Chapter 7

A Collection of Novel Algorithms for Wetland Classification with SAR and Optical Data

Bahram Salehi, Masoud Mahdianpari,
Meisam Amani, Fariba M. Manesh, Jean Granger,
Sahel Mahdavi and Brian Brisco

Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/intechopen.80688

Abstract

Wetlands are valuable natural resources that provide many benefits to the environment, and thus, mapping wetlands is crucially important. We have developed land cover and wetland classification algorithms that have general applicability to different geographical locations. We also want a high level of classification accuracy (i.e., more than 90%). Over that past 2 years, we have been developing an operational wetland classification approach aimed at a Newfoundland/Labrador province-wide wetland inventory. We have developed and published several algorithms to classify wetlands using multi-source data (i.e., polarimetric SAR and multi-spectral optical imagery), object-based image analysis, and advanced machine-learning tools. The algorithms have been tested and verified on many large pilot sites across the province and provided overall and class-based accuracies of about 90%. The developed methods have general applicability to other Canadian provinces (with field validation data) allowing the creation of a nation-wide wetland inventory system.

Keywords: canadian wetlands, remote sensing, SAR, optical imagery, wetland inventory

1. Introduction

1.1. What are wetlands?

Wetlands are among the most productive and biodiverse ecosystems in the world, covering an estimated 5–10% of the total global land surface [1]. For comparison, forests (the most dominant terrestrial ecosystem) make up an estimated 30% of the total global land surface [2, 3]. Though the term wetland has various definitions depending on the country of origin or application, most definitions share three common characteristics: the presence of water at or near the surface, the presence of unique soil conditions, and the presence of vegetation adapted to the wet conditions [4, 5]. Despite these commonalities, wetlands manifest in a variety of forms that have resulted in the production of numerous classification systems [6–8].

Wetlands form as a result of complex interactions among climatological, geological, geographical, geomorphological, chemical, floral, and faunal components of the environment [5, 9]. Variations within each of these environmental components and the way in which these components interact can produce wetlands that, while sharing similarities in the sense that they have a water table near the surface or vegetation adapted to wetland conditions [5], appear to be vastly different. The umbrella of wetlands includes ecosystems such as flooded forests with tall trees, sprawling tree-less bogs, rice paddies [10], and even transitory pools of water present only during the rainy season [11]. Certainly, what is, and is not, considered a wetland depends on governing body, location, and area of study [7]. In Canada, one wide-spread classification system describing these variable ecosystems is the Canadian Wetland Classification System (CWCS) [8]. See **Table 1** and **Figure 1** for examples of wetland classes described by the CWCS.

Although a popular topic today, the biology and beneficial services provided by wetlands were historically not well understood, and in the face of growing global populations and increasing urban and industrial sprawl, wetlands have been extensively lost and damaged [12, 13]. Currently, it is estimated that between 54 and 70% of the world's wetlands have been destroyed of damaged [1, 13]. Threats to wetlands today include not only land-use conversion but also complex global phenomena such as climate change [14]. This loss in turn has resulted in a decrease in the quality and quantity of locally and globally important ecosystem services that are often difficult to replace [15].

1.2. Wetlands functions and services

In recent times, there has been increased interest in wetlands due to both the historic and present rates of loss and a better understanding of the benefits wetlands provide to humans, other animals, and plants. These benefits, generally referred to ecosystem values or services, are the result of the natural functional processes that wetlands carry out through interactions

Wetland class	Wetland description
Bog	Peatland dominated by *Sphagnum* moss species and ericaceous shrubs, receiving water only from atmospheric sources.
Fen	Peatland dominated by graminoids (sedges and grasses and brown mosses, receiving water from multiple (precipitation, ground, surface) sources.
Swamp	Peatland or mineral wetland dominated by woody vegetation, potentially with standing water during certain times of the year.
Marsh	Mineral wetland dominated by hydrophytic emergent vegetation such as emergent graminoids and forbs, with standing or moving water.
Shallow water	Mineral wetland dominated by submerged or floating vegetation, with standing water up to two meters deep.

Table 1. Canadian wetland classes [8].

http://dx.doi.org/10.5772/intechopen.80688

Figure 1. Wetland classes in Newfoundland and Labrador. From top left to bottom: bog, fen, swamp, marsh, and shallow water.

and feedback among their geographical, morphological, chemical, floral, and faunal components [16]. These functions are the natural processes wetlands conduct outside of the context of humans, and services are the benefits humans derive from wetlands, upon which monetary or well-being value may be derived [16]. Functions can include, for example, water storage or nutrient cycling, while associated services include flood protection, reduction of downstream nutrient loading respectively [16, 17]. Wetlands of different types [6, 8] carry out different functions and different rates, and thus, different types of wetlands provide different kinds of services of variable quality (see **Table 2**).

The types of services wetlands provide can range from recreational to natural disaster mitigation [16, 18]. For example, wetlands of many types support biodiversity at rates disproportionate to their area [1] and provide habitat for numerous unique or threated species [19, 20]. At regional and local scales, wetlands play roles in flood risk reduction, drought mitigation,

Wetland class	Services
Bog	Source of nutrients and organic carbon, water storage, groundwater recharge, carbon storage, fuel and fiber source, plant and animal habitat.
Fen	Flood regulation, climate regulation, water filtration, source of nutrients and organic carbon, carbon storage, plant and animal habitat.
Swamp	Flood regulation, erosion protection, climate regulation, water filtration, carbon storage, plant and animal habitat, recreation.
Marsh	Flood regulation, erosion protection, ground water recharge, climate regulation, water filtration, carbon storage, plant and animal habitat, recreation (fowl hunting).
Shallow water	Flood regulation, erosion protection, water filtration, plant and animal habitat, recreation (fishing).

Table 2. Services associated with the five Canadian wetlands [16, 17].

shoreline protection, nutrient cycling, pollutant and sediment filtering, and recreational activities such as berry picking or fowl hunting [3, 16, 21–23]. In some parts of the world, local economies rely heavily on wetlands in the form of fishing, agriculture, and peat-harvesting [24–26]. Numerous studies have shown the direct effects of wetland loss on humans both in terms of monetary and quality of life [27, 28]. At a global scale, wetlands play important roles in biogeochemical cycles and are of importance in considering the effects and mitigation of a changing climate [14, 28–30].

1.3. Canadian wetlands

In Canada, the national estimate of wetland extent states that there is ~150 million hectares (1.5 million km^2) of wetlands, making up roughly one-fourth of global wetlands [8, 20]. Based on estimates of land-area, Manitoba, Ontario, Newfoundland and Labrador (NL), and Saskatchewan have the greatest extents of wetlands, the majority of which are composed of peatlands [4]. It has been estimated that up to 70% of Canada's non-peat wetlands have been lost [8]. The loss of Canadian wetlands has been documented as far back as the seventeenth century, during which around 85% of the salt marshes in the Bay of Fundy were drained by Acadian settlers [31]. Although wetlands and the services they provided were generally poorly understood, the impact of their loss was felt by communities reliant on those services. The Mi'kmaq, for example, noted the decreased presence of ducks and geese in and around the Bay of Fundy during the time of Acadian drainage [31]. More recently, flooding in provinces like Manitoba has been partially attributed to wetland loss [32]. Despite such extensive loss, Canada continues to rank as one of the countries containing the greatest extent of wetlands [33], making up 24% of the total global wetlands [8].

