Big Data for a Big Country: The Second Generation Canadian Wetland Inventory Map at 10 Meters Resolution

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Abstract

Recently, there has been a significant increase in efforts to better inventory and manage important ecosystems across Canada using advanced remote sensing techniques. In this study, we improved the method used in creating the first generation Canadian wetland inventory map at 10-m resolution. The main contribution of this study, as it compares to the previous one, is training Random Forest (RF) models on the Google Earth Engine (GEE) platform within the boundaries of ecozones rather than provinces, in order to increase wetland classification accuracy. The ecozone boundaries divide the Canadian landscape based on similar biotic and abiotic factors, i.e., land cover, human activity, climate, wildlife, soil, vegetation, and geomorphology. Therefore, it should produce more accurate and meaningful wetland classification results. In the first generation of this product, there was a lack of training data in some ecozones, making it impossible to apply the classification method at the ecozone level, as training data is a significant bottleneck in the machine learning algorithms. In this study, a considerable effort has been devoted to data collection, preparation, standardization of datasets for each ecozone. The result of data cleaning reveals a data gap in several Northern ecozones. Accordingly, high-resolution optical data, from Worldview-2 and Pleiades, were acquired to delineate wetland training data based on visual interpretation in those regions. By using this well-distributed training data, the second generation of a Canadian wetland inventory map was improved by an overall accuracy approaching 86%. This wetland map represents an improvement of 7% compared to the first generation map. Accuracy varied from 76% to 91% in different ecozones, depending on available resources. Furthermore, the results of RF variable importance, which was carried out for each ecozone, demonstrate that $\frac{|S_{VV}|^2}{|S_{VH}|^2}$ and NDVI extracted from Sentinel-1 and Sentinel-2 data, respectively, were the most important features for wetland mapping.

Keywords: Wetland classification, remote sensing, Random Forest, Google Earth Engine, Sentinel, feature extraction, Canad

1. Introduction

Until very recently, land cover mapping at large scales has been a challenging, and in some cases, an impossible task, given the required costs and resources for image analysis (Hu et al., 2017). In particular, collecting, storing and processing the datasets required to cover large geographic areas, and the hardware limitations associated with such data processing, were a significant barrier for the production of large-scale land cover maps (Mahdianpari et al., 2020; Shelestov et al., 2017). This issue is often referred to as the *geo big data* problem and is currently being addressed through the application of newly available technologies and resources designed for best managing large volumes of geospatial imagery (Gorelick et al., 2017a).

Fortunately, the ever-increasing availability of high-resolution open-access Earth Observation (EO) data and powerful cloud computing resources provide unprecedented opportunities for applications at spatial and temporal scales previously impossible in the geospatial sciences (Mahdianpari et al., 2018; Zhou et al., 2020). For example, data collected from the Copernicus programs by the European Space Agency (ESA) through the Sentinel missions have contributed significantly to the global monitoring of the environment over the past few years (Aschbacher and Milagro-Pérez, 2012). The accessibility and usability of these and other open-access EO data across large geographic areas and at high temporal frequencies has been made possible via advances in cloud computing resources, such as NASA Earth Exchange, Amazon's Web Services, Microsoft's Azure, and Google cloud platforms (Liu, 2015). Among these cloud computing resources, Google Earth Engine (GEE) has been recognized as a well-established, open-access tool that hosts a vast pool of satellite imagery and offers tools for advanced web-based algorithm developments and result visualization (Shelestov et al., 2017). These developments have now made it possible for the Earth to be mapped at a large geographical scale, opening up research possibilities in the ocean and ecological sciences, as well as in natural resource management (Aschbacher and Milagro-Pérez, 2012; Chen et al., 2017; Mahdianpari et al., 2020, 2018; Sidhu et al., 2018; Zhou et al., 2020), to name only a few.

Nation-wide wetland inventory development, and in turn wetland management, monitoring, and conservation, is one of the numerous areas that are expected to benefit from the increasing availability of big data technologies. This new technology is of particular importance for countries with extensive wetland coverage, such as Canada (Mahdianpari et al., 2020). Prior to 2019, a majority of Canada's wetland inventories were created at local, regional, and provincial scales, for example (DeLancey et al., 2020; Dingle Robertson et al., 2015; Jahncke et al., 2018; Mahdianpari et al., 2018; Millard and Richardson, 2015; Mohammadimanesh et al., 2018b; Rezaee et al., 2018; White et al., 2017). Many of these inventories were derived using a variety of methods (e.g., visual assessment, optical and/or RADAR, topographical, and field-work), wetland definitions (Chen et al., 2010; van der Kamp et al., 2016) classification systems (Alberta Environment and Sustainable Resource Development, 2015; Ducks Unlimited Canada, 2014; Gerbeaux et al., 2016; National Wetlands Working Group, 1997), and under various contexts were constrained by budgets, available resources, locations, and objectives. While useful under some circumstances, the methods used and purposes of these inventories impact their applicability within national or global contexts (Hu et al., 2017). These issues, along with spectral and structural similarities between various types of wetlands, and the lack of clear-cut borders between successional wetland classes, have limited the capability of the machine learning tools for large-scale wetland mapping and resulted in insufficient classification accuracies in some cases (Hu et al., 2017). Other issues arise when comparing and contrasting spatial wetland information across political, geographical, or disciplinary boundaries which can in-turn impact the quality, development and assessment of wetland-related management and policies (Fournier et al., 2007; Hu et al., 2017).

Another major issue related to wetland mapping at national and global scales is the collection of sufficient high-quality reference data (Mahdianpari et al., 2020). Developing a quality nation-wide wetland inventory using supervised remote sensing methods requires a large amount of training and testing data distributed across the entire country, to best represent Canada's expansive and diverse landscape (Statistics Canada, 2018). Like many of Canada's wetland inventories, most available training and testing data have been collected under a variety of contexts, using different local and regional wetland definitions, for a number of purposes (often not remote sensing focused), and using a variety of different methods. Additionally, obtaining such data is not always a simple task, requiring the willing contribution of numerous collaborators and/or the collection of freely available data with variable metadata quality or sometimes limited explanatory information. While these discrepancies are an issue, they are not unexpected and as a result, training and testing data in a large-scale study will require collaboration, substantial editing, and standardization. Other issues include gathering accurate non-wetland land cover information which often requires the use of freely available datasets and visual interpretation of satellite imagery available via Google Earth. Like the wetland datasets, the non-wetland land cover data requires standardization in terms of naming conventions, definitions, and polygon boundaries. The development of the training and testing dataset is of utmost-importance, as the quality and accuracy of these inputs are ultimately reflected in the final inventory output (Millard and Richardson, 2015; Mui et al., 2015).

In the face of increasing globalization, continued wetland loss, increasing population, urban sprawl, and human-induced climate change, the importance and availability of consistent and reliable large-scale wetland inventories both in Canada and around the globe has never been greater. Such large-scale inventories will contribute to the improvement of the nation- and global-wide wetland management, protection initiatives, and policies, allow for consistent estimations of yearly trends in wetland loss or gain, analysis of biodiversity, and help improve the outputs of large-scale climate models and estimates (Erwin, 2009).

