data (Cordeiro and Rossetti 2015) and can be efficiently combined with supplementary data sets without a complicated data fusion process (Dronova 2015).
- OBIA minimizes the effect of unusual pixels, such as shadows or isolated elements (Reif et al. 2009; Dronova 2015).
- By applying OBIA, it is possible to work with images on several scales, which can be nested in each other.

Because of the mentioned advantages, OBIA has been widely used for wetland classification compared to pixel-based methods (Grenier et al. 2007; Grenier et al. 2008b; Bourgeau-Chavez et al. 2009; Powers, Hay, and Chen 2012; Qian et al. 2014; Cordeiro and Rossetti 2015; Franklin and Ahmed 2017).

However, choosing the optimum scale for segmentation in an object-based classification is difficult (Dronova 2015). Besides, mismatching image layers and errors in their co-registration might influence OBIA (Dronova 2015). Another difficulty associated with object-based classification is that there are many object-based features, and an expert needs to know what features result in the best accuracy (Cordeiro and Rossetti 2015). It should be considered that spectral features in classification are much more important than other object-based features (Dronova 2015). Geometric objects are also less commonly used in wetlands, as wetlands rarely exhibit a regular or consistent shapes and sizes (Dronova 2015). The most commonly used contextual variables for the identification of wetland classes are also distance, proximity, adjacency, and relative border to specific classes, such as water bodies (Dronova 2015).

Different algorithms for wetland classification

Supervised classification. There are many classification algorithms, most commonly used of which are *K* nearest neighbors (KNN, Fix and Hodges 1951), Maximum Likelihood

(ML, Aldrich 1997), support vector machine (SVM, Cortes and Vapnik 1995), decision tree (DT, Breiman 2001), and random forest (RF, Breiman 2001). In each of the classifiers, there are factors that can greatly affect the classification accuracy. The image segmentation phase, selection of training samples, feature selection, and the setting of tuning parameters are amongst the most important factors (Duro, Franklin, and Dubé 2012). It is important to bear in mind that classification accuracy is not the only thing to be considered about the classifier if the classifier can be used for operational monitoring purposes is also important (McNairn et al. 2009). In summary, there is no single classification method considered to be optimal for all applications and, thus, the desired algorithm should be selected based on the objectives and study area (Adam, Mutanga, and Rugege 2010). The most famous classification algorithms are explained below.

KNN: The KNN classifier is based on the distance of unknown pixels/objects from training samples in a feature space. The *K* nearest training sample(s) determine the class of an unknown pixel with a majority vote (Fix and Hodges 1951). Because of several limitations of the KNN algorithm, only a few studies have utilized this classifier for wetland mapping (Qian et al. 2014; Hong et al. 2015).

ML: The ML algorithm is based on Bayesian statistics and assumes that feature vectors of each class are normally distributed (Qian et al. 2014). Based on the normal distribution, a discriminant function is defined for each class, and the unknown pixel is assigned to the class with the highest value of the discriminant function for that pixel (Duda, Hart, and Stork 2001). An advantage of the ML algorithm is that it adopts a tangible and clear statistical approach for classification, and does not contain a black box as in RF or SVM (Moser et al. 2016). The algorithm was the most widely used classifier selected for wetland classification in the early years of the 2000s (Ozesmi and Bauer 2002). As a result of the advantages of the ML algorithm, there are many studies that have used the classifier for wetland classification (Wang et al. 1998; Arzandeh and Wang 2002; Brisco et al. 2011; Gosselin, Touzi, and Cavayas 2014).

SVM: The SVM classification method is a nonparametric algorithm. The algorithm defines a hyperplane, which maximizes the distance between the training samples of two classes, and then, classifies the other pixels/objects based on this hyperplane (Qian et al. 2014). SVM is also less sensitive to the amount of training samples and can result in a higher classification accuracy given a relatively small number of samples compared to other classification algorithms (Qian et al. 2014). However, it should be noted that SVM needs a kernel function, defining which is time-consuming and subjective (Kavzoglu and Colkesen 2009; Qian et al. 2014). Several studies, including Duro, Franklin, and Dubé (2012), Qian et al. (2014), and Adam et al. (2014), have evaluated the accuracy of the SVM classifier for wetland classification.

DT: The DT classifier, belonging to the category of classification and regression trees (CART), includes several nodes, by which the input data are divided into mutually exclusive groups based on their attributes, such that each group has the most homogeneous objects. The division recursively continues into increasingly homogeneous subsets until each node represents one of the desired classes (Breiman et al. 1984; Li and Chen 2005; Cordeiro and Rossetti 2015). DT is a fast, simple, and flexible classification method, which is more effective in the prediction of class labels when the boundary between classes is not linear. The DT algorithm does not need any assumption regarding the distribution of the classes (Li and Chen 2005; Adam, Mutanga, and Rugege 2010; De Sousa et al. 2012; Powers, Hay, and Chen 2012; Cordeiro and Rossetti 2015). A problem associated with DT, however, is that it cannot be adapted to regional or national scales because the algorithm overfits the training samples (Grenier et al. 2007). There are several recent studies that have adopted the DT algorithm for wetland classification (Powers, Hay, and Chen 2012; Reschke et al. 2012; Gosselin, Touzi, and Cavayas 2014; Qian et al. 2014).

