The Second Generation Canadian Wetland Inventory Map at 10 Meters Resolution Using Google Earth Engine

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The Second Generation Canadian Wetland Inventory Map at 10 Meters Resolution Using Google Earth Engine

La deuxième génération de la carte de l'inventaire canadien des milieux humides à une résolution de 10 mètres en utilisant Google Earth Engine

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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 and results of our first-generation Canadian wetland inventory map at 10-m resolution. Iin order to increase wetland classification accuracy, the main contributions of this new study are adding more training data to the classification process and training Random Forest (RF) models on the Google Earth Engine (GEE) platform within the boundaries of ecozones rather than provinces. A considerable effort has been devoted to data collection, preparation, standardization of datasets for each ecozone. The 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, this second generation wetland inventory 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.

RÉSUMÉ
Récemment, on a constaté une augmentation significative des efforts visant à mieux inventorier et gérer les écosystèmes importants au Canada en utilisant des techniques de télédétection avancées. Dans le cadre de cette étude, nous avons amélioré la méthode et les résultats de notre carte de l'inventaire canadien des milieux humides de première génération à une résolution de 10 m. Afin d'accroître la précision de la classification des milieux humides, les principales contributions de cette nouvelle étude sont l'ajout de donnees d'apprentissage supplémentaires au processus de classification et la formation de modèles de forêts aléatoires (FA) sur la plateforme Google Earth Engine (GEE) dans les limites des écozones plutôt que des provinces, Un effort considérable a été consacré à la collecte de données, à la préparation, et à la normalisation des ensembles de données pour chaque écozone. Le nettoyage des données a révélé un manque de données dans plusieurs écozones nordiques. En conséquence, des données optiques à haute résolution, provenant de Worldview-2 et de Pléiades, ont été acquises pour délimiter les zones d'apprentissage des milieux humides basées sur l'interprétation visuelle dans ces régions. En utilisant ces données bien réparties, la deuxième génération de la carte d'inventaire des milieux humides représente une amélioration de 7% par rapport à celle de la première génération. La précision varie de 76% à 91% dans les différentes écozones, en fonction des ressources disponibles. En outre, l'analyse des variables significatives du FA, réalisée pour chaque écozone, montre que $\frac{|S_{VV}|^2}{|S_{VH}|^2}$ et NDVI, extraits respectivement des données Sentinel-1 et Sentinel-2, étaient les caractéristiques les plus importantes pour la cartographie des milieux humides.

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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. 2020b; 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 (Tamiminia et al. 2020).

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. 2018a; Wulder et al. 2018a; 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 (Gorelick et al. 2017; Mahdianpari et al. 2020a; Shelestov et al. 2017). Advancements in methods for land cover mapping and more are discussed in greater detail by Wulder et al. (2018a). Such 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 various sectors of natural resource management (Beaton et al. 2019; Duan et al. 2020; Fuentes et al. 2020; Hermosilla et al. 2018), including wetlands (Chen et al. 2017; Mahdianpari et al. 2018a, 2020b; Wulder et al. 2018b) 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 and has been exemplified in recent work by both Wulder et al. (2018b) and Mahdianpari et al. (2020b). Prior to 2018, a majority of Canada's wetland inventories were created at local, regional, and provincial scales, for example (DeLancey et al. 2019; Dingle Robertson et al. 2015; Jahncke et al. 2018; Mahdianpari et al. 2017, 2018a; Millard and Richardson, 2015; Mohammadimanesh et al. 2018c; 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. 2020b). 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 because the quality and accuracy of these inputs are ultimately reflected in the final inventory output (Mahdianpari et al. 2018b; Millard and Richardson 2015; Mohammadimanesh et al. 2018a; 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.

Methodology

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 "Reference data".

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 common non-wetland classes including water, foreset, shrub/grassland, agriculture, and exposed/urban. Descriptions of these classes can be found in Table 2. Generally, the wetland data for this study were gathered from multiple collaborators across Canada, and the non-wetland data were 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 were 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