Therefore, the overarching goal of the current study was to leverage state-of-the-art remote sensing tools for the production of large-scale wetland inventory maps for Canada. Specifically, the main objectives are to: (1) prepare structured, cleaned, consistent, and well-distributed training and testing data for each of Canada's ecozones; (2) produce the second generation Canada-wide wetland inventory; (3) improve the wetland classification accuracy compared to the first generation Canadian wetland inventory map by running classifications within ecozones rather than provincial boundaries; and (4) determine the most important features for national wetland mapping via RF algorithms using built-in capacities in GEE.

2. Methodology

2.1. Study Area

The Ecological Framework of Canada (Statistics Canada, 2018), which delineates ecologically distinct areas across Canada, defines a total of 15 ecozones. Ecozones represent areas of Canada's land surface characterized by interacting abiotic and biotic factors. These ecozones are displayed in Figure 1. The size of these ecozones ranges from 117,240 km^2 (Mixed wood Plains) to 1,857,530 km^2 (Boreal Shield). Please refer to Table 1 for a summary of the general characteristics of each ecozone. Note that the three northern ecozones (Southern Arctic, Northern Arctic, and the Arctic Cordillera) are referred to as the Northern Ecozones throughout the remainder of this study. These three ecozones are grouped together for purposes of reference data development, processing, and classification as a result of the limited available wetland data for this area. Additionally, the Boreal

Shield was split into two areas (east and west), and the Boreal and Taiga Cordillera ecozones were merged into one (Boreal/Taiga Cordillera), for processing and training data development purposes. The reasoning for this is discussed in section 2.2.

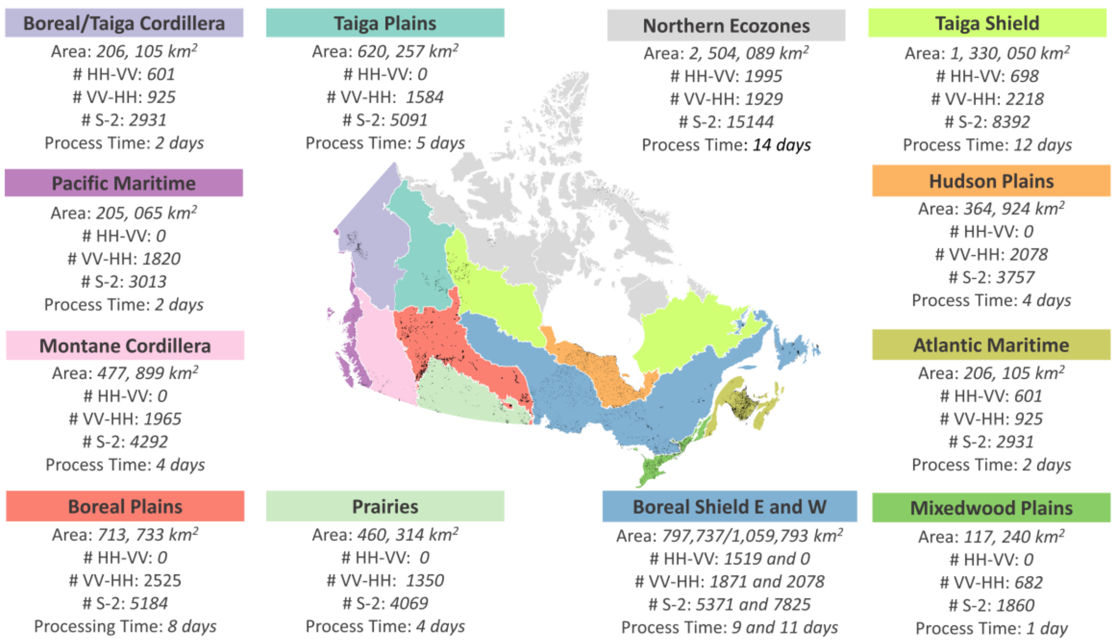
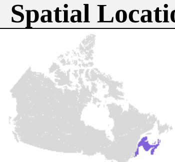
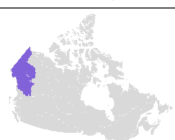
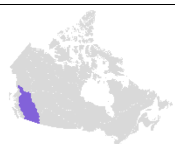
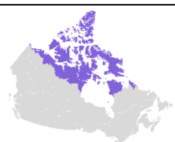
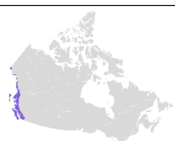
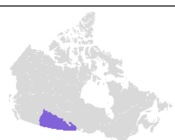
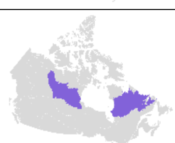


Figure 1. Canadian ecozones, ecozone sizes, and the processing time and the number of Sentinel-1 and -2 images required to produce classifications. Reference data distribution across Canada is displayed in black.

Table 1. A summary of the typical land cover characteristics of each ecozone (Ecosystem Classification Group, 2010; Environment and Climate Change Canada, 2016; Federal, Provincial, and Territorial Governments of Canada, 2010; Smith et al., 2004).

Ecozone	Spatial Location	Description
Atlantic Maritime (AM)		Has a typical maritime climate, generally cool and wet year round. The most common land cover type here is the forest. Agricultural activity is the most common human activity. The most common wetlands in this area are treed (swamp, bog, and fen).
Boreal and Taiga Cordillera (Boc / TC)		Summers are short and cool, and winters are long and cold. Dominating land cover includes extensive mountains and tundra to the north and forests to the south. Wetlands, and particularly peatlands, are less common here than the neighboring Taiga Plains. Forest and wetlands are most common in valleys and slopes.
Boreal Plains (BP)		Has a typical continental climate, with cold winters and cool summers. Forest is the most common natural land cover type and agriculture the most common anthropogenic land cover. Agricultural activity is largely present along the southern edge of the ecozone and to the north-east. The most common types of wetlands include conifer swamps, fens, and bogs.

Boreal Shield (BS)		Moderate summer and winter temperatures. The largest ecozone in Canada. Low elevation land dominated by forest and shrubland with relatively minimal anthropogenic land cover. Peatlands, including bog and fen, are the most common, particularly on the eastern side.
Hudson Plains (HP)		Has a maritime climate, and as a result, extensive wetlands are present, particularly peatlands. Marsh is more common along with the northern coast. This area is often referred to as Canada’s largest wetland complex. There is relatively little forest cover present.
Mixedwood Plains (MP)		The most populated ecozone characterized by a climate of warm summers and cool winters. The landscape is generally flat and dominated by extensive agricultural land cover. Most wetland cover is located along the edge of the ecozone and the northeast. Swamp, bog, and fen are the most common.
Montane Cordillera (MC)		The most diverse topography and climate relative to other ecozones, with various mountain ranges present. Forest covers over half of the total land surface. There is relatively little wetland coverage and is mostly located along rivers and in valleys.
Northern Ecozones (NE)		Characterized by very low temperatures, permafrost, and limited vegetation. Mountains and glaciers dominate the furthest north, giving way to tundra barrens, hills, and plains to the south. There is relatively little human presence in these areas. Wetlands, particularly peatlands, are dispersed throughout the barrens and along waterways.
Pacific Maritime (PM)		Located along the coast of the Pacific Ocean with a mountainous maritime climate. The Cost mountains and extensive forests dominate most of this ecozone. Most anthropogenic land cover is located at the southern end of the ecozone. There are relatively few wetlands here.
Prairies (Pr)		More variable climate than other ecozones. Almost entirely covered in agriculture. The most common natural land cover is grassland. There are very few wetlands located here, having been lost to agricultural development. Wetlands that are present are very small “prairie potholes.”
Taiga Plains (TP)		Largely flat area. The colder climate in the north part of the ecozone versus the warmer south. Most land cover is boreal forest and shrub, and there is a relatively small human presence. Wetlands of many types are widespread, including large deltas, swamps along rivers, peatlands, and marsh.
Taiga Shield (TS)		Open forest that transitions to shrub and tundra moving north. Temperatures are colder in the west versus the east. There is relatively little human activity here. Wetlands make up are an estimated 13% of [SH1]in this area, though there are trends indicating wetland expansion due to changes in weather patterns and permafrost melting.