RF: The RF algorithm, also belonging to the category of CART, is actually an extension of DT. RF consists of an ensemble of decision trees, in which each tree is constructed using a subset of training samples with replacements. Only a subset of features is used for finding the best split at each node, which is a constant number over all nodes and all trees. After training, the input feature vector is ingested into every single tree and then is assigned a class label to each pixel/object at the terminal node based on the majority of votes (Breiman 2001). Like the SVM and DT algorithms, RF is also a nonparametric classifier. Nonparametric methods do not require any assumptions for the distribution of the data sets and, therefore, have several advantages compared to the parametric algorithms, such as the ML classifier. It is also worth mentioning that the RF algorithm has recently gained increasing attention in wetland monitoring (Pal 2005; Whitcomb et al. 2007; Mutanga, Adam, and Cho 2012; Whiteside and Bartolo 2015; Franklin and Ahmed 2017).

Recommendations

In this section, several recommendations are provided that can contribute to the improvement of wetlands management:

- The creation of more specialized classification systems that are compatible with the nationwide classification system (Zoltai and Vitt 1995) would be an asset. This would create a common baseline and facilitate the exchange of information across different wetland classifications. An example of such a system is the Ducks Unlimited Enhanced Wetland Classification System (Smith et al. 2007). This classification system was developed for the purpose of inventorying and addressing the diversity of wetlands (Smith et al. 2007; Ducks Unlimited Canada 2011).
- Applying advanced automatic or semi-automatic methods, specific to wetlands, for the purpose of wetland mapping is valuable. For example, for the wetland classes that are very similar to each other, fuzzy classification can be applied. In the fuzzy method, the object/pixel is not strictly classified into one of the wetland classes, but a certain probability is assigned to the membership of the object/pixel to each wetland class.
- The method and the applied data set for wetland mapping should be wisely selected according to the target classes and the required accuracy.
- The need for field data collection should be reduced with advanced RS techniques that give reasonable accuracy with a small amount of training samples.
- Instead of concentrating over a small area over a short period of time for wetland classification, the proposed methods should be operational over large geographical regions. Moreover, researchers should make the most of the freely available satellite images because these images provide the possibility of producing maps over large regions with frequently updating it. In the case of wetland mapping, the operationality and the cost of the method is often as important as the accuracy of the final map.
- The potential of quad-polarimetric or compact-polarimetric images should be fully exploited in wetland mapping.

Summary and conclusion

This review is an attempt to acquaint readers with wetland definition, benefits, extent, and loss. Wetland inventory and classification schemes are also defined and examples are provided. Furthermore, various RS methods for wetland classification along with their values and limitations were reviewed. There are also sections describing object-based classifications and the characteristics of various classifiers.

Although some studies have estimated the global wetland coverage, a more up-to-date and precise estimation is required because for the most part the current estimation for the global wetland coverage is not accurate. The reason for the inaccurate global wetland estimation might partly lay in the fact that several wetland inventories are usually incomplete, out of date, or imprecise. The Cowardin and CWCS classification systems are designed to be general enough so that the classifications are relevant across geographically large areas and, thus, ecologically, climatologically, and geologically diverse areas. As a result, these countrywide classification systems often do not contain enough information for addressing more specific wetland-related questions (Zoltai and Vitt 1995).

Considering the advantages of the satellite RS methods, including its cost-efficiency, timeliness, and potential to be applied with regular frequency at the global level, it is the best method for generating and updating wetland inventories. Based on the literature it can be concluded that the red edge and near-infrared bands are the most useful bands in optical imagery for wetland classification. In terms of SAR imagery, generally steep incidence angles and long wavelengths are suitable for the detection of shrubby or forested wetlands, while large incidence angles and short wavelengths are proper for the detection of herbaceous wetlands. Full polarimetric images are ideal for wetland mapping, but HH polarization is the best amongst other polarizations for this purpose. Additionally, multisource and multitemporal classifications are promising for the delineation of wetlands. At the same time, RF classifier has proved most promising for wetland mapping since various types of data with different sources can be utilized in RF and reasonable accuracies can be achieved without the problem of overfitting to the training samples.

It is hoped that the current review helps researchers to adopt a method, which provides the opportunity for accurate mapping of wetlands, as well as continuously monitoring them.

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