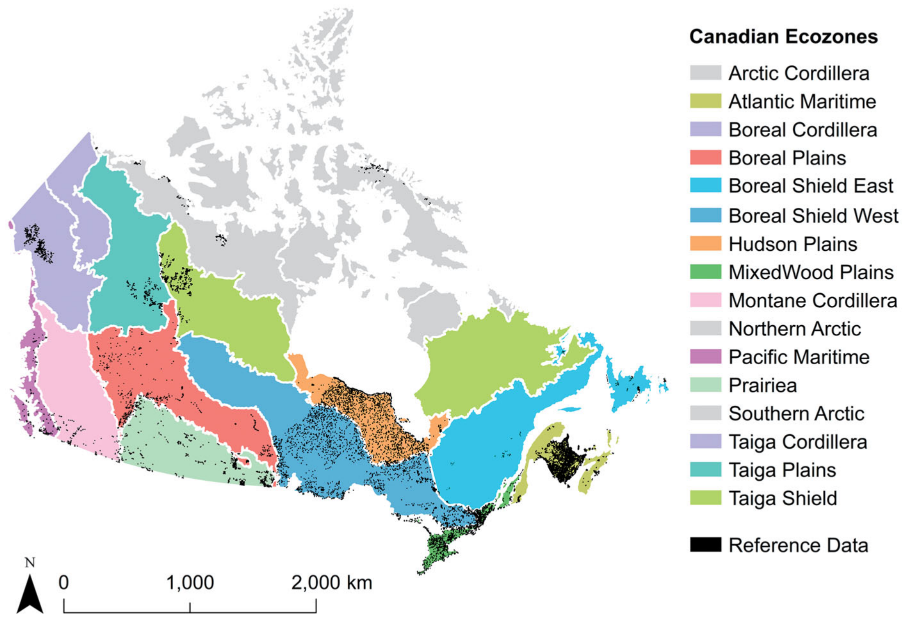

Figure 1. Canadian ecozones, with reference data distribution across Canada displayed in black. The Boreal Shield ecozone has been split into two. For the purposes of this research, the 3 northern-most ecozones (Arctic Cordillera, Northern Arctic and Southern Arctic) have been combined into a single area. The Taiga and Boreal Cordillera ecozones have also been combined into a single area.

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 because 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 a small number of 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 sharing similar landscape features. These ecozones include the Taiga Cordillera and the three northern-most ecozones (Arctic Cordillera, Nortern Arctic, and Southern Arctic), which were merged to create two broad multi-ecozone boundaries. The three northern ecozones were merged with one another because each lacked any wetland reference data and all three are located above the treeline. Though the Taiga Cordillera ecozone shares a boundary with two ecozones (Boreal Cordillera and Taiga Plains), the Taiga Cordillera was ultimately merged with the Boreal Cordillera due to shared landscape characteristics such as substantial mountainous areas (Ecosystem Classification Group 2010) and relatively low estimates of wetland presence (Environment and Climate Change Canada 2016), verses the Taiga Plains characterized by lowlands (Federal, Provincial, and Territorial Governments of Canada 2010) and extensive wetlands (Environment and Climate Change Canada 2016). Note that by merging ecozones, there will likely be an impact on the accuracy of wetland classification in these areas. The Boreal Cordillera dataset, for example, will likely not characterize wetlands in the Taiga Cordillera as accuractly, impacting final classification results. Additional data cleaning steps, including the standardization of naming conventions to conform to the classes outlined in Table 2, 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 were not any wetland data available to this study for the northern-most ecozones, and because Google Earth has limited or inconsistent imagery in northern Canada, very high resolution (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. Effort was made to select the most recent summer imagery available, though the selection was constrained by image

Table 1. A summary of 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 sizes, and the processing time and the number of Sentinel-1 and -2 images required to produce classifications.

Ecozone	Spatial location	Area (km^2)	# Sentinel images	Process time (days)	Description
Atlantic Maritime (AM)		206,105	HH-VV: 601 VV-HH: 925 S2: 2931	2	Has a maritime climate. The most common land cover is forest. Agriculture is the most common human activity. The most common wetlands are treed (swamp, bog, fen).
Boreal and Taiga Cordillera (Boc)		206,104	HH-VV: 601 VV-HH: 925 S2: 2931	2	Summers are short and cool. Dominating land cover includes mountains and tundra to the north and forests to the south. Wetlands are less common here than the neighboring Taiga Plains. Wetlands are most common in valleys.
Boreal Plains (BP)		713,733	HH-VV: 0 VV-HH: 2525 S2: 5184	0	Has a continental climate. Forest is the most common natural land cover type. Agriculture mostly present along the south edge and the north-east. The most common wetlands include conifer swamps, fens, and bogs.
Boreal Shield East (BSE)		797,737	HH-VV: 1519 VV-HH: 1871 S2: 5371	9	Moderate summer and winter temperatures. Part of he largest Canadian ecozone. Low elevations dominated by forest and shrubs with minimal anthropogenic land cover. Peatlands are the most common.
Boreal Shield West (BSW)		1,059,793	HH-VV: 0 VV-HH: 2078 S2: 7825	11	Moderate summer and winter temperatures. Part of the he largest Canadian ecozone. Low elevations dominated by forest and shrubs with minimal anthropogenic land cover.
Hudson Plains (HP)		364, 924	HH-VV: 0 VV-HH: 2078 S2: 3757	4	Has a maritime climate. Extensive wetlands are present, particularly peatlands. Marsh is common along the north. This area is often referred to as Canada's largest wetland complex. There is relatively little forest present.
Mixedwood Plains (MP)		117, 240	HH-VV: 0 VV-HH: 682 S2: 1860	1	The most populated ecozone characterized by a climate of warm summers and cool winters. The landscape is flat and dominated by agriculture. Most wetlands are located along the edge of the ecozone and to the northeast.
Montane Cordillera (MC)		477, 899	HH-VV: 0 VV-HH: 1965 S2: 4292	4	The most diverse topography and climate relative to other ecozones, with various mountain ranges present. Forest covers over half of the land surface. There is little wetland coverage, mostly located along rivers and in valleys.
Northern Ecozones (NE)		2, 504, 089	HH-VV: 1995 VV-HH: 1929 S2: 15144	14	Characterized by low temperatures and permafrost. Mountains and glaciers dominate the north, and barrens and plains to the south. There is little human presence. Wetlands, particularly peatlands, are dispersed through the barrens and along waterways.
Pacific Maritime (PM)		205, 065	HH-VV: 0 VV-HH: 1820 S2: 3013	2	Has a mountainous maritime climate. The Coast Mountains and extensive forests dominate the landscape. Most anthropogenic land cover is located at the southern end of the ecozone. There are relatively few wetlands here.