2.2. Reference Data

Broadly, the development of the reference data for this study required, for each ecozone, a dataset comprised of accurately-delineated polygons representing bog, fen, swamp, and marsh wetland classes, and polygons representing the most dominant non-wetland land-use. Generally, the wetland data for this study was gathered from multiple collaborators across Canada, and the non-wetland data was derived via visual polygon delineation with the aid of the Agriculture and Agri-foods Canada 2018 Crop Inventory map (Agriculture and Agri-food Canada, 2018), with some exceptions which are discussed below.

The wetland data for this study was acquired from a number of sources across Canada. Ultimately, these wetland data were used to produce training and validation datasets for each ecozone. These datasets were collected for a variety of purposes, over several years, at different scales, and using different field, classification, and polygon delineation methods. As a result, the distribution and amount of data available within each ecozone vary considerably (see Figure 1). For these reasons, the datasets needed to go through several rounds of editing before being functionally incorporated into an ecozone final reference dataset.

As a first step, the data were filtered to remove any polygons smaller than 1 hectare and greater than 100 hectares, as small polygons would not contain any helpful spectral information for the classifier according to the minimum mapping unit of this study, and the large polygons had a higher chance of being highly spectrally heterogeneous. Next, some datasets were clipped to ensure that each ecozone had its own specific dataset associated with it. This is because a number of these datasets spanned the boundaries of multiple ecozones. Note that some ecozones did not have any wetland training data located within their boundaries, and as a result, these ecozones were instead classified using the reference data in an adjacent ecozone. These ecozones include the Taiga Cordillera and the three northern-most ecozones. The three northern ecozones and the Taiga and Boreal Cordillera ecozone boundaries were merged to create two broad multi-ecozone boundaries. Additional data cleaning steps, including the standardization of naming conventions, removal of some inaccurate polygons, re-classification of some polygons, and boundary modification of others, were also performed. Additionally, in datasets where there were thousands of wetland polygons (i.e., local wetland maps), a subset of these polygons was randomly selected for incorporation into the final reference dataset.

Notably, there was no wetland data available to this study in the northern-most ecozones, and because google earth has limited or inconsistent imagery in northern Canada, VHR imagery was acquired for purposes of producing a northern ecozone wetland dataset. Wet areas along the northern-coast were identified to collect coincident WorldView-2 and Pleaide's imagery for these areas. An effort was made to select as the most recent summer imagery as possible, though the selection was constrained by image availability, cloud cover, and cost. Because cloud-cover is a significant issue in northern Canada, the most recent summer dates for which we could obtain cloud-free imagery was during the summers of 2015 and 2016. Figure 2 shows some peatland and swamp delineation via visual assessment in a WorldView-2 image taken near Kugluktuk, Nunavut (top), and in a Pleaide's image near Bathurst Inlet (bottom). Because the assessor did not feel confident differentiating between bog and fen wetlands in the imagery, all delineated peatlands were referred to as fen. This imagery was essential for producing wetland data for the northern ecozones; however, the dataset remained small due to the limited extents of the imagery. Non-wetland classes were delineated using the VHR imagery as well.

Figure 2: Wetland delineation using VHR imagery. Top: Peatland delineation using June 29th 2016 Pleaides imagery. Bottom: Swamp delineation using June 29th, 2015 WorldView-2 imagery.

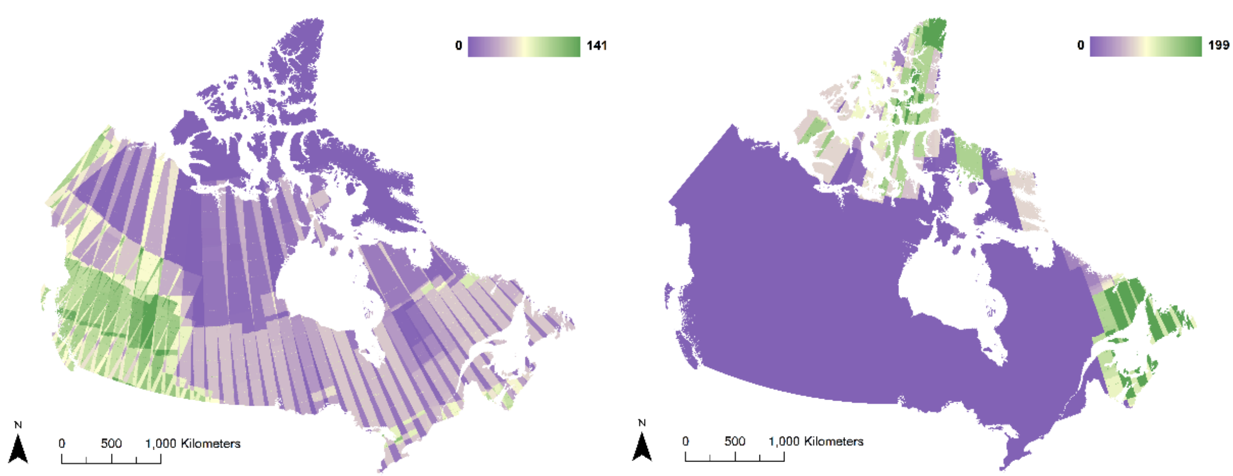
The Agriculture Agri-Food Canada 2018 Annual Crop Inventory map (Agriculture and Agri-food Canada, 2018) guided the delineation of non-wetland polygons. As a first step, the most common non-wetland land cover within each ecozone was calculated using the Crop Inventory map. Next, polygons representing the most common land cover types were manually delineated, using both Google Earth and the crop inventory map as a visual aid. Some ecozones did not have any coverage by the crop inventory dataset, most commonly in ecozones located in the northern parts of Canada. As such, visual identification of some common land cover types was conducted using the interpretation of very high resolution (VHR) imagery or ancillary land cover datasets, including multiple local land cover geospatial datasets and the 30 m resolution land cover map of Canada provided by the Canada Centre for Mapping and Earth Observation (CCMEO). Table 2 summarizes the number of wetland reference polygons and their areal coverage for each ecozone. To produce the final reference data, the wetland and non-wetland polygons for each ecozone were randomly divided into two groups: 50% for training and 50% for testing. Specifics of the data preparation for each ecozone are discussed below.

