SPECTRAL ANALYSIS OF WETLANDS IN NEWFOUNDLAND USING SENTINEL 2A AND LANDSAT 8 IMAGERY

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ABSTRACT

Wetlands play a key role in providing food, water, and shelter to a multitude of plants and animals. While much of Island of Newfoundland, which is located within Canada, is covered by wetlands, they have not been studied sufficiently in the province. Therefore, the study of these wetlands' characteristics is an important task in the province. In this regard, remote sensing satellites provide useful and accurate information. In this study, the spectral characteristics of five wetland types, including bog, fen, marsh, swamp, and shallow water, in a pilot site in Newfoundland were analyzed. This study used the data acquired by the two satellites, Sentinel 2A and Landsat 8. According to the analyses, the best spectral bands for wetlands discrimination and classification were selected. Then, the optimum bands were inserted into an object-based Random Forest algorithm to classify wetlands in the study area. The overall classification accuracy was 84% with a Kappa Coefficient of 0.77.

KEYWORDS: Wetlands, Remote Sensing, Spectral Analysis, Newfoundland

INTRODUCTION

Wetlands play a key role in regional and global environments and communities. Their benefits include flood control, water quality management, peat harvesting, shoreline protection, and recreation (Rundquist et al., 2001; Grenier et al., 2007; Tiner et al., 2015). A vast portion of Newfoundland and Labrador, a province located in Canada, is covered by various types of wetlands. Although the importance of wetlands has already been realized around the world, and efforts are currently being made for the conservation of wetlands, wetlands have not seriously been studied in Newfoundland. As a consequence, there is no wetland inventory in the province. Here is where satellite imagery is most helpful.

Generally, wetland studies and classifications can be carried out using two methods: *in situ* and remote sensing. While *in situ* works are necessary, they are costly, labor-intensive, and sometimes require classification to be performed using vague visual estimates of wetland characteristics. In addition, field work is only feasibly applied within small a geographical area (Adam et al., 2010; Moser et al., 2016), although there are current needs for wetland information at national, continental and global scales. *In situ* methods are also restricted based on accessibility and time, as many wetlands are located in remote areas and have characteristics which can change daily, seasonally, and annually (Henderson and Lewis, 2008). However, remote sensing technology has many advantages over the traditional *in situ* method for analyzing and identifying wetland characteristics, providing a continuous record of various types of satellite and airborne data. One useful method for classifying wetlands is analyzing their spectral characteristics through optical remote sensing data. Optical sensors collect reflected energy from the earth in various spectral bands, including visible, infrared, and thermal bands. Moreover, there are many optical satellites that provide high spatial resolution data, in which the corresponding data can be effectively used to discriminate different types of wetlands (Wang et al., 1998; Baker et al., 2007).

There are considerable similarities between the ecological characteristics of wetlands. This fact is more serious for some wetlands like bog and fen. Therefore, wetlands pose similar spectral behavior in optical remote sensing data. This confusion between various wetland types using the information obtained from optical remote sensing data has been reported in many studies (e.g. Wang et al., 1998; Baker et al., 2007; Grenier et al., 2007; Adam et al. 2010; Dronova, 2015). In this study the spectral characteristics of wetlands were analyzed in different spectral bands. By doing so, the most optimal bands for classifying wetlands were selected and discussed. Finally, the most effective bands were inserted to an object-based Random Forest (RF) classifier to map wetlands in a pilot site in Newfoundland.

STUDY AREA AND DATA

Study Area

The Gros Morne pilot site (Figure 1) was selected as the study area. The pilot site is approximately 700 km^2, and is located on the Great Northern Peninsula on the west coast of Newfoundland. Dominant land cover across the pilot site includes low-lying peatlands, minor towns, and communities along the west coast. Furthermore, mountainous areas dominated by balsam fir and black spruce forests are located in the east of Gros Morne (South, 1983). Five wetland types (i.e. bog, fen, marsh, swamp, and shallow water) are found throughout the pilot site.