(*Continued*)

Table 1. Continued.

Ecozone	Spatial location	Area (km^2)	# Sentinel images	Process time (days)	Description
Prairies (Pr)		460, 314	HH-VV: 0 VV-HH: 1350 S2: 4069	4	More variable climate than other ecozones. Almost entirely covered in agriculture. There are very few wetlands located here, having been lost to agriculture. Wetlands that are present are very small “prairie potholes.”
Taiga Plains (TP)		620, 257	HH-VV: 0 VV-HH: 1584 S2: 5091	5	A argely flat area. There is a colder climate in the north verses the south. Most land cover is forest and shrub, and little human presence. Wetlands of many types are widespread, including swamps, peatlands, and marsh.
Taiga Shield (TS)		1, 330, 050	HH-VV: 698 VV-HH: 2218 S2: 8392	12	Open forest transitions to shrub and tundra moving north. There is little human activity. Wetlands make up around 13% of the area, but trends indicate wetland expansion due to changes in weather and permafrost.

Table 2. Wetland and non-wetland reference data classes (Agriculture and Agri-food Canada, 2018; National Wetlands Working Group, 1997).

Ecozones	Type	Description
Bog	Wetland	Peatland dominated by sphagnum moss and ericaceous shrubs receiving water and nutrients from precipitation only.
Fen	Wetland	Peatland dominated by mosses, sedges and shrubs receiving water and nutrients from multiple sources.
Swamp	Wetland	Wetland dominated by woody tree and shrub vegetation with standing or moving water present, depending on the the season.
Marsh	Wetland	Wetlands dominated by emergent sedges, reeds and rushes with persistant or frequent standing or slow moving nutrient-rich water.
Water	Non-wetland	Open fresh and salt water bodies including lakes, ponds, rivers, stream, bays, etc.
Forest	Non-wetland	Dry landscapes dominated by trees including coniferous and deciduous species.
Shrub/Grassland	Non-wetland	Dry landscapes dominated by low-lying vegetation including woody and herbaceous plants.
Agriculture	Non-wetland	Land used for growing crops of all kinds and pastures growing grassy vegetation for hay.

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 were 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. The fen classification was chosen rather than bog as the fen class better captures the variation present in peatland vegetation composition. This imagery was essential for producing wetland data for the northern ecozones; however, the dataset remained small in spatial extent due to the limited extents of the imagery, and as a result will likely impact the accuracy of the final classification result, particularly in areas furthest from the reference polygons. Non-wetland classes were delineated using the VHR imagery as well.

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 VHR imagery or ancillary land cover datasets, including the 30 m resolution land cover map of Canada provided by the Canada Centre for Mapping and Earth Observation (CCMEO 2019). These data were checked against recent Google Earth and Sentinel-2 imagery for accuracy, and to correct any classification errors that may result as land cover changes over time. Table 3 summarizes the number of