The province of NL has an estimated 18% of its land area covered by wetlands, 17% of which is peatlands [4]. The dominance of peatlands (bogs, fens, and swamps) in NL is expected, given both the oceanic climate [34] and deglaciation roughly 10,000 years ago [35] that created landscape features such as depressions and ponds that are ideal for peatland development via terrestrialization (i.e., the process of vegetation occupying the saturated land adjacent to the lake encroaching further into the lake while depositing and building litter resulting in, over time, the filling of the lake) [36, 37]. Additionally, extensive areas of poorly drained soils and acidic and nutrient poor seepage waters, a result of the type of dominant bedrock, contribute to broad peatland coverage in the eastern portion of the island [34]. Other wetlands, such as marsh and shallow water, are comparatively less prominent both in size and number. NL has yet to conduct a province-wide inventory and, until recently, was the only Atlantic Canadian province that had not yet initiated one [26, 38]. Recently, a project conducted between 2015 and 2017 began the process of inventorying wetlands in the province through the development of a remote sensing-based methodology to inventory wetlands down to five classes (bog, fen, swamp, marsh, and shallow water [26, 38].

Effective management and protection of not only wetlands in NL but also wetlands around the word requires the development and application of numerous methodologies, including but not limited to inventories and maps, water level and vegetation monitoring, and condition assessment. Historically, these methods would require extensive, costly, and time-consuming *in situ* field work campaigns, and unfortunately, given the expansive nature or wetlands and the rate at which these ecosystems are being lost, *in situ* methods are infeasible. This is not only due to the cost and time budgets but also because most wetlands are located in remote areas that make field visits difficult or impossible [39]. These problems can be effectively addressed through applying remote sensing methods, and a suite of such applications can be seen in various researches being conducted currently in NL, including the use of synthetic aperture radar (SAR) and optical imagery for wetland classification and mapping [26, 38, 40, 41] and wetland water level monitoring [42].

1.4. Remote sensing of wetlands

Given the current need for up-to-date wetland inventories, as well as the widespread coverage of wetland, remote sensing (RS) has been demonstrated to be the most efficient and cost-effective method for wetland mapping, classification, and monitoring [19]. Since 2016, we have been working on developing state-of-the-art algorithms using remote sensing technologies for operational wetland classification. For more information on our ongoing wetland work, please refer to (www.nlwetlands.ca). The following sections present a summary of our developed methods, discussed in more detail in our journal publications. For a list of these publications, please see Conclusion.

2. Wetland classification using SAR data

SAR is an active imaging system, capable of recoding the electromagnetic spectrum at much longer wavelengths compared to optical sensors. Unlike optical sensors, which collect ground target information at the cellular and molecular level, SAR sensors are responsive to physical (e.g., water content and size) and structural (e.g., roughness) characteristics of ground targets [43]. Over the past two decades, synthetic aperture radar (SAR) sensors have provided valuable data for wetland vegetation mapping. In particular, they are of great use when the efficiency of optical sensors is hampered by cloud cover and day/night conditions. Furthermore, SAR signal penetration depth through vegetation and soil offers additional information unavailable from optical remote sensing data [44, 45]. This is of great importance for monitoring the flooding status of vegetation due to enhanced double bounce scattering effects. Notably, the primary characteristics of SAR signals, such as wavelength, polarization, and incidence angle, with regard to key specifications of the ground targets, such as dielectric constant, roughness, and structure, determine the amount of SAR backscattered energy detected by SAR sensors [43]. Despite these benefits, SAR images are affected by speckle noise that degrades the radiometric quality of image, imposing challenges for several subsequent SAR processing tasks [46, 47]. Fortunately, Mahdianpari et al. [41] demonstrated the effect of applying an efficient despeckling method on the accuracy of wetland classification.

2.1. SAR wavelength

SAR wavelength is another influential factor for wetland vegetation mapping. To date, most SAR satellites have operated in three microwave bands, including X-, C-, and L-bands with wavelength of 3.1, 5.6, and 23.6 cm, respectively. Each wavelength has its own advantages and disadvantages. The selection of an appropriate SAR wavelength depends on the wetland classes since the interaction of SAR wavelengths varies widely with different vegetation types depending on their size. For example, longer wavelengths (L-band) can pass through the vegetation canopy and detect water beneath the flooded trees and/or dense vegetation. Accordingly, several studies reported the superior capability of L-band relative to the shorter wavelengths (e.g., C- and X-band) for monitoring woody wetlands (e.g., swamp), since the incident SAR signal interacts with larger trunk and branch components [48, 49]. In particular, L-band holds great promise in discriminating between forested wetland (e.g., swamp) and dry forest [45, 50]. However, shorter wavelengths are preferred for monitoring herbaceous vegetation because SAR wavelength and vegetation canopies (e.g., leaf) are relatively the same size [51].

Observations from SEASAT L-band data were among the first applications of SAR data for mapping the flooding status of vegetation [52, 53]. Later studies confirmed the suitability of L-band observations for mapping inundation in forested wetlands using JERS-1 and ALOS PALSAR-1 [50, 54]. Following the successful launch of C-band satellites, such as ERS1/2 and RADARSAT-1, several studies have also examined the capacity of C-band observation for wetland mapping. Most of those early studies reported the superior capability of L-band for mapping forested wetlands relative to C-band [44, 55].

2.2. SAR polarization

Overall, the HH polarized signal has been the most efficient for monitoring the flooding status of vegetation, since it is more sensitive to double bounce scattering associated with tree trunks in swamp forest and stems in freshwater marshes [54, 56]. VV polarization can also be useful when plants have begun to grow in terms of height but have a less developed canopy [51]. This is because in the middle of the growing season the vertically oriented structure of vegetation enhances the attenuation of VV polarization signals and, as such, the radar signal cannot penetrate to the water surface below the vegetation [48]. Cross polarization observation (HV and VH) has also been characterized as being highly sensitive to differences in biomass [57].

2.3. Wetland mapping using PolSAR data

Although single-polarized SAR data have been less useful for wetland classification, they have demonstrated great promise for monitoring open water surfaces in different applications, such as water body extraction and flood mapping [57]. This is because of the side-looking data acquisition geometry of SAR sensors. In particular, a large portion of the microwave signals transmitted to calm open water are scattered away from the SAR sensor, and therefore, open water appears dark in a SAR image, making it distinguishable from surrounding land [45]. Unlike single-polarized SAR data, polarimetric SAR (PolSAR) imagery was found to be extremely useful for wetland vegetation mapping. This is because a full polarimetric SAR sensor (e.g., RADARSAT-2) collects the full scattering matrix, providing comprehensive information about ground targets for each imaging pixel [58]. Furthermore, PolSAR data allow the employment of polarimetric decomposition techniques to identify the different backscattering mechanisms of the ground targets and, accordingly, regions of flooded vegetation [45, 49, 59]. Unlike coherent decompositions (e.g., Krogager decomposition), which are only useful for man-made structures with deterministic targets, incoherent decompositions determine the relative contributions from different scattering mechanisms. Thus, they may be more efficient for obtaining information from natural scatterers, such as wetland ecosystems [59–61]. Cloude-Pottier, Freeman-Durden, Yamaguchi, Van Zyl, and Touzi decompositions are among the well-known incoherent decomposition techniques useful for wetland mapping using PolSAR data [45, 49, 61, 62].