Table 2. Summary of the reference data employed for each ecozone.

Ecozones	# Wetland polygons	# Upland polygons	Discussion
AM	3000	802	Majority of the wetland reference data came from a large New Brunswick Wetlands dataset containing thousands of polygons. Removing polygons smaller than 1 hectare and greater than 100 hectares reduced the total size. Non-wetland polygons were produced using the crop inventory maps and Google Earth. The areal coverage of the polygons for each wetland class are similar.
Boc & TC	348	336	There is no Crop Inventory coverage in this area so non-wetland polygons were produced using visual assessment in Google Earth. The dataset is located in and around the Yukon communities of Haines Junction and Whitehorse. The dataset contains thousands of wetland polygons. The number of bog polygons is much smaller relative to the other classes such as a fen, marsh and swamp.
BP	200	480	Wetland data came from five datasets. The crop inventory maps guided all non-wetland land cover delineation. Because the reference data for this ecozone were derived from five different sources (unlike most of the other ecozones which had testing and training data derived from only one or two sources), it is likely that there is great variation in how bog, fen, swamp, and marsh wetlands were delineated.
BS East	612	550	Wetland data derived from multiple wetland-related datasets across various locations in Newfoundland and Labrador, originally for purposes of wetland classification using remote sensing data, using similar methods. Notably, there is a greater amount of bog wetlands, in terms of aerial coverage, verses some of the other wetlands. The crop inventory maps guided all non-wetland land cover delineation, for which this area had coverage.
BS West	2154	548	Wetland information derived from a very large wetland dataset in Ontario. Because the number of wetland polygons in this dataset was so great, after removing all wetlands less than 1 hectare and greater than 100 hectares in size, a further reduction was made by only keeping those wetlands that had been listed as being verified and evaluated. The areal coverage of the polygons in each wetland class are relatively similar. The crop inventory maps guided all non-wetland land cover delineation.
HP	2000	345	Because a large portion of the Hudson Plains ecozone fell within the province of Ontario, the Ontario wetland dataset was used to derive wetland polygons for this ecozone. Please refer to the section discussing the data for the Boreal Shield West ecozone for more information. However, because this area lacked crop inventory coverage, non-wetland polygons were delineated based on a visual assessment of Google Earth imagery.
MP	1165	600	The wetlands for this ecozone were derived from the Ontario wetland dataset. Please refer to the section discussing the data for the Boreal Shield West ecozone for more information. The crop inventory maps guided all non-wetland land cover delineation.
MC	26	209	No wetland data sourced for this ecosystem. As such, the Canadian Wetland Inventory by Ducks Unlimited (DCI), which is available online, was referred to. From the DCI, a small number of wetland polygons were gathered. Unfortunately, most of the data on the DCI map were very small and not useful for this study. Additionally, there were no bog polygons and very few fen polygons. As a result, the dataset for this ecozone is very small, relative to all other ecozones that have training datasets available.
NE	120	294	No available wetland data or crop inventory coverage of the three most northern ecozones. To address this problem, three 50 cm resolution summer images (i.e., one WorldView-2 and two Pleiades) were acquired covering some coastal low-land areas within the Southern Arctic ecozone. Using these images, visual interpretation was carried out to define wetland and non-wetlands. Because the interpreters did not feel confidant in their ability to define bog wetlands in these images, only fen, swamp, and marsh polygons are present in the final dataset. While these images were certainly helpful, the amount of wetland reference data was limited by their extents.
PM	117	296	Wetland polygons for this ecozone was derived from a dataset collected in and around the Vancouver area. Relative to the marsh and swamp polygons, there was very little data for the bog class. Additionally, most of the bog polygons are derived from a single large bog, known as the Burns bog. As a result, these polygons may not be representative of other bog wetlands within the ecozone, particularly in the less-populated areas further north.
Pr	250	600	Datasets were all gathered around the Assinboine River Valley and Whitewater Lake in Manitoba. While these datasets contained a large number of wetland polygons, only a small number of them were of the appropriate size. There were also no bog polygons. The crop inventory map was used to delineate the non-wetland polygons.
TP	230	213	Datasets located within this ecozone were collected around the vicinity of Great Slave Lake in the Northwest Territories. Only half of the total polygons fell directly within the Taiga Plains ecozone (the other half fell within the Taiga Shield Ecozone). These datasets also provided training polygons for non-wetland land cover. This was welcome as this ecozone lacks any coverage by the Crop Inventory map. Using Google Earth, some additional non-wetland polygons were delineated.
TS	220	327	Wetland polygons obtained from the same dataset discussed in the Taiga Plains ecozone above. Only half of the training polygons provided by these datasets fell within the Taiga Shield. These datasets also provided training polygons for non-wetland land cover, which was welcome as this ecozone had no coverage by the Crop Inventory map. Using Google Earth, some additional non-wetland polygons were delineated via visual assessment. There was relatively little swamp data.

2.3. Remote Sensing Data and Image Processing

The Sentinel Earth Observation missions from the Copernicus program managed by the European Commission in partnership with the ESA, consist of both radar and super-spectral imaging systems for the land, ocean, and atmospheric monitoring. To improve the revisit time and coverage capability, each mission benefits from a constellation of two satellites. In this study, the GEE data catalog was used to obtain satellite imagery over our study area during 2017-2019 from Sentinel-1 and Sentinel-2 data (Gorelick et al., 2017b). A total of 4,813 and 22,955 C-band Level-1 Ground Range Detected (GRD) images were acquired in the HH-HV and VV-VH polarization modes of Sentinel-1, respectively. Due to the mission of Sentinel-1, single-(HH) or dual-(HH-HV) polarized data are collected over sea ice zones and single-(VV) or dual- (VV-VH) polarized data are collected over all other observation zones (e.g., lands), we have the greater availability of VV-VH compared to HH-HV polarization mode. Figure 3 demonstrates the spatial distribution of all available Sentinel-1 observations.



(a) (b)

Figure 3. The total number of (a) Sentinel-1in VV/VH mode and (b) Sentinel-1 HH/HV in mode observation during the summers of 2017-2019 in Canada. The color bar represents the number of collected images.

It should be noted that different pre-processing steps, including noise removal, radiometric calibration, and terrain correction, were already applied to the Sentinel-1 GRD data available in the GEE data catalog. To reduce the speckle noise from Sentinel-1 data, an adaptive sigma Lee filter with a pixel size of 7x7 was then applied. Next, SAR backscatter values and other derivatives of these values were extracted and incorporated into the classification scheme. Table 3 presents extracted features from Sentinel-1 and Sentinel-2 imagery for wetland classification.

Table 3. Features extracted from Sentinel-1 and Sentinel-2 imagery in this study.