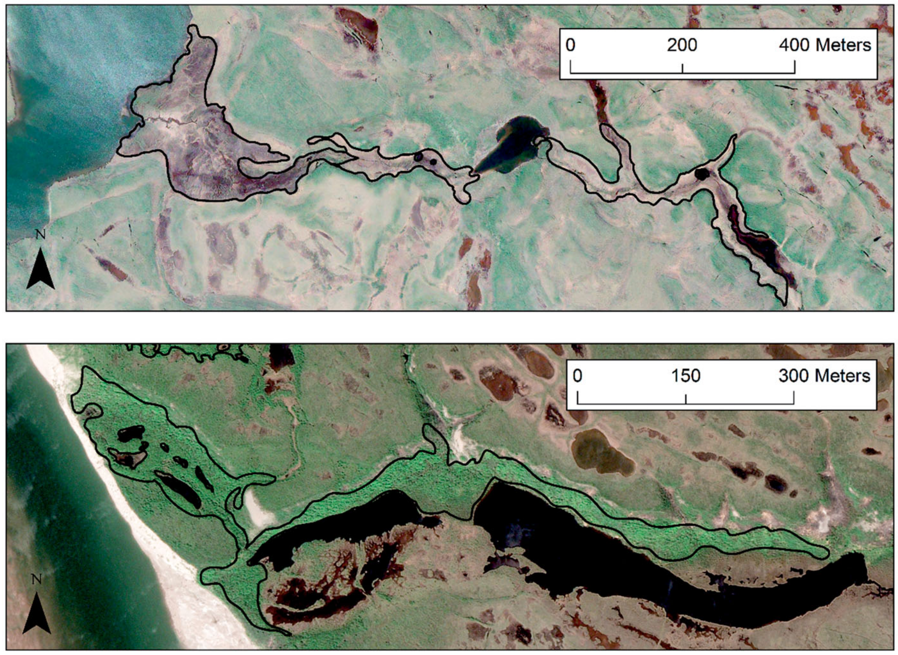

Figure 2: Wetland delineation using VHR imagery. Top: Peatland delineation using June 29th 2016 Pleaides imagery. Bottom: Swamp delineation using June 29th, 2015 WorldView-2 imagery.

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.

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 summers of 2017-2019 from Sentinel-1 and Sentinel-2 data (Gorelick et al. 2017). 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.

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 7×7 was then applied. Next, SAR backscatter values and other derivatives of these values were extracted and incorporated into the classification scheme. Table 4 presents extracted features from Sentinel-1 and Sentinel-2 imagery for wetland classification.

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 non-flooded vegetation from herbaceous wetlands (Mohammadimanesh et al. 2018b). 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.

Table 3. Summary of the reference data employed for each ecozone.

Ecozones	# Wetland polygons	# Upland polygons	Description
AM	3000	802	The wetland reference data were selected randomly from a New Brunswick dataset gathered between 2013 and 2015. Dataset came with ancillary descriptions of hydrology and vegetation. Non-wetland polygons were produced using the Crop Inventory maps and Google Earth.
Boc & TC	348	336	There is no Crop Inventory coverage here, so non-wetland polygons were produced using visual assessment in Google Earth. The dataset is dated 2016 and is located in and around the Yukon communities of Haines Junction and Whitehorse. Little ancillary information available.
BP	200	480	Wetland data came from five datasets collected between 2013 to 2016. The Crop Inventory maps guided non-wetland land cover delineation. Because the reference dataset was derived from five sources, there is likely great variation in how wetlands were classified and delineated.
BS East	612	550	Wetland data derived from multiple datasets across Newfoundland and Labrador dated between 2015-2019. The original purpose of the data was for wetland classification using remote sensing. The Crop Inventory maps guided all non-wetland land cover delineation.
BS West	2154	548	Wetland information derived from a very large wetland dataset in Ontario dated between 2013 to 2018. Onlythose wetlands that had been listed as being verified and evaluated were kept. The Crop Inventory maps guided all non-wetland land cover delineation.
HP	2000	345	The Ontario wetland dataset was used to derive wetland polygons. Refer to the section discussing the data for the Boreal Shield West ecozone for more information. Because this area lacked Crop Inventory coverage, non-wetland polygons were delineated based on assessment of Google Earth.
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 online Canadian Wetland Inventory by Ducks Unlimited (DCI) was referred to from which a small number of 2012 wetland polygons were gathered. There were no bog polygons and very few fen polygons.
NE	120	294	No available wetland data or Crop Inventory coverage of the three most northern ecozones. Details on development of a dataset for this area using VHR imgery discussed earlier in this section.
PM	117	296	Wetland polygons were derived from a dataset collected in and around the Vancouver area in 2016. There was very little data for the bog class. Additionally, most of the bog polygons are derived from a single large bog (Burns bog). Crop inventory was used to obtain non-wetland polygons.
Pr	250	600	Datasets were all gathered around the Assinboine River Valley and Whitewater Lake in Manitoba between 2007 to 2009. Only a small numer of polygons 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 between 2015 and 2020. Only half of the total polygons fell within the Taiga Plains ecozone. These datasets also provided training polygons for non-wetland land cover.
TS	220	327	Wetland polygons obtained from the same dataset discussed in the Taiga Plains ecozone. 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 as well.