Despite the efficiency of the polarimetric decomposition technique to characterize different scattering mechanisms of ground targets that correspond to different wetland classes, the accuracy of wetland classification could be improved. This is attributed to both the highly dynamic nature of wetland ecosystems and the similarity of different wetland classes. The former of which can be alleviated by using multi-temporal SAR data to accurately characterize wetland dynamics during growing seasons [41, 51, 61, 62]. Furthermore, some studies employed a large number of input features to tackle the problem of similarity between different wetland classes [63]. Despite the promising results obtained from such an approach to date, it may not necessarily be optimal approach due to both computational complexity and redundant information within a large number of input data. Furthermore, some wetland classes can be easily distinguished using a minimal of input features. For example, the shallow water class can be easily separated using a SAR backscattering analysis and employing a threshold. However, this similarity is more pronounced among herbaceous wetlands, indicating the necessity of incorporating a larger number of input data [45]. As such, a hierarchical classification scheme can be useful to optimize the number of input features according to the similarity of wetland classes, which should be distinguished at each classification level. Some recent studies also noted that the discrimination of wetland classes can be further increased by applying a feature weighting approach using the Fisher Linear Discriminant Analysis technique [61, 64]. Such an efficient approach eliminates the necessity for the inclusion of large number of input data.

2.4. Wetland mapping using compact polarimetry data

The information content within SAR data increases given the polarization hierarchy, starting from single polarization to dual polarization and reaching both compact and full polarimetric data [65]. Specifically, fully polarimetric data are of great importance for land cover and, in particular, wetland mapping. Such a SAR sensor is constructed based on the standard linear basis (i.e., horizontal [H] and vertical [V]), wherein the sensor interleaves pulse with H and V polarization toward the ground targets and record both received polarizations simultaneously and coherently [65]. As such, the first disadvantage of full polarimetric SAR sensors is a time constraint because two orthogonal polarizations are transmitted alternately. Furthermore, such a configuration implies complexity due to doubled pulse repetition frequency, as well as an increase in the data rate by a factor of four relative to a single-polarized SAR system [65]. Accordingly, the image swath width of FP SAR images is halved, resulting in reduced coverage and an increase in satellite revisit time [66]. Finally, this configuration allows a limited range of incidence angles compared to that of single/dual polarization modes [67].

An attractive alternative, which addresses the limitations of full polarimetric SAR sensors, is a compact polarimetry (CP) SAR configuration. The CP SAR image is expected to maintain polarimetric information as close as possible to that of full polarimetric SAR mode imagery while alleviating its primary limitations [68]. In particular, CP sensors collect a greater amount of scattering information compared to single- and dual-polarization modes while covering twice the swath width of full polarization SAR systems [69]. Thus, CP SAR configurations decrease the complexity, cost, mass, and data rate of a SAR system while preserving several advantages of a full polarimetric SAR system [70]. m-delta [71], m-chi [72], and m-alpha [73] are common decomposition techniques of compact polarimetry data. Importantly, the upcoming RADARSAT Constellation Mission (RCM), which will operate in the Circular Transmitting Linear Receiving (CTLR) mode, offers improved operational capabilities (e.g., ecosystem monitoring) along with a much shorter satellite revisit period. Specifically, RCM provides daily coverage over Canada with 350-km imaging swaths [74]. This is of great significance for highly dynamic phenomenon such as wetland complexes. Some recent studies reported the efficiency of simulated compact polarimetric data for wetland mapping [68, 75].

2.5. Wetland monitoring using InSAR

Hydrological monitoring of wetlands is another subject of interest, since they are water-dependent ecosystems. SAR images have shown to be useful for wetland hydrological monitoring using both SAR backscattering responses [76] and a more detailed and sophisticated technique, Interferometric SAR (InSAR) [77]. This is because the flooded and non-flooded statuses of vegetation in wetland environments have distinct differences in radar backscattering responses that play an important role in the hydrological monitoring of wetlands. Specifically, a time series analysis of SAR backscatter signatures has offered information of seasonal patterns of flooding in wetland ecosystems, and the enhanced SAR backscatter signature of flooded vegetation has been examined in a number of studies [76, 78–81].

Although several studies reported the potential of InSAR for wetland water level monitoring, its application in wetlands presents challenges. This is primarily due to the substantial altering of reflectance and energy backscatter of wetland environments, even within hours or days [82], and the low backscatter of the water surface. Under these conditions, interferometric coherence, which quantifies the degree of similarity of the same pixel in the time interval between two SAR acquisitions, cannot be maintained [51].

Interferometric coherence is a quality indicator of InSAR observations. The variation of coherence in wetlands is a function of the complex mixture of several factors that contribute to coherence maintenance. The temporal baseline is one of the main parameters that hampers the application of InSAR for wetland monitoring [83]. Herbaceous vegetation, one of the most substantive components of wetland ecosystems, may easily lose coherence within a day or week. In the case of using shorter wavelengths (e.g., C- and X-band), interferometric coherence may be lost due to the shallow penetration depths of the shorter wavelengths. In contrast, longer wavelengths have deeper penetration depth but have been previously associated with longer temporal baselines (46 and 44 days for ALOS PALSAR-1 and JERS-1, respectively), which could cause a loss of coherence. However, this drawback has been addressed in the currently operating L-band SAR sensor (i.e., ALOS-2), wherein the temporal baseline is 14 days. Thus, ALOS-2 repeat-pass SAR images offer a promising source of data for wetland InSAR applications. Geometric decorrelation caused by different satellite look angles, volumetric decorrelation caused by vegetation volume scattering [83, 84], the Doppler centroid effect, and co-registration error during interferometric processing [65, 85] are other sources of decorrelation over wetlands.

Despite these limitations, several studies reported the feasibility of InSAR for wetland water level monitoring. In particular, when the vegetation within or adjacent to standing water is able to backscatter the radar pulse toward satellite sensor, water level changes are observable from the phase data [86, 87]. Also, vegetation should not be too dense for the penetration of microwave energy [65]. The efficiency of the InSAR technique for wetland monitoring has been initially investigated in the Amazon floodplain [77]. Subsequent investigations have been carried out for a number of other wetland sites such as Florida Everglades [49, 77, 87, 88], the Louisiana Coastal wetland [56, 89], and China wetlands [89, 90].

In addition to hydrological monitoring of wetlands using InSAR, the interferometric coherence can be used for other wetland applications, such as change detection and classification [51, 91]. This is because coherence has a diagnostic function and can be used along with SAR backscatter and polarimetric decomposition techniques for classification of different wetlands. Each feature has specific characteristics and, accordingly, plays a different role for discriminating wetland classes. For example, SAR intensity depends on the electromagnetic structure of the targets, while the interferometric coherence reflects their mechanical and dielectric stability. Thus, an integration of different input feature augments land cover information and improves classification accuracy of wetland types [51].

3. Spectral and backscattering analyses of wetlands using multi-source optical and SAR data

Wetlands are complex landscapes and ecologically share similar characteristics. However, each wetland type contains its own specifications, which can be effectively investigated using various satellite imageries. In this regard, both optical and SAR data are the most common remote sensing data, which have so far proved to be significantly helpful in discriminating wetland species. Numerous types of features can be extracted from multi-source optical and SAR data. However, since all the extracted features cannot be inserted into a classification algorithm, the most important features should be selected for classification. As such, the best optical and SAR satellites, spectral bands, spectral indices, SAR features, SAR channels, backscattering mechanisms, decomposition methods, and textural features can be defined for wetland studies. To this end, various separability measures have already been developed and employed for differentiating wetland classes.

Before separability analysis, several pre-processing steps should be performed on the datasets, the most important being variance analysis of field samples. This should be carried out on both individual classes and class pairs. For this, Eqs. (1) and (2) can be used, respectively.

$$Var = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu\right)^2 \tag{1}$$

$$F = \frac{Var_B}{Var_W} \tag{2}$$

in which, x_i indicates the value of a field sample; μ is the mean value of samples; N is the number of field samples in a feature; F indicates the Fisher-test; and Var_B and Var_W indicate the between and within variance values in each class pair, respectively. These two variance analyses are more important in the case of wetlands because they are complex environments, and thus, the field samples collected for a wetland class can contain high variance in satellite imagery, especially those acquired by the SAR systems. **Figure 2** illustrates an optical spectral band and a SAR feature, for which the variations of field samples are high, and consequently, they should be removed before separability analyses as noisy and poor features.