Sentinel-1 (VV-VH)	Sentinel-1 (HH-HV)	Sentinel-2
σ^0_{VV} σ^0_{VH}	σ^0_{HH} σ^0_{HV}	$Blue: B_2$ $Green: B_3$
$\frac{\lvert S_{VV}\rvert^2}{\lvert S_{VH}\rvert^2}$	$\frac{\lvert S_{HH}\rvert^2}{\lvert S_{HV}\rvert^2}$	$Red: B_4$
$\lvert S_{VV}\rvert^2 + \lvert S_{VH}\rvert^2$	$\lvert S_{HH}\rvert^2 + \lvert S_{HV}\rvert^2$	$NIR: B_8$
		$NDVI = \frac{B_8 - B_4}{B_8 + B_4}$
		$GCVI = \frac{B_8}{B_3} - 1$

Among the extracted features from a dual-pol SAR data, σ^0_{HH} is the most useful and frequently used for wetland mapping (Brisco et al., 2013; Mahdianpari et al., 2017; White et al., 2017; Mohammadimanesh et al. 2018c). This is because σ^0_{HH} values are effective for characterizing the flooding status of wetland vegetation, and it is the most favorable SAR-based derivative for distinguishing flooded vegetation from herbaceous wetlands (Mohammadimanesh et al., 2018a). In cases of sparse canopy closure, σ^0_{VV} values can also be appropriate for discriminating herbaceous wetland classes. The dominant backscattered signal from wetland' vegetation canopies is volume scattering, which is better represented by σ^0_{HV}. Accordingly, all extracted SAR features in this study were stacked to generate a seasonal Sentinel-1 data composite using the GEE's array-based computational approach, and then, the images from multiple years (2017–2019) were combined.

We obtained Sentinel-2A and Sentinel-2B Level-1C top of atmosphere images acquired on a tri-monthly period, from June to August. This is because generating a 10-m cloud-free Sentinel-2 composite for Canada over a shorter time was challenging. This period is also an optimum time for wetland mapping in Canada due to the high value of wetland phenological information (reflected in the range of spectral signatures for different classes), and the availability of more cloud-free Sentinel-2 imagery at this time. A total of 72,046 Sentinel-2 images (with cloud-cover less than 20%) from the summers of 2017-2019 were queried from the GEE data catalog. It should be noted that in this study, we only used the four multispectral bands with 10m resolution to produce a high-resolution (10m) wetland inventory map. Compared to our previous study, we added an optical feature, Green Chlorophyll Vegetation Index (GCVI), to our analysis to investigate the capability of different vegetation indices extracted from Sentinel-2 imagery. Other pre-processing steps to prepare multi-spectral features for classification were explained in detail in our previous work (Mahdianpari et al., 2020). Figure 4 demonstrates the spatial distribution of all available Sentinel-2 observations.

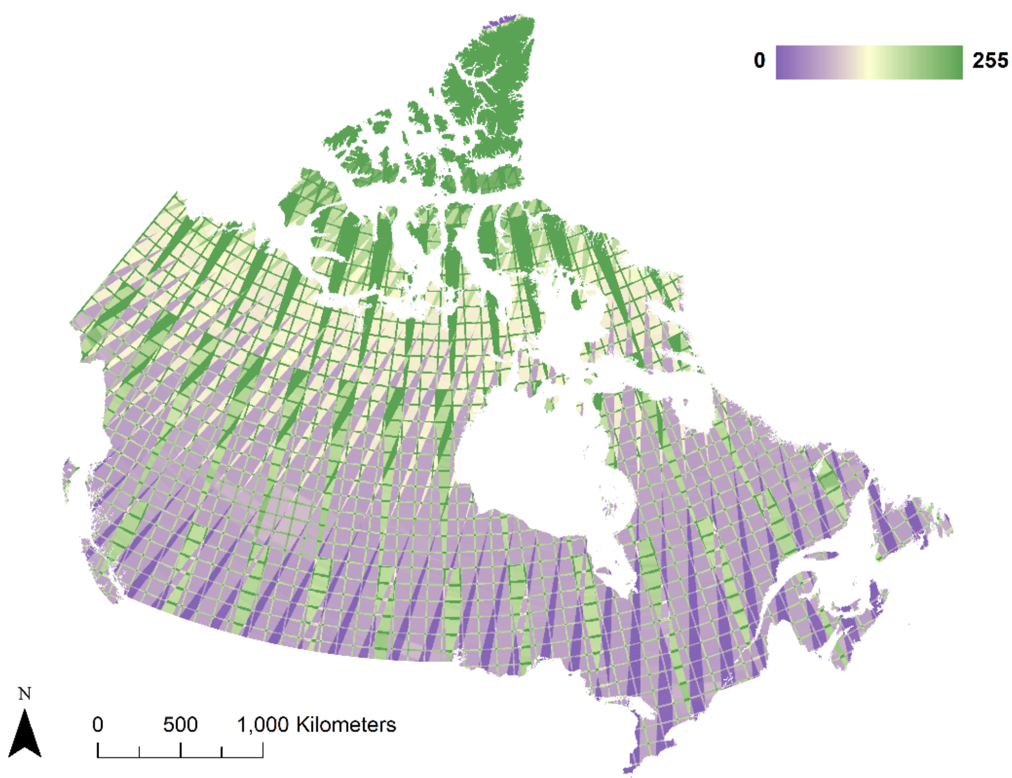
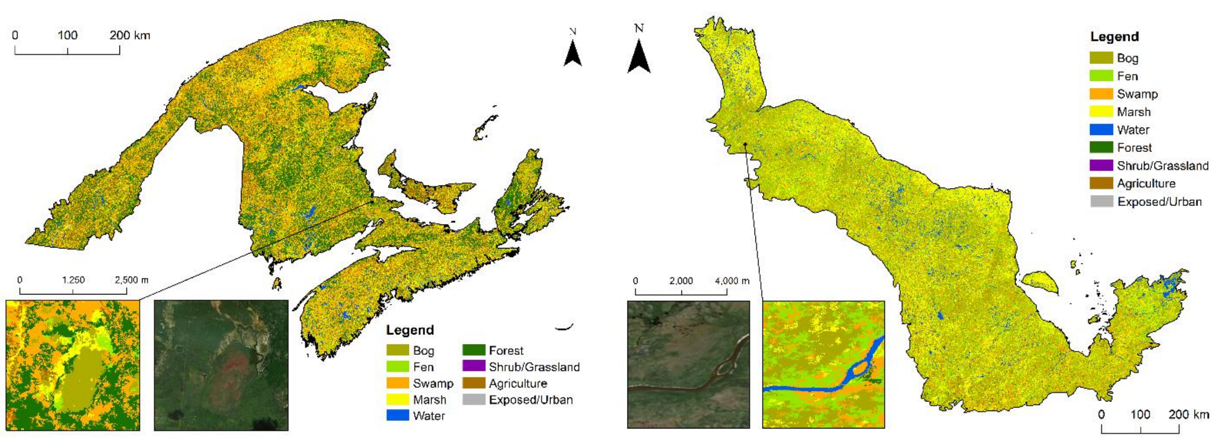


Figure 4: The spatial distribution of all available Sentinel-2 observations during the summers of 2017-2019 in Canada. The color bar represents the number of collected images.