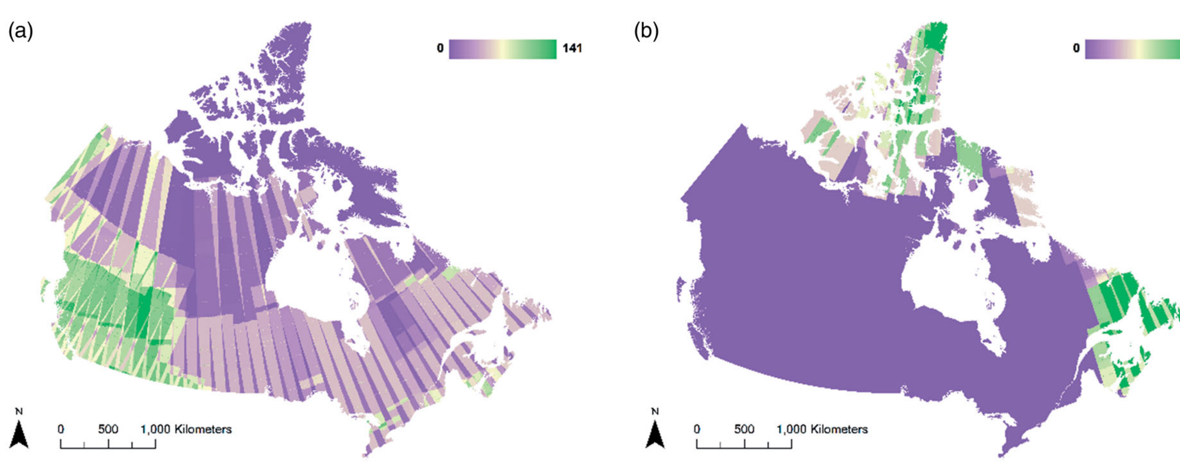

Figure 3. The total number of (a) Sentinel-1in VV-VH mode and (b) Sentinel-1 HH-HV in mode observation during the summers of 2017–2019 in Canada. The color bar represents the number of collected images.

Table 4. Features extracted from Sentinel-1 and Sentinel-2 imagery in this study. σ^0_{XX} and σ^0_{XY} denote co- and cross-polarized sigma nought in the logarithmic scale (dB).

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

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 10 m resolution to produce a high-resolution (10 m) wetland inventory map. To detect and mask out the remaining clouds and cirrus, the QA60' bitmask band (a quality flag band) available in the metadata of Sentine-2 imagry was employed. To remove other clouds and aerosols a thresholding technique was then applied using the Sentinel-2 aerosol band (band1 > 1800). Figure 4 demonstrates the spatial distribution of all available Sentinel-2 observations. In addition to the normalized difference vegetation index (NDVI) that used in our previous study (Mahdianpari et al. 2020b), 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. Leveraging the GEE composite function, each seasonal group of images were stacked into a single median composite on a per-pixel, per-band basis, including four spectral bands, NDVI, and GCVI.

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. 2020b); 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 provincial borders (He et al. 2012; Pickell et al. 2016). 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 because training data can be a major bottleneck in the machine learning algorithms. The processing time for training RF models in different ecozones is presented in Table 1.

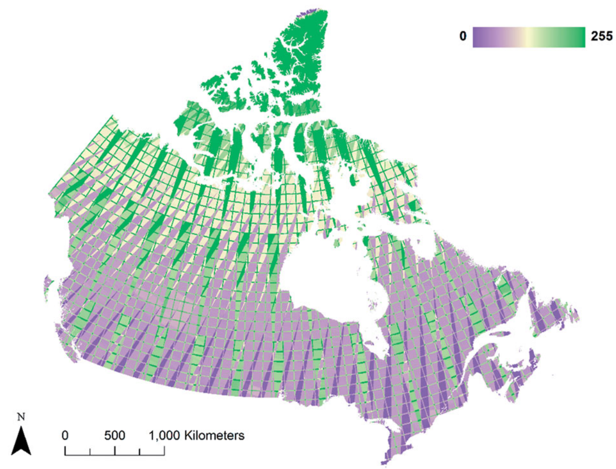

Figure 4. The spatial distribution of all available Sentinel-2 observations during the summers of 2017–2019 in Canada. The color bar represents the number of collected images.

Results and Discussion

Three examples of classified wetland ecozone maps, in ecozones with average, high and low wetland coverage, are presented in this section. Figure 5 demonstrates the wetland inventory map of the MP, HP, and Pr.

Figure 5a shows the results of the MP classification. A little less than half of the ecozone is covered in wetlands, the most common being swamp, bog and fen, largely located along the north and north-east edge. Marsh wetlands are very rare. The spatial extent and location of wetlands, and the dominance of swamp and peatland classes, is consistent with a previous assessment of this ecozone, which states that swamp is the most common wetlands in the ecozone (ESTR Secretariat 2014). The most common non-wetland land cover in the MP is agriculture by far. The majorty of wetlands are restricted along the edges of the agricultural areas, though several small wetlands are located distributed throughout.