So far, different separability measures have been developed, which can generally be classified into two categories: parametric and non-parametric. Unlike parametric methods (e.g. t-test), non-parametric techniques, such as Mann-Whitney U-test, do not assume a normal distribution of the samples and evaluate the separability of samples by their ranks [92]. Considering

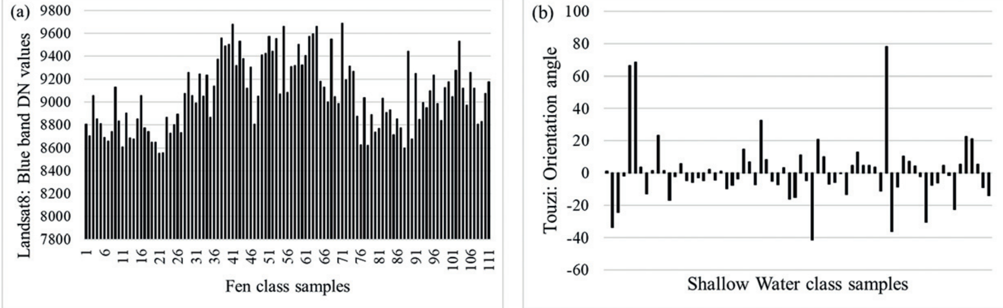

Figure 2. Spectral and Backscattering values for field samples for two types of wetlands: (a) Fen, and (b) Shallow water.

the high variance of field samples of wetlands, the recommendation is to employ a non-parametric distance. After removing the poor features using variance analyses and obtaining the separability measures that each feature provides, the most effective features are inserted into a classification algorithm to produce a highly accurate wetland map.

Table 3 summarizes the results of separability analyses performed by U-test on five wetland classes (bog, fen, marsh, swamp, and shallow water) using multi-source optical (RapidEye,

	Bog	**Fen**	**Marsh**	**Swamp**	**Shallow water**
Bog	×	CP: alpha Tz: alpha_s FD: double-bounce CP: entropy S1: HH/HV	Tz: alpha_s CP: alpha FD: volume-scattering CP: anisotropy R2: HV/TP	R2: HH/TP R2: HH/HV Anisotropy12 A2: HH/HV Polarization-Asymmetry	CP: anisotropy N_derd R2: HH/VV FD: volume-scattering N_serd
Fen	A: $\frac{Green}{Brightness}$ A: NDWI R: $\frac{Red\ Edge}{Brightness}$ L8: $\frac{NIR}{Brightness}$ S2: $\frac{Red\ Edge}{Brightness}$	×	S1: HH/HV N_derd CP: anisotropy R2: HH/HV R2: HH/TP	A2: HH/HV serd R2: HH/HV R2: HH/TP N_serd	N_derd CP: anisotropy R2: HH/VV R2: HH/HV N_serd
Marsh	A: $\frac{Green}{Brightness}$ A: NDWI S2: $\frac{Red\ Edge}{Brightness}$ S2: NDWI R: $\frac{NIR}{Brightness}$	A: $\frac{NIR}{Brightness}$ R: $\frac{Green}{Brightness}$ S2: NDWI A: NDVI A: SAVI	×	R2: HH/HV R2: HV/TP R2: HH/TP A2: HV serd	CP: anisotropy S1: VV/HV N_derd R2: VV/TP R2: VV/HV
Swamp	S2: $\frac{Red\ Edge}{Brightness}$ L8: $\frac{NIR}{Brightness}$ L8: $\frac{Green}{Brightness}$ S2: NDVI S2: SAVI	L8: NDVI L8: SAVI L8: $\frac{NIR}{Brightness}$ A: $\frac{Red}{Brightness}$ A: NDWI	L8: NDVI L8: SAVI L8: $\frac{NIR}{Brightness}$ A: $\frac{Red}{Brightness}$ S2: NDVI	×	R2: HH/HV N_derd CP: anisotropy serd N_serd
Shallow water	A: $\frac{Green}{Brightness}$ A: NDWI R: $\frac{Red\ Edge}{Brightness}$ R: $\frac{Green}{Brightness}$ R: NDWI	R: $\frac{Red\ Edge}{Brightness}$ R: NDWI R: $\frac{NIR}{Brightness}$ S2: NDWI S2: $\frac{Red\ Edge}{Brightness}$	R: $\frac{Red\ Edge}{Brightness}$ R: NDWI R: $\frac{NIR}{Brightness}$ S2: $\frac{Red\ Edge}{Brightness}$ S2: NDWI	R: $\frac{NIR}{Brightness}$ R: NDWI R: $\frac{Green}{Brightness}$ R: $\frac{Red}{Brightness}$ A: $\frac{Green}{Brightness}$	×

L8: Landsat-8
S2: Sentinel-2A
S1: Sentinel-1
Tz: Touzi
SAVI: soil adjusted vegetation index
N_derd: normalized double-bounce eigenvalues relative difference
R: RapidEye
R2: RADARSAT-2
CP: Cloude-Pottier
NIR: near infrared
NDWI: normalized difference water index
serd: single-bounce eigenvalues relative difference
A: ASTER
A2: ALOS-2
FD: Freeman-Durden
NDVI: normalized difference vegetation index
TP: total power
N_serd: normalized single-bounce eigenvalues relative difference

Table 3. The most important optical (provided in the lower left half of the table) and SAR (provided in the upper right half of the table) features for delineating each pair of wetland class in June and August, respectively (the features are ordered based on their separability measures).

Landsat-8, Sentinel-2A, and ASTER) and SAR (Sentinel-1, RADARSAT-2, and ALOS-2) data in NL, Canada. As is clear from this table, the ratio features provided the highest separability measures. $\frac{NIR}{Brightness}$ and $\frac{Red\ Edge}{Brightness}$ ratios are most efficient regarding the optical data, and the ratios of HH/HV and HH/TP obtained from RADARSAT-2 full-polarimetric data are the most important SAR features for separating wetlands.

Comparing the optical spectral bands, the NIR and Red Edge bands are most effective for discriminating wetland classes. Two main characteristics of wetlands are vegetation and water, which can be efficiently studied by these two bands. This demonstrates that it is more efficient to use the optical satellites, in which both NIR and Red Edge bands are included (e.g. Sentinel-2A and RapidEye). In this regard, Sentinel-2A, which provides free imagery, is superior for employment in operational wetland mapping and monitoring. The red band is also helpful in separating wetlands, especially discrimination between bog and other wetlands, because of bogs' red appearance. Additionally, there is a high overlap between the spectral signatures of wetlands in the green, SWIR, and TIR bands, and thus, there is a difficulty in using these bands for wetland studies. Finally, the blue band is not very useful in most of the cases.

Comparing various decomposition methods, including Freeman-Durden, Cloude-Pottier, Touzi, Van Zyl, Yamaguchi, and Krogager, it is observed that coherent decomposition techniques, such Krogager, are not recommended for wetland classification. The reason is that the coherent decompositions are mostly applicable for detecting man-made features in urban areas and less useful for naturally distributed targets such as wetland classes [93]. In addition, the Cloude-Pottier and Freeman-Durden methods are most optimum for separating wetland species. In this regard, the volume scattering component of Freeman-Durden and Anisotropy element of Cloude-Pottier are generally the best. Moreover, some SAR features extracted from the eigenvalue/eigenvector of the coherency matrix demonstrated a high potential for separating wetland class pairs and all wetland classes. In this regard, the serd, normalized serd and normalized derd, introduced by [94], are frequently selected for wetlands separation.