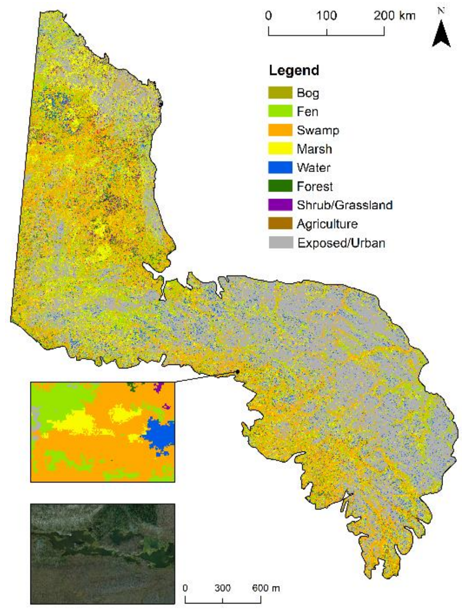
In this study, an object-based classification scheme consisting of a simple non-iterative clustering method, and the Random Forest algorithms were used. This classification framework is similar to our previous work (Mahdianpari et al., 2020); however, we applied the classification models within each ecozone rather than each province. This is because there is more commonality between wetland vegetation classes, in terms of climate, landform, human activities, wildlife, soil, and vegetation, within an ecozone, compared to within each provincial borders (Statistics Canada, 2018). In the first generation of the Canadian wetland inventory map, there was a lack of training data in some ecozones, making this study impossible at that time, as training data is a major bottleneck in the machine learning algorithms. The processing time for training RF models in different ecozones is presented in Figure 1.

3. Results and discussion

Three examples of classified wetland ecozone maps, located in eastern, central, and western Canada are presented in this section. Figure 5 demonstrates the wetland inventory map of the AM, HP, and TC.



(a) (b)



(c)

Figure 5: Classified maps of the (a) Atlantic Maritime, (b) Hudson Plains, and (c) Taiga Cordillera ecozones.[SH2]

Figure 5(a) shows the results of the AM classification. The most common wetlands in this area are swamp and marsh, followed by the peatlands (bog and fen). The spatial extent of wetlands, and dominance of the swamp class here, is consistent with a previous assessment of this ecozone, which states that treed wetlands are the most common type of wetland in the AM (ESTR Secretariat, 2014). However, our results likely over-estimate the extent of swamp wetlands, due in part to the limited number of training data and the difficulty in separating swamp wetlands from treed uplands (Jahncke et al., 2018). Peatlands tend to be limited to the south-east and centre of the ecozone. The most common non-wetland land cover in the AM is forest. Human-related land cover is mostly present along some of the edges of the ecozone.

Figure 5(b) illustrates the results for the HP, which by far, has the broadest wetland coverage relative to the results of all other ecozones. This is also in line with previous assessments of HP and reflects its reputation as the largest wetland complex in Canada, and the third-largest wetland complex in the world (Abraham and McKinnon, 2011). The most dominant wetland types here are bog and marsh, followed by fen, while the least dominant is the swamp. Most of the marsh is located along the coast to the north and north-west. This ecozone is known to have extensive coastal marshes, including tidal flats and salt marshes in this area (Abraham and McKinnon, 2011). Bog and fen wetlands are also known to commonly occur in this ecozone and make up a large portion of the wetland complex. Here, bog and fen occur across much of the ecozone, though they are mostly concentrated through the centre. Non-wetland land cover types are mostly absent.

Figure 5(c) demonstrates the results for the TC, wherein the most common wetland is the swamp, followed by the fen. Bog and marsh are much less common. It appears that there is likely an overestimation of wetland cover in this area if we consider previous descriptions of TC, which note the limited coverage of wetlands in this area (Ecosystem Classification Group, 2010). The over-estimation of wetlands, particularly swamp, is likely a result of misclassification of the forests and shrubby tundra in this region. Additionally, as discussed in section 2.2, there was no wetland training data available in this ecozone, and as a result, it was classified in tandem with the Boc ecozone. This lack of training data is reflected by the overall accuracy for this ecozone, which is the lowest (along with the Boc) overall accuracy of all ecozones (see Table 4.). [SH3]The most common upland classes are exposed areas, capturing the mountains along the north.

Table 4 shows the overall accuracy, Kappa, producer's, and user's accuracies for all ecozones. The ecozone with the highest overall accuracy is the Prairies, located mainly within southern Saskatchewan. Note that there was no bog data available within the Prairies ecozone, and most of this area is dominated by non-wetland agricultural land (Ahern et al., 2013). As previously mentioned, the ecozones with the lowest accuracies are the Boreal and Taiga Cordillera, at 76% accuracies. The reasoning for this is discussed in more detail in section 2.2. However, to summarize, the overall accuracy is likely a result of the lack of training data available for the Taiga Cordillera and the subsequent need to classify both the Taiga Cordillera and the Boreal Cordillera (an adjacent ecozone) at the same time, using the dataset only present within the Boreal Cordillera. Note that outside of the Taiga and Boreal Cordillera, all other ecozones were relatively well classified, with the overall accuracies higher than 80%, a majority of which (eight ecozones) are above 85%.

Table 4. Accuracy assessment indices determined for each ecozone.

Ecozone	Bog		Fen		Swamp		Marsh		Water		Upland		*OA*	*Kappa*
	UA	*PA*	*UA*	*PA*	*UA*	*PA*	*UA*	*PA*	*UA*	*PA*	*UA*	*PA*		
AM	0.85	0.90	0.88	0.84	0.87	0.85	0.88	0.86	0.93	0.93	0.90	0.83	0.88	0.87
Boc/TC	0.55	0.54	0.71	0.72	0.73	0.71	0.65	0.66	0.93	0.93	0.75	0.68	0.76	0.73
BP	0.94	0.75	0.80	0.90	0.86	0.84	0.78	0.84	0.94	0.94	0.89	0.84	0.87	0.86
BSE	0.83	0.92	0.81	0.70	0.83	0.81	0.86	0.76	0.93	0.94	0.87	0.83	0.86	0.84
SW	0.84	0.90	0.87	0.87	0.88	0.87	0.89	0.83	0.93	0.91	0.90	0.80	0.87	0.86
HP	0.85	0.88	0.87	0.86	0.88	0.86	0.90	0.91	0.94	0.94	0.91	0.76	0.88	0.87
MP	0.86	0.91	0.86	0.86	0.87	0.86	0.89	0.80	0.92	0.94	0.89	0.85	0.88	0.87
MC	na	na	0.94	0.65	0.77	0.63	0.77	0.63	0.94	0.94	0.79	0.77	0.85	0.83
NE	na	na	0.69	0.77	0.75	0.80	0.82	0.84	0.94	0.94	0.77	0.83	0.89	0.87
PM	0.73	0.82	0.91	0.90	0.85	0.59	0.83	0.80	0.93	0.94	0.71	0.74	0.84	0.82
Pr	na	na	0.91	0.90	0.85	0.87	0.89	0.88	0.93	0.94	0.91	0.90	0.91	0.90
TP	0.81	0.78	0.76	0.75	0.71	0.55	0.68	0.78	0.94	0.94	0.81	0.75	0.82	0.79
TS	0.74	0.72	0.62	0.64	0.54	0.39	0.70	0.66	0.94	0.94	0.76	0.76	0.84	0.79

Figure 6 illustrates the second generation of the Canada-wide wetland inventory map at a spatial resolution of 10m using the object-based RF classification.