Figure 5b 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

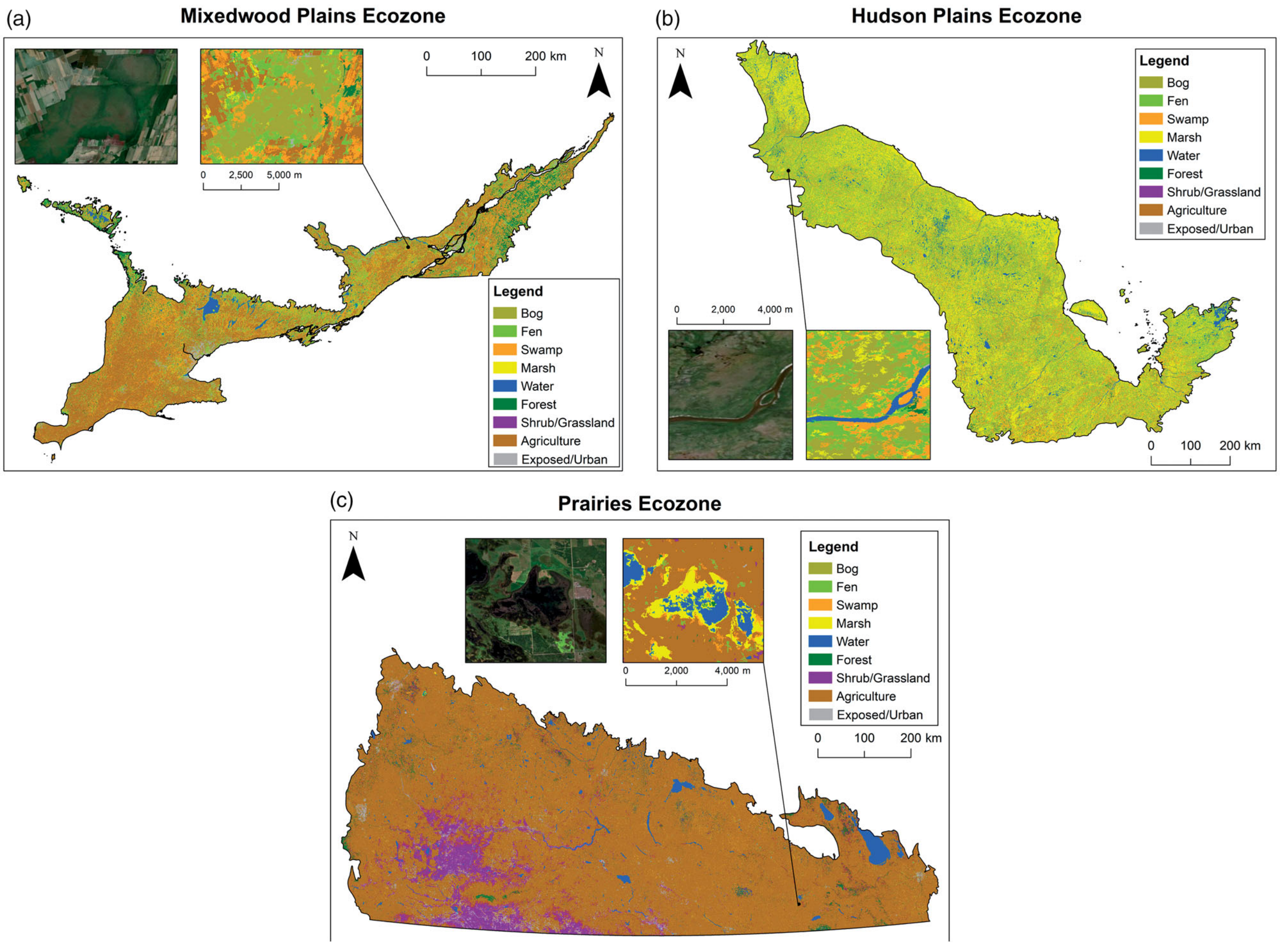

Figure 5. Classified maps of the (a) Mixedwood Plains, (b) Hudson Plains, and (c) Prairies ecozones.

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 center. Non-wetland land cover types are mostly absent.

Figure 5c demonstrates the results for the Pr, wherein wetlands are shown to cover a little less than 3% of the total ecozone area. The most common wetland classes here includes marsh and swamp. Peatland presence is minimal. These results reflect previous assessments of wetlands in this ecozone, which state that around 3% of the ecozone are made up of wetlands largely comprised of praire pot holes. (Ecosystem Classification Group 2010). Praire pot holes are small shallow water wetlands, and in this classification are represented by the marsh class. These wetlands are located in small areas throughout the agricultural landscape, making up almost the entirely of the ecozones landscape.