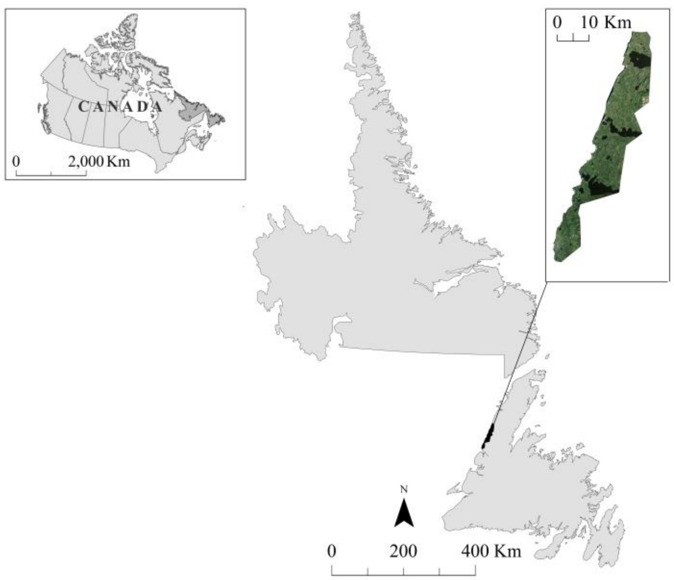

Figure 1. Study area.

Field Data

Field work was conducted by the Nature Conservancy of Canada in August 2015 and July 2016. The sites were flagged for visitation via the visual analysis of satellite imagery (Google Earth), as well as prior knowledge of the area. 107 wetland sites were visited in 2015 and 2016. The wetland class, which was found the most, was bog, followed by marsh, swamp, fen, and shallow water. Moreover, ancillary information, including GPS points, on-site photographs, and field notes on dominant vegetation, hydrology, and surrounding landscape was collected at each wetland site.

Remote Sensing Imagery

Two images, acquired by Sentinel 2A and Landsat 8, were used in this study (Table 1). Landsat 8 data consists of 9 spectral bands (spatial resolution=30 m for bands 1 to 7 and 9, spatial resolution= 15 m for band 8) and 2 thermal bands (spatial resolution=100 m for bands 10 and 11). In this study, only the visible, Near Infrared (NIR) and Shortwave Infrared (SWIR) bands, as well as a thermal band of Landsat 8 were used (see Table 1). Band 11 of Landsat 8 was not used because there were uncertainties in the calibration of this band, as discussed in Montanaro et al. (2014) and https://landsat.usgs.gov/calibration_notices.php. Sentinel 2A was also launched in June 2015. The satellite has 13 spectral bands in the visible, NIR, and SWIR spectral range. The spatial resolution of the bands varies from 10 to 60 meters. In this study, the visible, Red Edge (RE), NIR, and SWIR bands of Sentinel 2A were analyzed (see Table 1). Other bands include the coastal aerosol, water vapor, and cirrus, which were not important in analyzing wetland characteristics.

Table 1. Remote sensing data used in this study and the corresponding information (B=Band, RE=Red Edge, NIR= Near Infrared, SWIR=Shortwave Infrared).

Satellite	Date of Acquisition	Spectral bands	Wavelength (micrometers)	Spatial resolution (meters)
Sentinel 2A	2016/06/25	B2 (Blue)	0.458-0.523	10
		B3 (Green)	0.543-0.578	10
		B4 (Red)	0.65-0.68	10
		B5 (RE)	0.698-0.713	20
		B6 (RE)	0.733-0.748	20
		B7 (RE)	0.765-0.785	20
		B8 (NIR)	0.785-0.9	10
		B8A (RE)	0.855-0.875	20
		B11 (SWIR)	1.565-1.655	20
		B12 (SWIR)	2.1-2.28	20
Landsat 8	2016/07/12	B2 (Blue)	0.45-0.51	30
		B3 (Green)	0.53-0.59	30
		B4 (Red)	0.64-0.67	30
		B5 (NIR)	0.85-0.88	30
		B6 (SWIR)	1.57-1.65	30
		B7 (SWIR)	2.11-2.29	30
		B10 (Thermal)	11.5-12.51	100

METHOD

Wetlands are complex environments and share many ecological characteristics. For example, one particular wetland type can have different characteristics in different areas, and consequently, it can pose different spectral reflectance in each of those areas. The first section of the analysis attempts to show this fact, where the spectral values of a wetland class for different field samples are analyzed. Moreover, different wetland types can produce a similar spectral response. Therefore, the spectral signature of wetlands obtained from both Sentinel 2A and Landsat 8 are also analyzed. By doing this, the bands that provide the most useful information for wetlands separation are identified. The textural information obtained from those spectral bands is also evaluated in the second section of this study by using the standard deviation values of the reflectance of the various types of wetlands, as the main factor showing the textural information. Finally, a visual comparison of spectral and textural signatures of wetland classes is conducted and the optimum features are inserted to an object-based RF algorithm to classify wetlands in the study area.