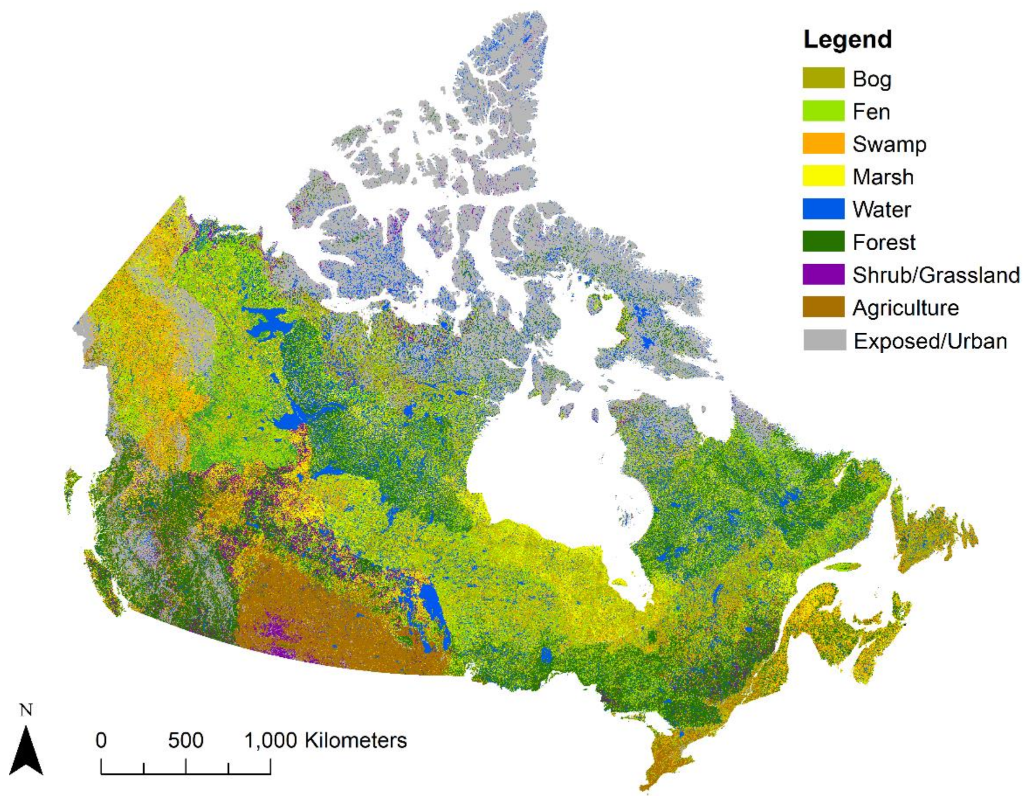


Figure 6: The second generation of Canada-wide wetland inventory map.

According to our results, peatlands (bog and fen) are the most common wetland class in Canada, which is reflective of Canada's reputation of having extensive peatland wetlands (Mahdianpari et al., 2020). The dominance of peatlands is mostly the result of Canada's general climate, which facilitates the build-up of peat (higher precipitation than evaporation). Peatlands appear to be distributed mainly across the centre portion of Canada, from Newfoundland and Labrador to the Yukon. The ecozones that contain the highest amount of peatland include the BS, HP, MP, TP, and TS, which have been reported previously as being the major peatland-containing ecozones in Canada (Webster et al., 2018). Peatlands occur less frequently in southern Canada, where forest and anthropogenic land cover seem to dominate. Marsh wetlands are the least common of all wetland classes, with the most significant coverage by-far occurring in the HP ecozone, where there are known expansive coastal marshes and tidal flats (Abraham and McKinnon, 2011). The ecozones with the least marsh are in the MP and Pr ecozones, of which the landscapes ha been highly modified as a result of human activity, in particular, agriculture.

Swamp wetlands are also estimated as being a typical wetland; however, this must be interpreted in relation to the known difficulty related to remotely-classifying swamp wetlands and differentiating this class from the upland forest (Jahncke et al., 2018). Here, swamp appears to be over-classified versus the other wetland types. However, results may be improved by increasing upland forest training data, using higher resolution imagery as well as L-band for better swamp forest separation, or incorporating high-resolution topographic information. However, this is not always a simple solution at such large scales. Additionally, many of the swamp wetlands occur along streams and rivers, and as a result, the training data polygons for these wetlands are not always optimally shaped (long and thin) for use at medium spatial resolutions. Compared to the first generation results (Mahdianpari et al., 2020), swamp appears to be much more common. This increase may be attributed to a general increase in available wetland training data versus the first generation, particularly in the Maritime Provinces. The difficulties in mapping treed wetlands, such as swamp, using remote sensing has been discussed in similar studies (Jahncke et al., 2018), and is of even greater difficulty when using 10m resolution imagery, or when topographical data cannot be applied as is often the case with large-scale studies such as this. Notably, ecozones with the greatest swamp coverage include the Boc and TC (Figure 5(c)), which, as discussed previously, were the ecozones with the lowest training data and overall accuracy (Table 4).

One of the significant advantages of the RF classifier is its capability to determine the importance of input features (i.e., variable ranking). This is beneficial when a large number of input features are incorporated into the classification scheme. The RF variable ranking has been recently added to GEE as an output of the random forest classifier. Figure 7 demonstrates the most important features, by ecozones.