Figure 6 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 "Reference data". 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.

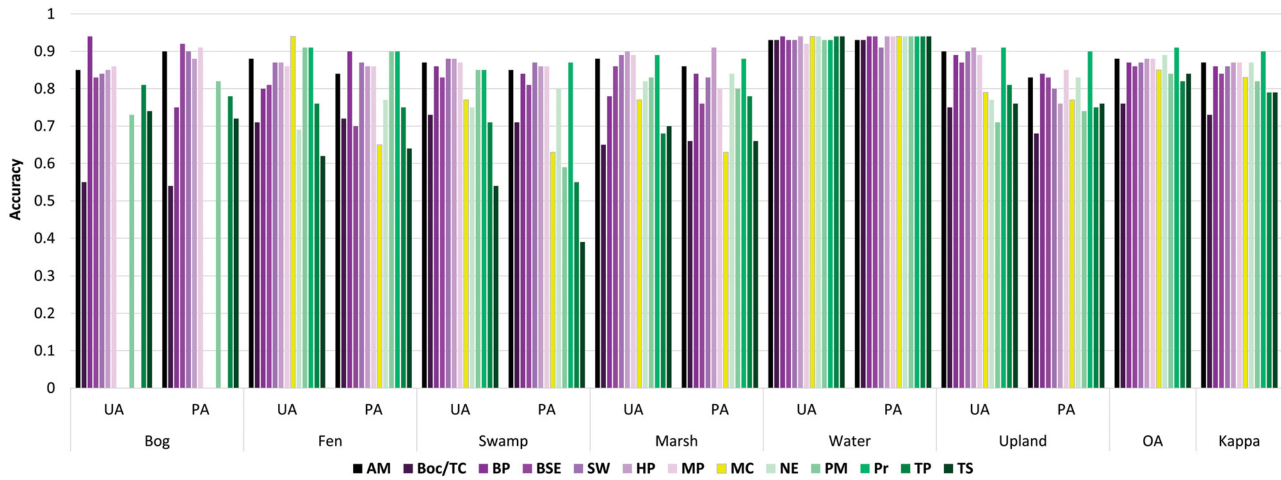

Figure 6. Accuracy assessment indices determined for each ecozone (UA: User's accuracy; PA: Producer's accuracy, OA: Overal accuracy, Kappa: Kappa coefficient, AM: Atlantic Maritime; Boc/TC: Boreal and Taiga Cordillera; BP: Boreal Plains; BSE: Boreal Shield East; BSW: Boreal Shield West; HP: Hudson Plains; MP: Mixedwood Plains; MC: Montane Cordillera; NE: Northern Ecozones; PM: Pacific Maritime; Pr: Prairies; TP: Taiga Plains; TS: Taiga Shield).

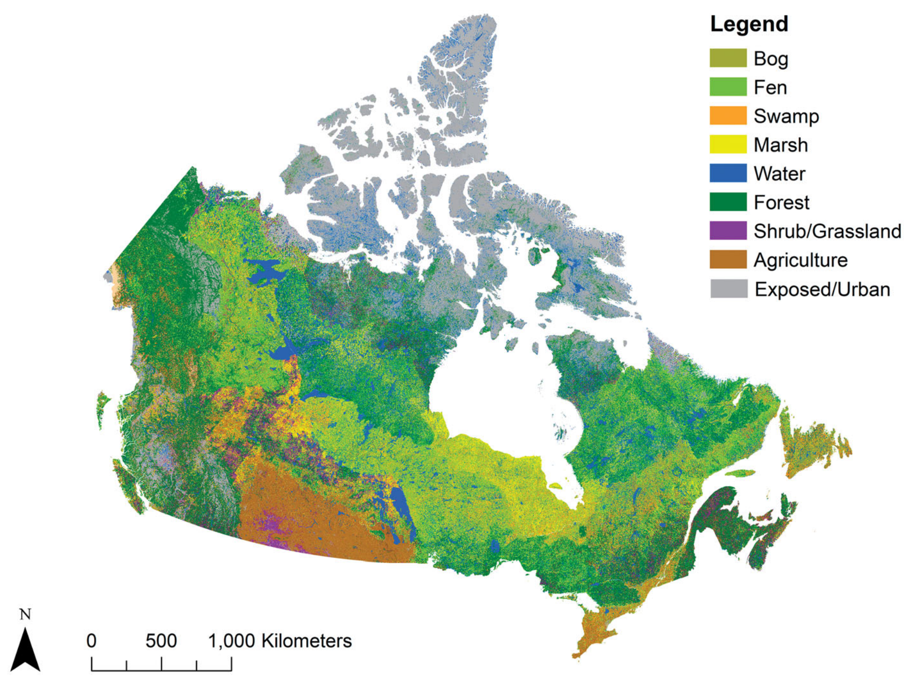

Figure 7. The second generation of Canada-wide wetland inventory map.