4. A multiple classifier system to improve classification accuracy of wetlands using SAR data

So far, numerous classification algorithms have been developed to classify various land covers, each containing its own advantages and limitations. Random Forest algorithm has proved its high potential for wetland classification in many studies (e.g. [40, 26, 61]). However, the most promising approach to obtain a high classification accuracy is fusing different classifiers in a way that the advantages of each are ensembled. The obtained ensemble classifier is called multiple classifier system (MCS [38, 95]). The system is more important when classifying complex landscapes, such as wetlands, because achieving high accuracy for individual classes is significantly challenging in these cases. This becomes even more serious when only SAR data are applied for discriminating wetlands. There are several studies which developed new MCSs to improve the classification accuracy of similar

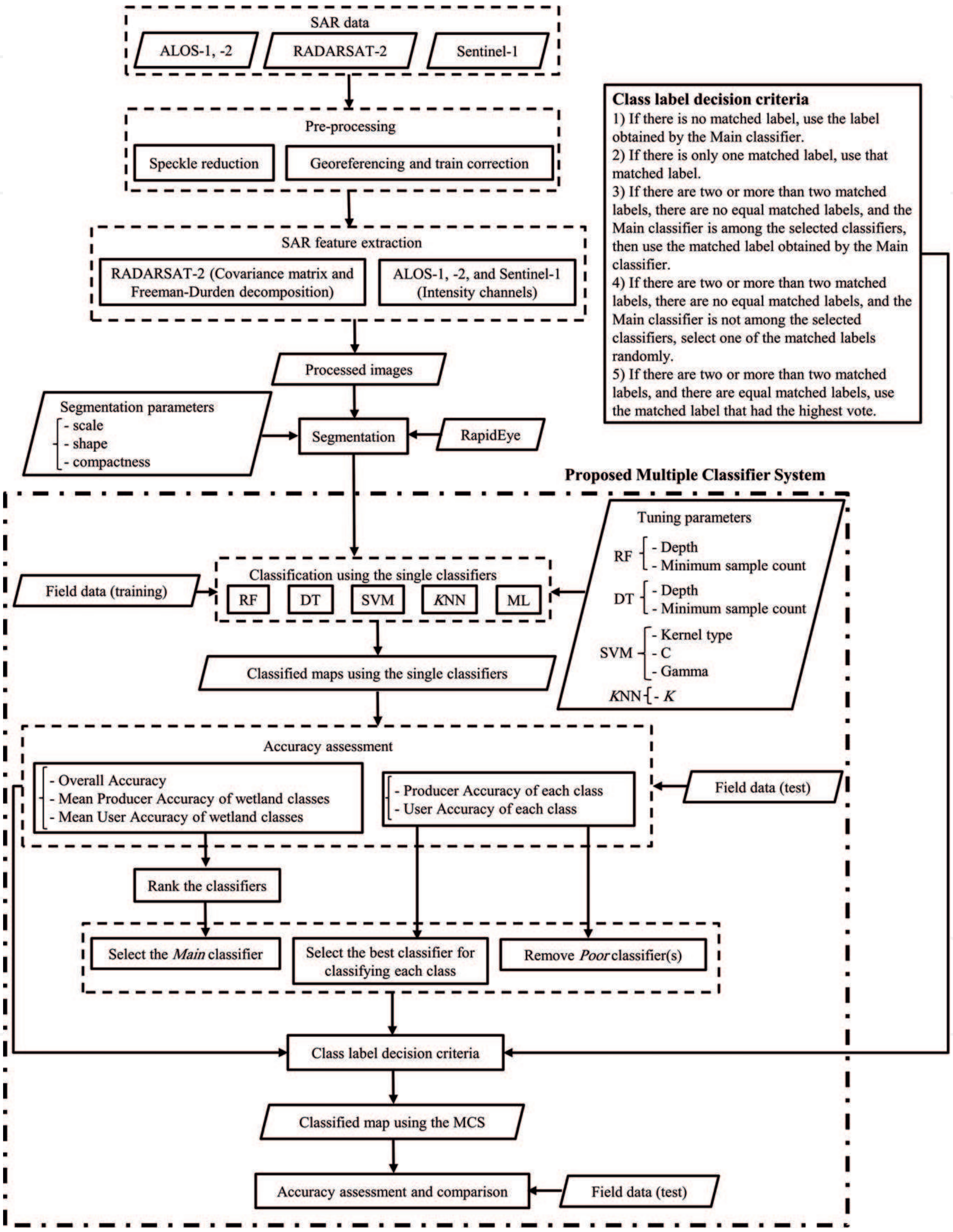

Figure 3. Proposed multiple classifier system by Amani et al. [38] to improve the classification accuracy of the complex environments.

landscapes (e.g. [96, 97]). Regarding wetland classification, Amani et al. [38] proposed a novel MCS to increase wetland classification accuracy using only SAR data in NL, Canada, in terms of both individual class and overall accuracies. The system initially removes poor classifiers and selects the best classification algorithm to identify each wetland class. Then, the final label is selected for each random pixel/object using the class label decision criteria introduced by the authors. The flowchart of the proposed MCS along with the corresponding criteria is illustrated in **Figure 3**. The proposed MCS outperformed the single classifiers and produced the highest producer and user accuracies for almost all wetland and non-wetland classes. It also increased the overall classification accuracy and kappa coefficient by 5–8 and 9–16%, respectively.

5. Conclusion

Wetlands are productive and diverse ecosystems providing numerous ecological services that are biologically important as well as playing a key role in surface water hydrology and flood risk. Wetlands are and have been threatened by land-use conversion, increased urbanization, industrial development, and climate change, resulting in more than half of the world's wetlands threatened, damaged, or destroyed. Earth observation provides a new cost-effective approach to mapping wetlands to aid in their management especially in remote and difficult to access regions. A combination of optical and SAR data provides adequate input data to use an object-based classification with machine learning algorithms such as Random Forest resulting in classification accuracies exceeding 90% for study sites in Newfoundland/Labrador.

For more details on some of the information discussed in this chapter, please refer to our published papers [3, 26, 38, 40–42, 45–48, 50, 51, 61, 64, 68, 69, 98–100]. While [42] is a literature review paper on the use of interferometric synthetic aperture radar (InSAR) data for water level monitoring of wetlands, the rest mainly introduces new machine learning methods for wetland classification using optical, SAR data, or the combination of both.

Acknowledgements

This project was undertaken with the financial support of the Government of Canada, Federal Department of Environment and Climate Change, the Research and Development Corporation (RDC) of Government of Newfoundland and Labrador (now InnovateNL), and Natural Sciences and Engineering Research Council of Canada (NSERC) under Grant to B. Salehi (NSERC RGPIN-2015-05027). The SAR imagery was provided by the Canada Center for Mapping and Earth Observation and Environment and Climate Change Canada. Field data were collected by various organizations, including Ducks Unlimited Canada, Government of Newfoundland and Labrador Department of Environment and Conservation, and Nature Conservancy Canada. The authors thank these organizations for the generous financial supports and providing such valuable datasets.

http://dx.doi.org/10.5772/intechopen.80688

Conflict of interest

The authors declare no conflict of interest.

Thanks

Thanks to Brian Huberty, U.S. Fish & Wildlife Service, National Wetland Inventory program for reviewing this chapter.