RESULTS AND DISCUSSION

Spectral Characteristic of Wetlands

There were several objects (polygons) overlaid on the image, each of which showed one type of wetland. These polygons were obtained by visiting the field. Figure 2 demonstrates the mean spectral values of each of those objects, extracted from the Sentinel 2A image for various types of wetlands to show the complexity of wetlands' characteristics. Since it was not possible to show the object values of all wetlands in all spectral bands, only five examples are provided in this figure. It is clear that the object values obtained from field samples of one specific wetland class were not in the same range. This fact makes the classification of wetlands using optical remote sensing data more challenging. One solution for this issue is dividing each wetland class to several subclasses. For example, the Ducks Unlimited Canada Enhanced Wetland Classification System (DUCEWCS) classified wetlands into 19 subclasses (Ducks Unlimited Canada, 2011). Brisco et al. (2011) and Whiteside and Bartolo (2015) have also used sub-classification of wetlands in their researches.

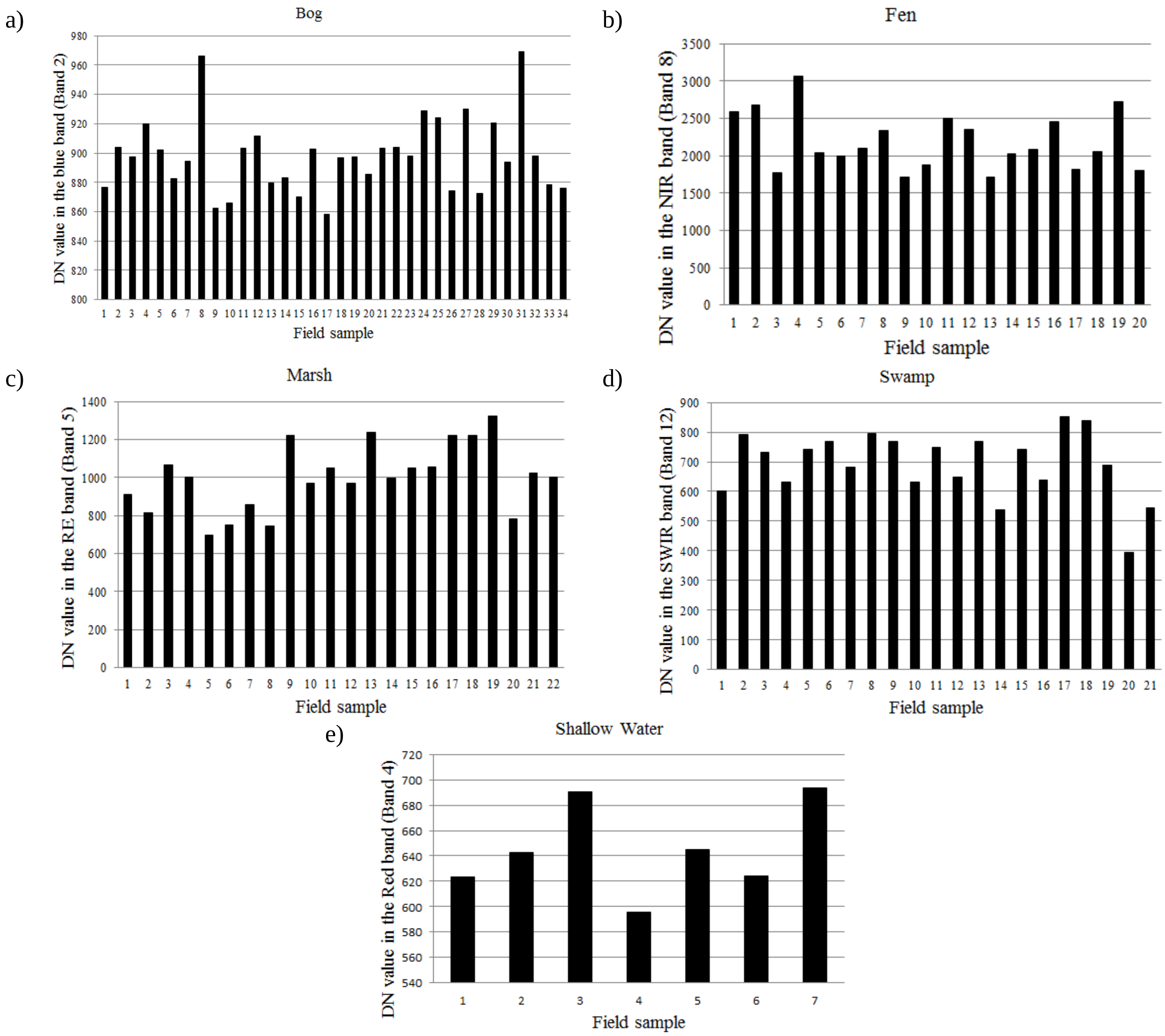

Figure 2. Mean object values of different bands of Sentinel 2A for field samples of wetland classes.

Figure 3 illustrates the spectral signature of wetlands, which were obtained from Sentinel 2A and Landsat 8 data. It is clear that the spectral trends of wetlands are almost similar in the corresponding bands of both satellites, which demonstrates