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%. However, it should also be noted that while the overall accuracy for the Northern Ecozone is high at 87%, this is likely inflated due to the limited test and train data available to classify this large area.

Figure 7 illustrates the second generation of the Canada-wide wetland inventory map at a spatial resolution of 10 m using the object-based RF classification.

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 was devoted to 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 was found the most important optical feature, followed by GCVI and near- infrared (NIR) band. Among the SAR features, $\frac{|\sigma^0_{VV}|^2}{|\sigma^0_{VH}|^2}$ and σ^0_{VH} 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.

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. 2020b). 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 center 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 has 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. 2020b), 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 10 m resolution imagery, or when topographical data cannot be applied as is often the case with large-scale studies such as this.

One of the significant advantages of the RF classifier is its capability to determine the importance of input features (i.e., variable ranking; Mohammadimanesh et al. 2019). 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 8 demonstrates the most important features, by ecozones.

Overall, the extracted features from optical data (i.e., spectral bands: B_2, B_3, B_4, B_8, NDVI, and GCVI) are more helpful for achieving higher accuracies, compared to SAR features (i.e., normalized Radar cross section, ratio, and span in both HH-HV and VV-VH modes). NDVI is the most important feature in many ecozones, particularly in ecozones with dominant agricultural activities (e.g. AM and Pr). GCVI and NIR (B_8) 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 B_2 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's ecozones. These features are illustrated with dark blue in Figure 8 in those regions. Similar to NDVI, albeit with a lower rank, $\frac{|\sigma^0_{VV}|^2}{|\sigma^0_{VH}|^2}$ 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

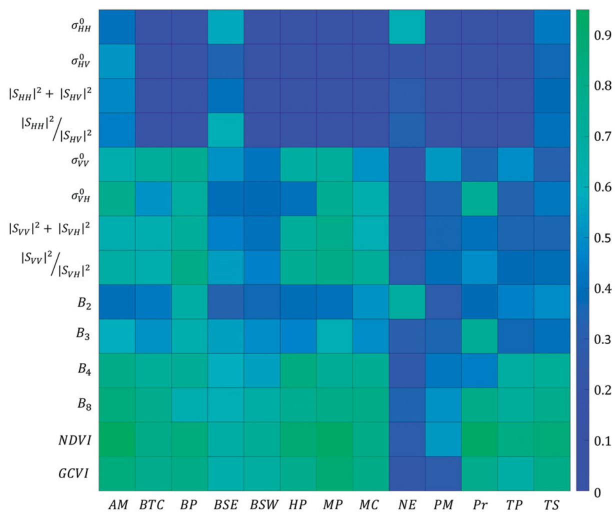

Figure 8. Normalized variable importance returned by random forest models trained on each ecozone.

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 a 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. It is important to note when working with such data the differences in the ways the various datasets were compiled. Each dataset will have been created by different people, using different methods, for different purposes (often not for the purposes of imagery classification), and during different time frames. These issues are entirely expected in studies such as these. Referring to Section "Reference data", 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. A 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. 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.

Beyond reference data collection, 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 Aperature Radar (NISAR), or Hybrid Compact Polarimetry (HCP) data from RADARSAT Constellation Mission (RCM) satellites (Adeli et al. 2020). It is expected that adding these valuable data will improve the classification accuracy considerably. Additionally, future work may improve upon current methods to more accurately classify in areas where there has been recent large-scale changes such as the fires in British Columbia in 2017 and 2018. Finally, it is recommended that land cover change be evaluated 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.

Conclusions

Wetland mapping and monitoring, especially at large scales, is challenging due to the inaccessibility and diversity of wetlands, fuzziness of wetlands' 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.

Overall accuracies for the 13 ecozones examined in this study ranged from 76% to 91%, 10 of which have overall accuracies greater than 81%. Ecozones with the lowest accuracies tended to occur in the northern parts of Canada (Taiga Plains, Taiga Shield, and the Boreal and Taiga Cordilleras) where little to no wetland reference data were available. The most important variables contributing the classification results in all ecozones include Sentinel-2 optical features such as NDVI, GCVI and NIR. SAR variables were ranked less important than optical vairables, though $\frac{|\sigma^0_{VV}|^2}{|\sigma^0_{VH}|^2}$ and σ^0_{VH} made the greatest contribution of all SAR variables investigated. Utimately, these results represent a 7% improvement over the first generation, through the use of ecozone rather than provincial boundaires, and through increased effort in reference data gathering and preparation.

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