Author details

Bahram Salehi[1]*, Masoud Mahdianpari[1], Meisam Amani[1], Fariba M. Manesh[1], Jean Granger[1], Sahel Mahdavi[1] and Brian Brisco[2]

*Address all correspondence to: bsalehi@esf.edu

1 State University of New York, College of Environmental Science and Forestry

2 Canada Centre for Remote Sensing, Ottawa, Ontario, Canada

References

[1] Kingsford RT, Basset A, Jackson L. Wetlands: Conservation's poor cousins. Aquatic Conservation: Marine and Freshwater Ecosystems. 2016;**6**:892-916

[2] Pan Y, Birdsey RA, Phillips OL, Jackson RB. The structure, distribution, and biomass of the world's forests. Annual Review of Ecology, Evolution, and Systematics. 2013;**44**:593-622

[3] Mahdavi S, Salehi B, Granger JE, Amani M, Brisco B, Huang W. Remote sensing for wetland classification: A comprehensive review. GIS & Remote Sensing. 2018;**55**:623-658. DOI: 10.1080/15481603.2017.1419602

[4] National Wetlands Working Group. Wetlands of Canada. Eco-logical Land Classifi cation Series, No. 24. Sustainable Development Branch, Environment Canada, Ottawa, Ontario, and Polyscience, Montreal, Québec. 1988. 452 p

[5] Hongjun C, Guoping W, Xianguo L. Wetland definitions: Creation, evolution and application. Wetland Science. 2010;**8**:299-304

[6] Cowardin LM, Carter V, Golet FC, LaRoe ET. Classification of Wetlands and Deepwater Habitats of the United States. Washington, DC: U.S. Department of Interior, Fish and Wildlife Service; 1979. 131 p

[7] Scott DA, Jones TA. Classification and inventory of wetlands: A global overview. Vegetatio. 1995;**118**:3-16

[8] National Wetlands Working Group. The Canadian Wetland Classification System. Waterloo, Canada: Wetlands Research Branch, University of Waterloo; 1997. 68 p

[9] Zoltai SC, Pollett FC. Wetlands in Canada: Their classification, distribution and use. In: Gore AJP, editor. Ecosystems of the World. Mires: Swamp, Bog, Fen and Moor. B. Regional Studies. Vol. 1983. Amsterdam, The Netherlands: Elsevier Scientific Publishing Company; 1983. pp. 245-268

[10] Verhoeven JTA, Setter TL. Agricultural use of wetlands: Opportunities and limitations. Annals of Botany. 2010;**105**:155-163

[11] Zedler PH. Vernal pools and the concept of isolated wetlands. Wetlands. 2003;**23**:597-607

[12] Gibbs JP. Wetland loss and biodiversity conservation. Conservation Biology. 2000;**14**:314-317

[13] Davidson NC. How much wetland has the world lost? Long-term and recent trends in global wetland area. Marine and Freshwater Research. 2014;**65**:934-941

[14] Karl TR, Melillo JM, Peterson TC, editors. Global Climate Change Impacts in the United States. Cambridge University Press; 2009. https://data.globalchange.gov/assets/4e/16/df9a1659784131dcd1ea020bce19/20page-highlights-brochure.pdf

[15] Hood GA, Bayley SE. Beaver (Castor canadensis) mitigate the effects of climate on the area of open water in boreal wetlands in western Canada. Biological Conservation. 2008;**141**:556-567

[16] Hanson A, Swanson L, Ewing D, Grabasm G, Meyyer S, Ross L, et al. Wetland Ecological Functions Assessment: An Overview of Approaches. Canadian Wildlife Service Technical Report Series No. 497. Atlantic Region. 2008. 59 p

[17] Kimmel K. Ecosystem services of peatlands: Implications for restoration. Progress in Physical Geography. 2010;**34**:491-514

[18] Belle JA, Collins N, Jordaan A. Managing wetlands for disaster risk reduction: A case study of the eastern Free State, South Africa. Journal of Disaster Risk Studies. 2018;**10**:400. DOI: 10.4102/jamba.v10i1.400

[19] Ozesmi SL, Bauer ME. Satellite remote sensing of wetlands. Wetlands Ecology and Management. 2002;**10**:381-402

[20] Reimer K. The need for a Canadian wetland inventory. The Conservator. 2009;**30**:37-45

[21] Grenier M, Demers A-M, Labrecque S, Benoit M, Fournier RA, Drolet B. An object-based method to map wetland using RADARSAT-1 and Landsat ETM images: Test case on two sites in Quebec, Canada. Canadian Journal of Remote Sensing. 2007;**33**:S28-S45

[22] Powers RP, Hay GJ, Chen G. How wetland type and area differ through scale: A GEOBIA case study in Alberta's Boreal Plains. Remote Sensing of Environment. 2012;**117**:135-145

[23] Turner RK, van den Bergh JCJM, Soderqvist T, Barendregt A, van der Straaten J, Maltby E, et al. Ecological-economic analysis of wetlands: Scientific integration for management and policy. Ecological Economics. 2000;**35**:7-23

[24] Whitfield PH, van der Kamp G, St-Hilaire A. Introduction to peatlands special issue: Improving hydrological prediction in Canadian peatlands. Canadian Water Resources Association. 2009;**34**:303-310

[25] Amanuel K. Gis and remote sensing-based analysis of population and environmental change: The case of jarmet wetland and its surrounding environments in western Ethiopia. AAU Journal. 2015

[26] Mahdavi S, Salehi B, Amani M, Granger JE, Brisco B, Huang W, et al. Object-based classification of wetlands in Newfoundland and Labrador using multi-temporal PolSAR data. Canadian Journal of Remote Sensing. 2017;**43**:432-450

[27] Mitchell B. The hydrological and policy contexts for water in Canada. In: Renzetti S, Dupont DP, editors. Water Policy and Governance in Canada. Switzerland: Springer International Publishing; 2017. pp. 13-28

[28] Narayan S, Beck MW, Wilson PT, Guerrero CJ, Shepard A, Reguero CC, et al. The value of coastal wetlands for flood damage reduction in the Northeastern USA. Scientific Reports. 2017;**7**:9463 1-12. DOI: 10.1038/s41598-017-09269-z

[29] Henderson FM, Lewis AJ. Radar detection of wetland ecosystems: A review. International Journal of Remote Sensing. 2008;**29**:5809-5835

[30] Zhang Z, Zimmermann NE, Stenke A, Li X, Hodson EL, Zhu G, et al. Emerging role of wetland methane emissions in driving 21st century climate change. Proceedings of the National Academy of Sciences of the United States of America. 2017;**114**:9647-9652

[31] McAlpine DF, Smith IM. Assessment of Species Diversity in the Atlantic Maritime Ecozone. NRC Research Press; 2010. http://www.nrcresearchpress.com/doi/book/10.1139/9780660198354

[32] Pomeroy JW, Shook K, Fang X, Dumanski S, Westbrook C, Brown T. Improving and Testing the Prairie Hydrological Model at Smith Creek Research Basin. Centre for Hydrology Report No. 14. Saskatoon, Saskatchewan, Canada: Centre for Hydrology, University of Saskatchewan; 2014

[33] Lehner B, Döll P. Development and validation of a global database of lakes, reservoirs and wetlands. Journal of Hydrology. 2004;**296**:1-22

[34] Wells ED. Peatlands of eastern Newfoundland: Distribution, morphology, vegetation and nutrient status. Canadian Journal of Botany. 1981;**59**:1978-1997

[35] Hoag RS, Price JS. A field-scale, natural gradient solute transport experiment in peat at a Newfoundland blanket bog. Journal of Hydrology. 1995;**172**:171-184