the robustness of results. There are overlaps in the spectral signatures of different wetlands in the visible bands (i.e. blue, green, and red), especially for those obtained from the Sentinel 2A image. The biggest difference between the reflectance of various wetland types was observed in the RE and NIR bands. Therefore, these bands are the most useful optical bands for the delineation of wetlands. The RE band provides useful information for monitoring vegetation and the quality of inland water bodies with relatively high phytoplankton content. 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 (Clevers et al., 2002; Mutanga et al., 2012). Among two SWIR bands (band 11 and 12 for Sentinel 2A and Bands 6 and 7 for Landsat 8), band 11 of Sentinel 2A and band 6 of Landsat 8 (both ranging between 1.57 and 1.66 micrometers) provided more information for discriminating wetlands compared to the other two SWIR bands because these bands are mostly sensitive to vegetation and soil moisture contents. The thermal band of Landsat 8 was also useful for discriminating shallow water areas from other wetland classes. A problem associated with the thermal band, however, is the coarse spatial resolution. However, the visible, NIR, and SWIR bands usually have higher spatial resolution than thermal bands, and therefore, provide more detailed information about wetlands.

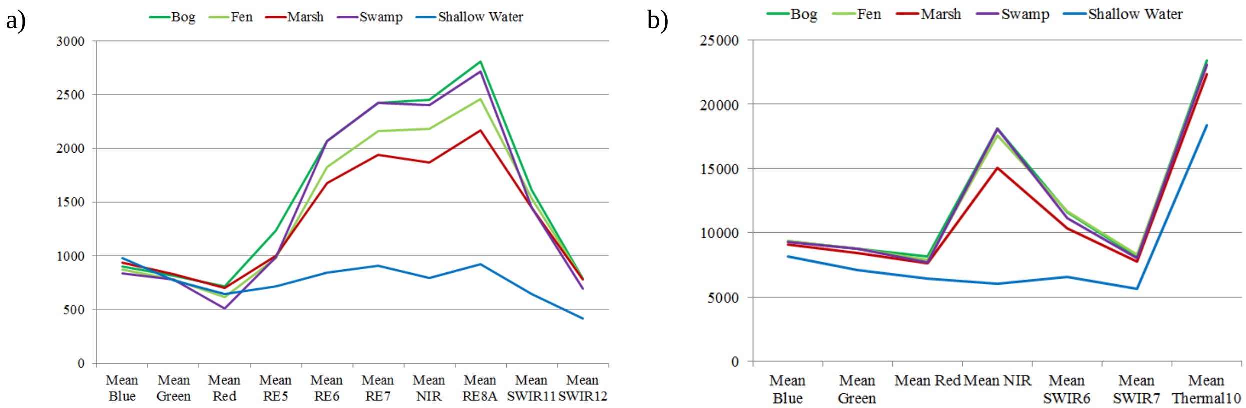

Figure 3. Spectral signatures of wetlands, obtained from a) Sentinel 2A, and b) Landsat 8 data.