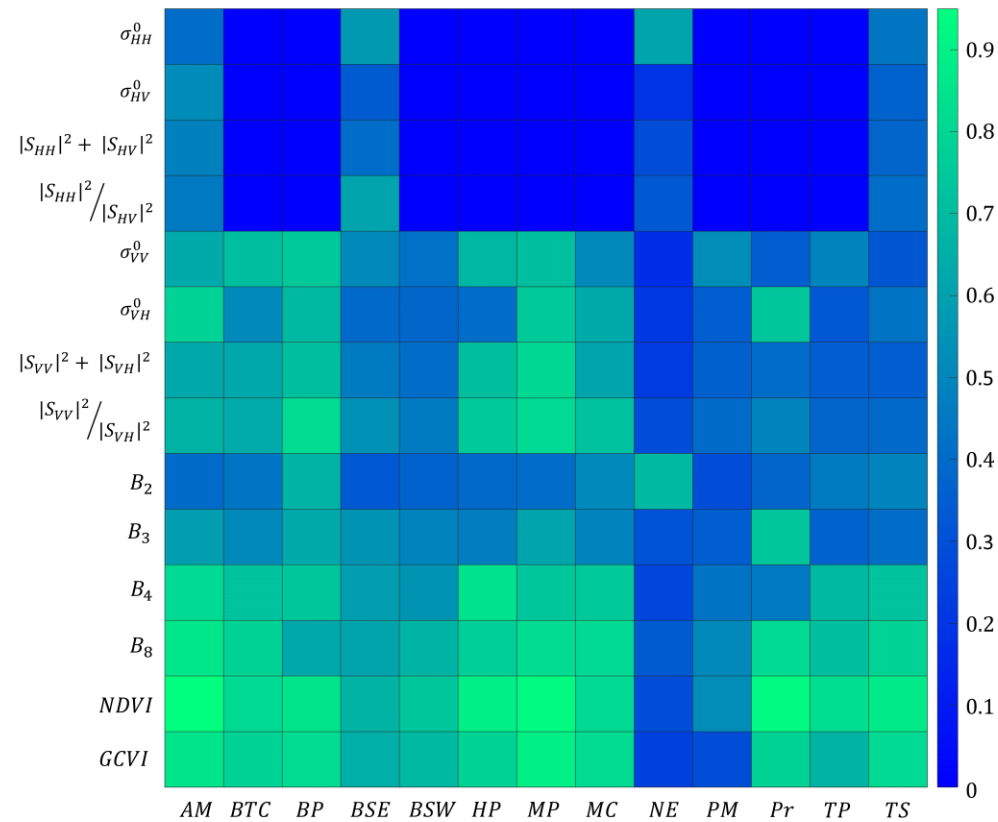


Figure 7. Normalized variable importance returned by random forest models trained on each ecozone.

Overall, the extracted features from optical data are more helpful for achieving higher accuracies, compared to SAR features. NDVI is the most important feature in many ecozones, particularly in ecozones with dominant agricultural activities (e.g., AM and Pr). GCVI and B_8 (Near-infrared) are also important features in several ecozones. This is expected, as forests, wetlands, and agricultural fields are dominant land cover classes throughout most of Canada’s ecozones. Although B2 is the least important optical features in most ecozones, it shows greater importance in the NE ecozone, given the presence of several small and big water bodies across this ecozone. Notably, there was a lack of dual-polarized HH-HV data in most of Canada ecozones. These features are illustrated with dark blue in Figure 7 in those regions. Similar to NDVI, albeit with a lower rank, $\frac{|S_{VV}|^2}{|S_{VH}|^2}$ was identified as an important feature for ecozones with dominant agricultural fields (e.g., AM). This is expected, as σ^0_{VV} observations are appropriate for discriminating herbaceous wetland classes, and dominant scattering mechanisms of vegetation are volume scattering, and they have the strongest responses in the cross-polarized signal (σ^0_{VH}). Span or total power, extracted from dual-polarized VV-VH data, and σ^0_{VH} are also among the useful SAR features in many ecozones.

It is often very challenging in the study like this to source a large amount of quality data from such a wide variety of organizations, collaborators, institutions, and more. The present study would be impossible without this data. In this study, we have managed to produce a Canada-wide wetland map with very high overall accuracies. It is important to note, however, that in the case of collected data such as this[SH4], there will naturally be differences in the methods which were used to collect and produce the data, the purposes for which the data was collected (many not for originally produced for application in imagery classification), the years these data were collected and so on. These issues are entirely expected in studies such as these. [SH5]Referring to section 2.2, there are large differences in the amount and characteristics of data available across and within individual ecozones. For example, some datasets may have more spectrally homogenous polygons than others, depending on their original purpose. Additionally, the distribution of the datasets does not always adequately represent the entirety of the ecozone area. All of this will have impacts on the quality of the final classifications and must be considered when interpreting the results. While effort was made to standardize across datasets, such as removing inappropriately sized polygons, and removing any obviously out-dated polygons, much more dedicated work is needed to modify and make these datasets as cohesive as possible, which was beyond the time and resources available to this study, and is an on-going process.

Nevertheless, these datasets may act as a substantial jumping-off point for the development of a Canada-wide wetland dataset suitable for applications in remote sensing. The significant effort would need to be dedicated to carefully examine all available wetland data, modifying their boundaries to produce more homogenous polygons, removing out-dated or inaccurate polygons, and perhaps further dividing the bog, fen, swamp, and marsh polygons into sub-classes based on broad vegetation characteristics (treed fen, shrub swamp, emergent marsh etc.,), which would also contribute to improving the homogeny of the polygons. [SH6]This, however, is made more difficult given the transient nature of wetland boundaries over the years, seasons, and even days. Incorporation of some hydrological and topographical data may improve the overall classification as well, particularly that of the swamp. Additionally, greater amounts of non-wetland land cover would contribute to a better overall-quality remote-sensing centered wetland dataset.

In addition to reference data collection, it is recommended to evaluate land cover change at local, regional-, or national-scales on a periodic basis, given the inherently dynamic nature of wetlands. Change detection based on multi-temporal satellite imagery provides a unique opportunity to monitor these changes in a cost- and time-efficient manner.

4. Conclusions

Wetland mapping and monitoring, especially at large scales, is challenging due to the inaccessibility and diversity of wetlands, fuzziness of wetland’s boundaries, as well as the cost and time requirement for field data collection. Nevertheless, recent advances in remote sensing tools, such as the availability of high-resolution open-access satellite imagery as well as powerful cloud computing resources, alleviate these issues to the feasible extent, offering unprecedented opportunities for monitoring these important natural resources using cost and time-efficient methods. By leveraging the state-of-the-art remote sensing techniques, this study produced the second generation of 10 m wetland inventory map of Canada using the RF classifier and data collected from dual-polarimetry Sentinel-1 SAR and multi-spectral Sentinel-2 optical Earth observations on the GEE cloud computing platform.

Compared to the first generation of this product, RF models were trained for each ecozone rather than each province or territory, which increased wetland classification accuracy. This improvement is a result of more commonality between wetland vegetation classes within an ecozone compared to the provincial administration borders. Furthermore, significant effort has been devoted to the data collection to prepare structured, cleaned, and consistent training data for each ecozone, which included data acquisition, labeling, and improvement of existing data. Because a data gap was identified in the Northern ecozones, high-resolution optical data from Worldview-2 and Pleiades were used to delineate wetland training data in those regions. Using this well distributed training data, the whole country was mapped with an overall accuracy approaching 86%, representing an improvement of 7% compared to the first generation. Accuracy varied from 76% to 91% in different ecozones, depending on available resources. Overall, the results of the RF variable ranking demonstrate the greater importance of the optical features compared to the SAR features in all ecozones. NDVI is found the most important optical feature, followed by GCVI and NIR band. Among the SAR features, $\frac{|S_{VV}|^2}{|S_{VH}|^2}$ and σ_{VH}^{o} illustrate the greater contribution to the overall accuracy relative to others. Nevertheless, there was a lack of dual-polarized HH-HV data in many ecozones. Thus, these results can not compare the capability of extracted features from HH-HV and VV-VH data with each other.

Future works can investigate the effect of incorporating additional high-quality satellite imagery collected by advanced SAR missions, such as L-band ALOS-2, L- and S- bands NASA-ISRO Synthetic Aperture Radar (NISAR), or Hybrid Compact Polarimetry (HCP) data from RADARSAT Constellation Mission (RCM) satellites. It is expected that adding these valuable data will improve the classification accuracy considerably.

Acknowledgment

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