[36] Joosten H, Clarke D. Wise Use of Mires and Peatlands—Background and Principles Including a Framework for Decision Making. Findland: International Mire Conservation Group and International Peat Society; 2002

[37] Tiner RW. Use of high-altitude aerial photography for inventorying forested wetlands in the United States. Forest Ecology and Management. 1990;**33**:593-604

[38] Amani M, Salehi B, Mahdavi S, Brisco B, Shehata M. A Multiple Classifier System to improve mapping complex land covers: A case study of wetland classification using SAR data in Newfoundland, Canada. International Journal of Remote Sensing. 2018;**39**:1-14

[39] Klema VV. Coastal and environmental remote sensing from unmanned aerial vehicles: An overview. Journal of Coastal Research. 2015;**31**:1260-1267

[40] Amani M, Salehi B, Mahdavi S, Granger J, Brisco B. Wetland classification in Newfoundland and Labrador using multi-source SAR and optical data integration. GIScience & Remote Sensing. 2017;**54**:779-796

[41] Mahdianpari M, Salehi B, Mohammadimanesh F. The effect of PolSAR image despeckling on wetland classification: Introducing a new adaptive method. Canadian Journal of Remote Sensing. 2017;**43**:485-503

[42] Mohammadimanesh F, Salehi B, Mahdianpari M, Brisco B, Motagh M. Wetland water level monitoring using interferometric synthetic aperture radar (InSAR): A review. Canadian Journal of Remote Sensing. 2017

[43] Lang M, Bourgeau-Chavez LL, Tiner RW, Klemas VV. Advances in remotely sensed data and techniques for wetland mapping and monitoring. In: Ralph WT, Megan WL, Victor VK, editors. Remote Sensing of Wetlands: Applications and Advances. Taylor & Francis; 2015. pp. 79-118

[44] Costa MPF, Silva TSF, Evans TL. Wetland classification. In: Remote Sensing of Natural Resources. Boca Raton-FL: CRC Press; 2013. pp. 461-478

[45] Mahdianpari M, Salehi B, Mohammadimanesh F, Motagh M. Random forest wetland classification using ALOS-2 L-band, RADARSAT-2 C-band, and TerraSAR-X imagery. ISPRS Journal of Photogrammetry and Remote Sensing. 2017;**130**:13-31

[46] Mahdianpari M, Salehi B, Mohammadimanesh F. A new speckle reduction algorithm of polsar images based on a combined Gaussian random field model and wavelet edge detection approach. In: International Geoscience and Remote Sensing Symposium (IGARSS); IEEE. Vol. 2017 July. 2017

[47] Mahdianpari M, Motagh M, Akbari V. Speckle reduction and restoration of synthetic aperture radar data with an adoptive markov random field model. In: Geoscience and Remote Sensing Symposium (IGARSS); IEEE. 2012; IEEE International; 2012. pp. 1-4

[48] Zhang M, Li Z, Tian B, Zhou J, Tang P. The backscattering characteristics of wetland vegetation and water-level changes detection using multi-mode SAR: A case study. International Journal of Applied Earth Observation and Geoinformation. 2016;**45**:1-13

[49] Brisco B, Murnaghan K, Wdowinski S, Hong S-H. Evaluation of RADARSAT-2 acquisition modes for wetland monitoring applications. Canadian Journal of Remote Sensing. 2015;**41**(5):431-439

[50] Martinez J-M, Le Toan T. Mapping of flood dynamics and spatial distribution of vegetation in the Amazon floodplain using multitemporal SAR data. Remote Sensing of Environment. 2007;**108**(3):209-223

[51] Mohammadimanesh F, Salehi B, Mahdianpari M, Brisco B, Motagh M. Multi-temporal, multi-frequency, and multi-polarization coherence and SAR backscatter analysis of wetlands. ISPRS Journal of Photogrammetry and Remote Sensing. 2018;**142**:78-93

[52] Hess LL, Melack JM, Simonett DS. Radar detection of flooding beneath the forest canopy: A review. International Journal of Remote Sensing. 1990;**11**(7):1313-1325

[53] Krohn MD, Milton NM, Segal DB. Seasat synthetic aperture radar (SAR) response to lowland vegetation types in eastern Maryland and Virginia. Journal of Geophysical Research, Oceans. 1983;**88**(C3):1937-1952

[54] Hess LL, Melack JM, Filoso S, Wang Y. Delineation of inundated area and vegetation along the Amazon floodplain with the SIR-C synthetic aperture radar. IEEE Transactions on Geoscience and Remote Sensing. 1995;**33**(4):896-904

[55] Lang MW, Kasischke ES. Using C-band synthetic aperture radar data to monitor forested wetland hydrology in Maryland's coastal plain, USA. IEEE Transactions on Geoscience and Remote Sensing. 2008;**46**(2):535-546

[56] Lu Z, Kwoun O-I. Interferometric synthetic aperture radar (InSAR) study of coastal wetlands over Southeastern Louisiana. Remote Sensing of Coastal Environments. 2009. pp. 26-57

[57] Bourgeau-Chavez LL, Riordan K, Powell RB, Miller N, Nowels M. Improving wetland characterization with multi-sensor, multi-temporal SAR and optical/infrared data fusion. In: Advances in Geoscience and Remote Sensing. Rijeka: InTech; 2009

[58] Ainsworth TL, Kelly JP, Lee J-S. Classification comparisons between dual-pol, compact polarimetric and quad-pol SAR imagery. ISPRS Journal of Photogrammetry and Remote Sensing. 2009;**64**(5):464-471

[59] Alberga V, Satalino G, Staykova DK. Comparison of polarimetric SAR observables in terms of classification performance. International Journal of Remote Sensing. 2008;**29**(14):4129-4150

[60] McNairn H, Shang J, Jiao X, Champagne C. The contribution of ALOS PALSAR multipolarization and polarimetric data to crop classification. IEEE Transactions on Geoscience and Remote Sensing. 2009;**47**(12):3981-3992

[61] Mahdianpari M, Salehi B, Mohammadimanesh F, Brisco B, Mahdavi S, Amani M, et al. Fisher linear discriminant analysis of coherency matrix for wetland classification using PolSAR imagery. Remote Sensing of Environment. 2018;**206**:300-317

[62] de Almeida Furtado LF, Silva TSF, de Moraes Novo EML. Dual-season and full-polarimetric C band SAR assessment for vegetation mapping in the Amazon várzea wetlands. Remote Sensing of Environment. 2016;**174**:212-222

[63] van Beijma S, Comber A, Lamb A. Random forest classification of salt marsh vegetation habitats using quad-polarimetric airborne SAR, elevation and optical RS data. Remote Sensing of Environment. 2014;**149**:118-129

[64] Mohammadimanesh F, Salehi B, Mahdianpari M, Homayouni S. Unsupervised wishart classfication of wetlands in Newfoundland, Canada using polsar data based on fisher linear discriminant analysis. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences—ISPRS Archives. Vol. 41. 2016

[65] Brisco B. Mapping and monitoring surface water and wetlands with synthetic aperture radar. In: Remote Sensing of Wetlands: Applications and Advances. Taylor & Francis; 2015. pp. 119-136

[66] Dubois-Fernandez PC, Souyris J-C, Angelliaume S, Garestier F. The compact polarimetry alternative for spaceborne SAR at low frequency. IEEE Transactions on Geoscience and Remote Sensing. 2008;**46**(10):3208-3222

[67] Nunziata F, Migliaccio M, Li X. Sea oil slick observation using hybrid-polarity SAR architecture. IEEE Journal of Oceanic Engineering. 2015;**40**(2):426-440