Textural Characteristics of Wetlands

Figure 4 demonstrates the standard deviation of wetlands in various spectral bands of Sentinel 2A and Landsat 8 imagery. Standard deviation is the main textural feature for image classification. Although the textural information obtained from optical data is not as informative as those obtained from Synthetic Aperture RADAR (SAR) textural information, it can be complementary information for wetland classification when only optical data are available. For example, according to Figure 3, the red band is not useful to separate wetlands. However, the textural information obtained from the red band of Landsat 8 is the most useful band for this task, as can be observed in Figure 4 (b). In addition, the swamp class is also not differentiable from other wetland classes using the spectral signatures of wetlands (Figure 3). However, according to Figure 4, the swamp class had the lowest standard deviation values, and therefore, was more easily differentiable from the other wetland types using textural information.

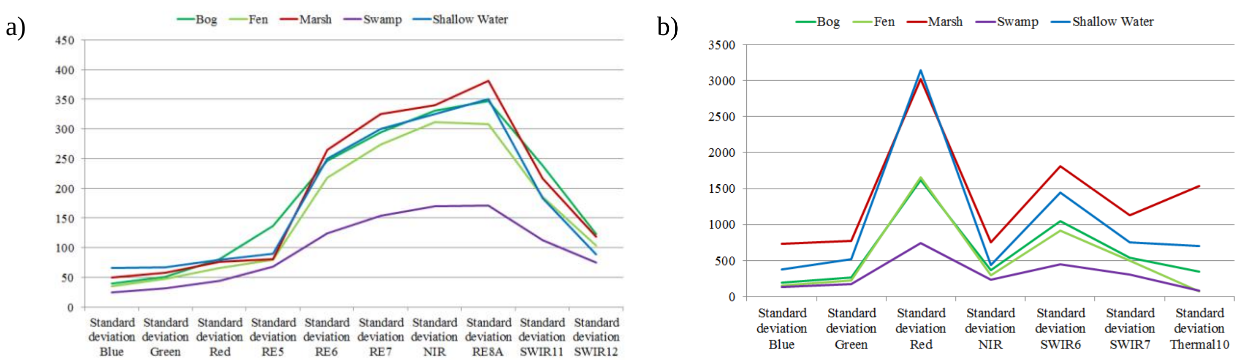

Figure 4. Standard deviation values of wetlands in different bands of a) Sentinel 2A d, and b) Landsat 8 data.

Wetlands Classification

According to the spectral analyses (Figure 3 and Figure 4), the most useful spectral bands of Sentinel 2A and Landsat 8 for wetland classification were selected and inserted into a RF classifier to map wetlands in the study area (Table 2).

Table 2. Selected features for wetlands classification in the Gros Morne pilot site.

Satellite	Feature	Spectral bands
Sentinel 2A	Mean value of objects	B5 (RE) B6 (RE) B7 (RE) B8 (NIR) B8A (RE)

		B11 (SWIR)
	Standard deviation of objects	B5 (RE) B6 (RE) B7 (RE) B8 (NIR) B8A (RE) B11 (SWIR)
Landsat 8	Mean value of objects	B5 (NIR) B6 (SWIR) B7 (SWIR) B10 (Thermal)
	Standard deviation of objects	B2 (Blue) B3 (Green) B4 (Red) B6 (SWIR) B7 (SWIR) B10 (Thermal)

Figure 5 demonstrates the wetland classification map in the study area. Three non-wetland classes (i.e. deep water, urban, and upland forest) were also included in the classification. The confusion matrix of the classification, which was calculated using 50% of the field data, is also provided in Table 3. The overall classification accuracy was 84% with a Kappa Coefficient value of 0.77. The highest producer and user accuracies were for the non-wetland classes because these classes are easily distinguishable from wetland classes in the optical imagery. The fen and swamp classes had the lowest class accuracies. As made clear from the confusion matrix there is a high confusion between fen and bog. For example, 1589 pixels of the fen class out of 2065 pixels of field data are misclassified as the bog class. There was also high confusion between the swamp and upland forest classes, where 2165 pixels of field upland forests are mistakenly classified as the swamp class.

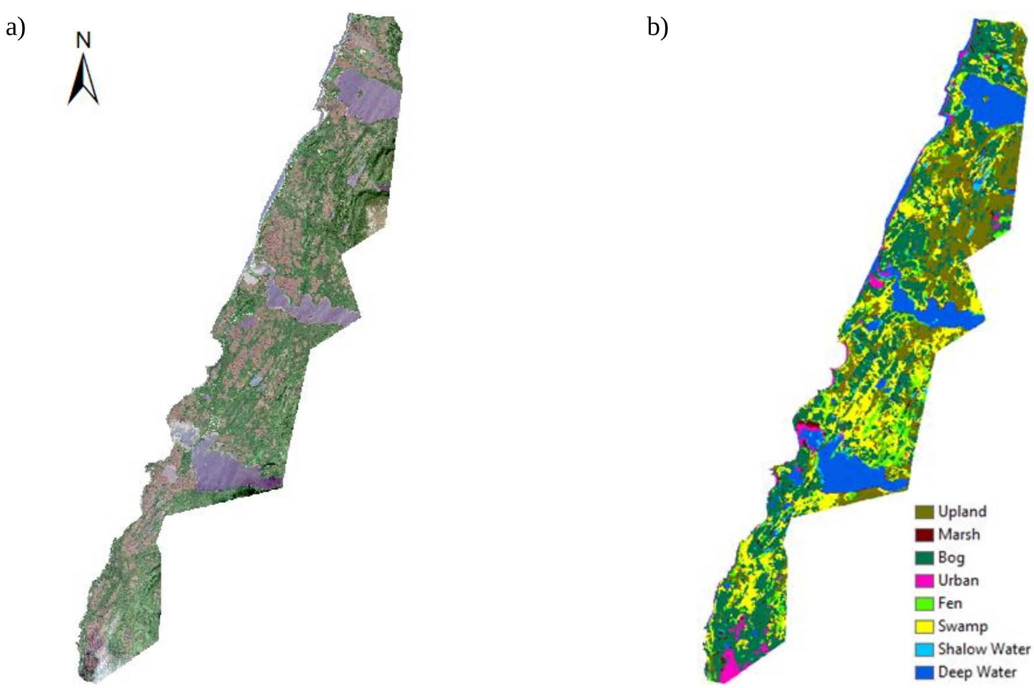

Figure 5. a) Sentinel 2A image from the study area, b) Classified image using object-based Random Forest algorithm.

Table. 3. Confusion matrix in terms of the number of pixels for the classification of the Gros Morne pilot site using Random Forest algorithm. Overall, producer, and user accuracies, as well as omission and commission errors are in %.

Classified Data	Reference Data										
		Up	M	B	Ur	F	S	SW	DW	Total	C	UA
	Up	**7395**	0	22	72	38	299	0	0	7826	6	95
	M	27	**589**	615	203	0	9	5	0	1448	59	41
	B	556	450	**26430**	1669	1589	599	33	0	31626	16	84
	Ur	4	3	1	**2242**	0	10	0	0	2260	1	99
	F	263	28	21	184	**223**	198	42	0	759	71	29
	S	2165	61	611	7	144	**335**	0	0	3223	90	10
	SW	0	11	2	0	71	0	**500**	803	1378	64	36
	DW	0	0	13	18	0	0	577	**14548**	15156	4	96
	Total	10410	1142	27715	4395	2065	1450	1157	15351	**63685**		
	O	29	48	5	49	89	87	57	5		**OA= 84**	
	PA	71	52	95	51	11	23	43	95		**K= 0.77**	

OA: Overall Accuracy	B: Bog	S: Swamp	C: Commission
K: Kappa Coefficient	F: Fen	Up: Upland	O: Omission
PA: Producer Accuracy	M: Marsh	DW: Deep Water	
UA: User Accuracy	SW: Shallow Water	Ur: Urban	

CONCLUSION

Wetlands are important environments in terms of both biological habitats and human services. Wetlands are complex landscapes, and therefore, classifying various types of wetlands using optical remote sensing is a challenging task. In this study, to show the complexity of wetlands, their spectral characteristics in various bands of Sentinel 2A and Landsat 8 were analyzed. By doing this, it was concluded that there were considerable overlaps between the spectral signatures of wetlands in several bands of both satellites. It was also found that the RE and NIR bands are the most useful optical bands for wetlands discrimination. In addition, it was concluded that textural information, obtained from spectral bands, can be useful for wetland classification. After selecting the best bands for wetland classification, the optimum features were ingested to an object-based RF algorithm to classify wetlands in the study area. For wetland classes, the most accurately identified classes were the bog and marsh classes. While, the lowest producer and user accuracies were for the fen and swamp classes, respectively. Overall, it was concluded that the obtained classified map had high accordance with real-world objects, and can be applied in the similar studies.

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