[68] Mahdianpari M, Salehi B, Mohammadimanesh F, Brisco B. An assessment of simulated compact polarimetric SAR data for wetland classification using random forest algorithm. Canadian Journal of Remote Sensing. 2017;**43**(5):468-484

[69] Collins MJ, Denbina M, Atteia G. On the reconstruction of quad-pol SAR data from compact polarimetry data for ocean target detection. IEEE Transactions on Geoscience and Remote Sensing. 2013;**51**(1):591-600

[70] Nord ME, Ainsworth TL, Lee J-S, Stacy NJS. Comparison of compact polarimetric synthetic aperture radar modes. IEEE Transactions on Geoscience and Remote Sensing. 2009;**47**(1):174-188

[71] Raney R. Hybrid-polarity SAR architecture. In: Geoscience and Remote Sensing Symposium, 2006. IEEE International Conference on IGARSS 2006. IEEE; 2006. pp. 3846-3848

[72] Raney RK, Cahill JTS, Patterson GW, Bussey DBJ. The m-chi decomposition of hybrid dual-polarimetric radar data. In: IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2012. IEEE; 2012. pp. 5093-5096

[73] Cloude SR, Goodenough DG, Chen H. Compact decomposition theory. IEEE Geoscience and Remote Sensing Letters. 2012;**9**(1):28-32

[74] Thompson AA. Overview of the RADARSAT constellation mission. Canadian Journal of Remote Sensing. 2015;**41**(5):401-407

[75] White L, Millard K, Banks S, Richardson M, Pasher J, Duffe J. Moving to the RADARSAT constellation mission: Comparing synthesized compact polarimetry and dual polarimetry data with fully polarimetric RADARSAT-2 data for image classification of peatlands. Remote Sensing. 2017;**9**(6):573

[76] Kasischke ES, Smith KB, Bourgeau-Chavez LL, Romanowicz EA, Brunzell S, Richardson CJ. Effects of seasonal hydrologic patterns in south Florida wetlands on radar backscatter measured from ERS-2 SAR imagery. Remote Sensing of Environment. 2003;**88**(4):423-441

[77] Wdowinski S, Kim S-W, Amelung F, Dixon TH, Miralles-Wilhelm F, Sonenshein R. Space-based detection of wetlands' surface water level changes from L-band SAR interferometry. Remote Sensing of Environment. 2008;**112**(3):681-696

[78] Wang Y, Hess LL, Filoso S, Melack JM. Understanding the radar backscattering from flooded and nonflooded Amazonian forests: Results from canopy backscatter modeling. Remote Sensing of Environment. 1995;**54**(3):324-332

[79] Townsend PA. Relationships between forest structure and the detection of flood inundation in forested wetlands using C-band SAR. International Journal of Remote Sensing. 2002;**23**(3):443-460

[80] Rebelo L-M. Eco-hydrological characterization of inland wetlands in Africa using L-band SAR. IEEE Journal of Selected Topicsin Applied Earth Observations and Remote Sensing. 2010;**3**(4):554-559

[81] Betbeder J, Gond V, Frappart F, Baghdadi NN, Briant G, Bartholomé E. Mapping of Central Africa forested wetlands using remote sensing. IEEE Journal of Selected Topicsin Applied Earth Observations and Remote Sensing. 2014;**7**(2):531-542

[82] Gallant A. The challenges of remote monitoring of wetlands. Remote Sensing. 2015;**7**(8): 10938-10950

[83] Ramsey Elijah III, Lu Z, Rangoonwala A, Rykhus R. Multiple baseline radar interferometry applied to coastal land cover classification and change analyses. GIScience & Remote Sensing. 2006;**43**(4):283-309

[84] Lu Z, Kwoun O. Radarsat-1 and ERS InSAR analysis over southeastern coastal Louisiana: Implications for mapping water-level changes beneath swamp forests. IEEE Transactions on Geoscience and Remote Sensing. 2008;**46**(8):2167-2184

[85] Charbonneau FJ, Brisco B, Raney RK, McNairn H, Liu C, Vachon PW, et al. Compact polarimetry overview and applications assessment. Canadian Journal of Remote Sensing. 2010;**36**(sup 2):S298-S315

[86] Pope KO, Rejmankova E, Paris JF, Woodruff R. Detecting seasonal flooding cycles in marshes of the Yucatan Peninsula with SIR-C polarimetric radar imagery. Remote Sensing of Environment. 1997;**59**(2):157-166

[87] Gondwe BRN, Hong S-H, Wdowinski S, Bauer-Gottwein P. Hydrologic dynamics of the ground-water-dependent Sian Ka'an wetlands, Mexico, derived from InSAR and SAR data. Wetlands. 2010;**30**(1):1-13

[88] Chen X, Xiang S, Liu C-L, Pan C-H. Vehicle detection in satellite images by hybrid deep convolutional neural networks. IEEE Geoscience and Remote Sensing Letters. 2014; **11**(10):1797-1801

[89] Kim J-W, Lu Z, Lee H, Shum CK, Swarzenski CM, Doyle TW, et al. Integrated analysis of PALSAR/Radarsat-1 InSAR and ENVISAT altimeter data for mapping of absolute water level changes in Louisiana wetlands. Remote Sensing of Environment. 2009;**113**(11): 2356-2365

[90] Xie C, Xu J, Shao Y, Cui B, Goel K, Zhang Y, et al. Long term detection of water depth changes of coastal wetlands in the Yellow River Delta based on distributed scatterer interferometry. Remote Sensing of Environment. 2015;**164**:238-253

[91] Brisco B, Ahern F, Murnaghan K, White L, Canisus F, Lancaster P. Seasonal change in wetland coherence as an aid to wetland monitoring. Remote Sensing. 2017;**9**(2):158

[92] Fay MP, Proschan MA. Wilcoxon-Mann-Whitney or t-test? On assumptions for hypothesis tests and multiple interpretations of decision rules. Statistics Surveys. 2010;**4**:1

[93] Maghsoudi Y. Analysis of Radarsat-2 full polarimetric data for forest mapping [Degree of PhD]. Department of Geomatics Engineering, University of Calgary; 2011

[94] Allain S, FerroFamil L, Potier E. New eigenvalue-based parameters for natural media characterization. In: Radar Conference, EURAD 2005. European: IEEE; 2005. pp. 177-180

[95] Du P, Xia J, Zhang W, Tan K, Liu Y, Liu S. Multiple classifier system for remote sensing image classification: A review. Sensors. 2012;**12**:4764-4792

[96] Maghsoudi Y, Collins M, Leckie DG. Polarimetric classification of Boreal forest using nonparametric feature selection and multiple classifiers. International Journal of Applied Earth Observation and Geoinformation. 2012;**19**:139-150

[97] Ceamanos X, Waske B, Benediktsson JA, Chanussot J, Fauvel M, Sveinsson JR. A classifier ensemble based on fusion of support vector machines for classifying hyperspectral data. International Journal of Image and Data Fusion. 2010;**1**:293-307

[98] Mohammadmanesh F, Salehi B, Mahdianpari M, Motagh M, Brisco B. An efficient feature optimization for wetland mapping by synergistic use of SAR intensity, interferometry, and polarimetry data. International Journal of Applied Earth Observation and Geoinformation. 2018;**73**:450-462

[99] Mahdianpari M, Salehi B, Rezaee M, Mohammadimanesh F, Zhang Y. Very deep convolutional neural networks for complex land cover mapping using multispectral remote sensing imagery. Remote Sensing. 2018;**10**:1119

[100] Rezaee M, Mahdianpari M, Zhang YA, Salehi B. Deep convolutional neural network for complex wetland classification using optical remote sensing imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 20187;**11**:3030-3093

IntechOpen